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Deep Learning Technique for Oil and Gas Pipeline Surveillance

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***Abstract*— This research presents a model for detecting pipeline vandalism in oil and gas sector. Feed-forward deep learning technique was applied. The methodology adopted the Rational Unified Process (RUP), Convolutional neural network and UML tools where applied for the system design. The architectural design consists of three input parameters stored in the hidden neurons, and one output. A back-propagation Convolutional neural network was used to train the parameters. The system was implemented using Hypertext Pre-processor (PHP) programming language. An input interactive interface was generated for predicting parameters threshold values for pipeline intrusion threat ranging from (0-18) pound by square inch(Psi) for threat while (19 and above Psi) for normal. Comparison has been carried out on the outcome between existing system and the proposed system. Results shown in the graph, denoting manual digging, pipeline leakage, walking on pipeline, and pressure. The intrusion point is indicated at line six in the result table where the pressure drops as a result of manual digging. The use of Convolutional neural network in pipeline surveillance system has shown that oil and gas pipeline intrusion can be monitored and controlled.

Keywords— Vandalism, Prediction, Deep learning, Convolutional Neural Network, Pipeline, Surveillance,

I. INTRODUCTION

Deep learning is a branch of the artificial neural network in which its main activities was centred on the regulation of the unsupervised learning in data. The network has input layer, hidden layer and output layer in which the neurons are stored in the hidden layer . Deep learning has the ability to function like the human brain; it has numerous neurons such as the interconnectivity of the brain structure in which some network inputs are regularly fed through a feed-forward pattern, this simply means that signals passes through in one direction only without backward looping or circling back of the signal to the input layer [1].

There are basically three approaches of deep learning namely: supervised, unsupervised, and semi-supervised which have yielded undoubted progress. It has scored high achievements in various domains, such as in technologies and medical sciences including oil and gas industry, for instance in industries and production centres. The potential of deep learning were inculcated into self –driving cars, where sensitive sensors were calibrated into the data electronic control unit (ECU) to enhance appropriate processing. The sensor assessed the driving condition of the car or driving situation being classified through data fusion based on the advent of external and internal sensors [2].

Oil and Gas transmission pipelines play important role in the transportation of this vital energy for the national economy. With aging oil and gas pipelines, pipelines have suffered from various defects such as corrosion, cracks, unwanted intrusions etc. Several technological tools have been used for various areas of oil and gas pipeline intrusion detection and so on. My motivation was to apply deep learning as a defending tool against failure of pipelines which could lead to destruction of human health and also, interruption of oil and gas supplies.

New advancement in deep learning techniques have ignited a boom, in oil and gas facilities, it is exceptionally fundamental and urgent in the analysis of surveillance and security as it addresses major aspects of a security industry; for example, facial recognition, vehicle detection, behaviour analysis to mention but a few. It also includes the use of shrewd cards (national ID or immigration cards), information security desk top logons and so on.

II. RELATED WORK

The research carried out by [3] on Wireless Sensor Network for long distance pipeline monitoring is more of a review work with a conceptual diagram of oil distribution system and monitoring using wireless sensor networks (WSN). They were able to look at WSN monitoring challenges, routing challenges and localization challenges. The work was not able to say exactly what the pipeline segment will measure along the pipeline segment.

A research on Fault Tolerant Wired and Wireless Sensor Network Architecture for monitoring pipeline infrastructure was carried out by [4]. In the research work, they were able to look at the capability and reliability of using both wired and wireless sensors to monitor pipeline infrastructure. However, there was no clear architecture illustrating how the individual sensor nodes will be deployed and what parameters to be measured for a specified fluid. Also security of using the Wired and Wireless sensors was not included.

A research on a Framework for Pipeline Infrastructure Monitoring using wireless sensor networks was conducted by [5]. The work was able to look at the various WSN scenarios which include network deployment, network maintenance process, network discovery phase, and data collection and communication packet structure. Generally, the work is limited technically to provide monitoring for pipeline infrastructure. That is to say there was no illustration on what data are to be measured by the sensors. More so, security of both the sensor nodes and communication links was not considered.

The work of [6] proposed system architecture for oil pipeline surveillance and security using WSN with the simulation of the proposed system. However, there was no clear and detailed explanation on what parameters are to be measured along the pipeline infrastructure. More so, there was no clear illustration regarding the sensor node and communication link security. Closed Circuit Television (CCTV) surveillance systems are continually upgraded to have the present-day software technological features. In countries such as Boston, an additional technology has been added to locate activities such as gunshots which automatically spurs a quick positioning of a medical personnel, a police officer, to the place where the gunshots were heard or shot [7].China in recent time has tested about 200,000 CCTV cameras to have the ability to quickly alert police personnel when unwarranted individuals cluster at certain locations. China‘s national identification database and facial recognition software is upgraded to allow police recognise individuals under video surveillance. A Soft-computing approach is adapted to detect and identify sensor node failure using a Principal Component Analysis (PCA), and wavelet decomposition. But this method is very complex having incorrect computation faults [8].

III. METHODOLOGY

A. Constructive Research Methodology

Constructive investigation is one of the basic techniques uniquely used in computer science research field. Constructive method is one way of problem solving through the structure or use of simulations [9]. Construct is a paradigm often used to present the intended framework that demonstrates and defines new contribution in the proposed setting. This kind of method stresses on a unique validation that doesn't depend on empirical based approach, In this study, the foremost idea of Constructive approach and the Object- Oriented tools were used in the system design and implementation, that all construction is based on the present knowledge that allows the introduction and inter-connectivity of other missing components.

B. Rational Unified Process

In line with the Constructive Research Methodology which involves iterative refinement and redesigning of the practitioners requirement, an iterative object oriented design software engineering methodology known as RUP was used. The RUP aims at ensuring the production of high-quality software that meets the needs of its end-users, within a predictable schedule and budget [10]. RUP development team works in collaboration with the customers, partners, Rationale's product groups as well as Rationale's consultant organization, to ensure that the process is continuously updated and improved upon to reflect recent experiences evolving and proven best practices. An RUP activity creates and maintains models and emphasizes the development and maintenance of model semantically rich representations of the software system under development [11]. RUP is a guide for how to effectively use the Unified Modelling Language (UML). The UML is an industry-standard language that allows the use of clear communication requirements, architectures and designs [12]. The UML was originally created by Rational Software, and is now maintained by the standards organization Object Management Group (OMG).

IV. SYSTEM DESIGN

The proposed system, wireless sensor cameras are trained using Convolutional Neural Network (CNN). These cameras are placed in an unattended environment to monitor and capture an intrusion of the pipeline. The historical database keeps track of these activities based on the incoming sensory information from the wireless sensor camera mounted at several pipeline areas. If a particular activity persist over time and is inconsistent with the set value of the area of interest, the fuzzy logic predicts it, otherwise it ignores (forgets) it. The predicted activity is passed to a threat alert which flags a particular threat to the pipeline system. The Surveillance camera captures the image and displays it on the console.

A. Effectiveness of Convolution Neural Network in Prediction

Convolution is one of the main parts in a CNN. Convolution is a mathematical term and refers to a combination of two functions to produce a third function, merging two sets of information. In the proposed system, numerous convolutions are performed on the input, where each operation uses a different filter, this results in different feature maps. After all, the feature maps are put together as a final output of the convolution layer.

A convolutional neural network can learn a task by repeated adjusting of weights.
CNN is made up of hierarchy of layers, and the neurons in the networks are arranged along these layers, theses neurons are connected to the external environment from input and output layers. The weights are now modified to bring the network input/output behaviour into line with that of the environment. When the neuron is supplied with the input and numerical weight, it has a means of computing its activation function and sends it as an output signal through the output link. The output signal can be raw data or output of other neurons. The output signal can either be the final solution to the problem or an input to other neurons. Neurons computes the weighted sum of the input signals and compares the result with a threshold value A. if the total input is less than the threshold, the neuron becomes activated and its output attains a value 1. Mathematical model description of the CNN neuron for simplicity is given below:

W: = w –α *

Where.
w stands for each learnable parameter.
α stands for a learning rate.
L stands for a loss function.
It is of note that, in practice, a learning rate is one of the most important hyper parameters to be set before the training starts. For prediction

y is the summation of xi greater b with i ranging from 1 to n

Where;
n : is the number of neuron inputs
b : the threshold value
x : is the value of input range from 0 to n
The function f will output the value 1 if the aggregation performed by the function g is greater than some threshold else it will return 0.

B. Oil and Gas Pipeline Monitoring using CNN

The main goal of this work is to exploit the available oil and gas pipeline contextual information to provide hypothesis on suspicious activities across the pipeline area. It is desired to red-flag any activity that persists over time and that approaches a restricted value or a set threshold based on the activity been carried out at a specific time. The architecture of the proposed pipeline monitoring system is a supervised learning based on CNN as shown below.

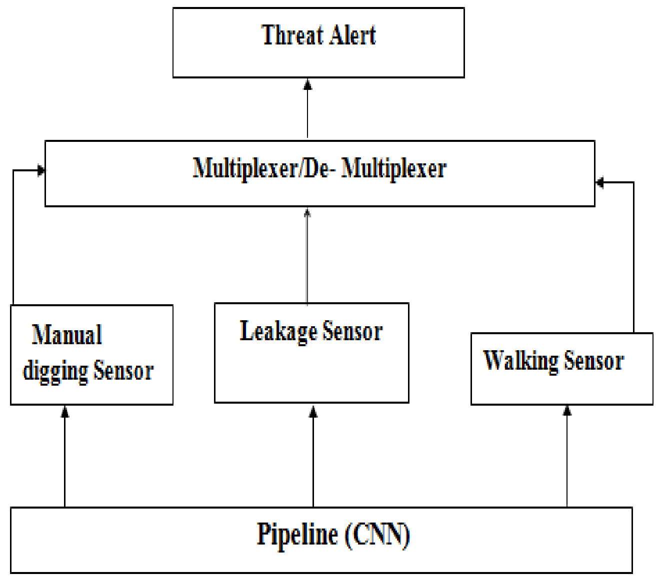

Fig 1: Proposed System Architecture

The system works as described; the contextual information (feature dataset) is broken down into a numerical context prediction activity; using the feature dataset module. The context information based on the help of sensors are fed to a CNN block which learns a sequential representation of the context in the previous time and then predicts the most likely sequences at the next time step. The predictions are then sent to a threat alert which flags predicted threat levels with high (abnormal) values.

A detail of the system is illustrated using a use case and a concept level design, as shown in fig.2 and in fig.3. Figure 2 captures a typical scenario in which wireless sensors are deployed in an unattended environment to monitor and collect data of certain threat related activities from the region of interest to a CNN AI Monitoring system and then to the control room where it is been seen by a human security personnel. The CNN Monitoring AI system model keeps track of these activities based on the incoming sensory information from the wireless sensors mounted at several pipeline areas. If a particular activity persist over time and is inconsistent with the set value of the area of interest, the system predicts it, otherwise it ignores (forgets) it. The predicted activity is passed to a threat alert which flags a particular threat to the pipeline.

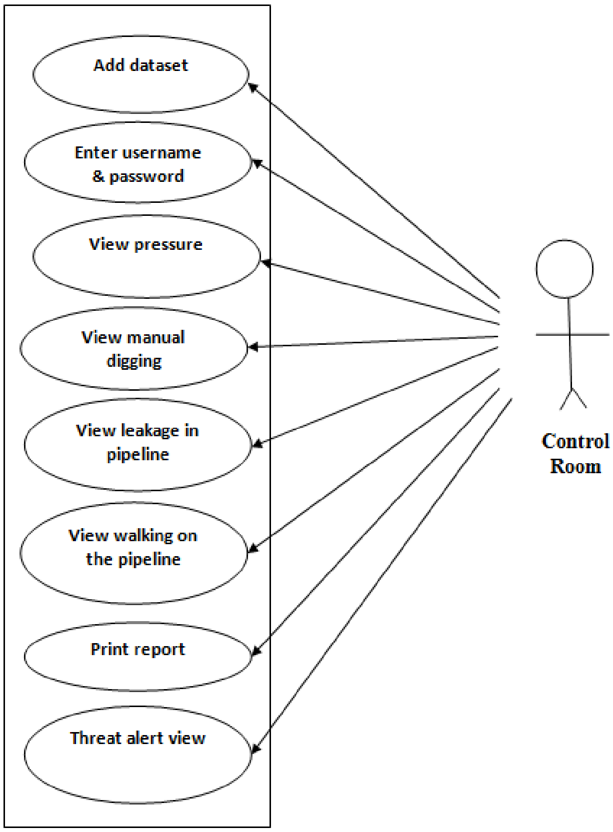

Fig 2: Use-case model of the Proposed Pipeline Monitoring System.

Fig.3 as can be observed contains concatenated local contextual parameters which are incorporated into Pipeline Monitoring System as traffic-ability values using wireless sensor. The traffic-ability is values between zero and one, where zero indicates no threat and one indicates threat. The pipeline local contextual data includes;

- Pipeline Leakage
- Manual Digging
- Walking on pipeline

The sensed signals (context parameters) are fed into the context learning module(CNN subsystem) through a multiplexer, and are transformed and seen by the CNN as words, The CNN subsystem keeps track of the sensed signals in the memory module and then passes these signals to the control subsystem (prediction module), which combines the individual traffic-ability values corresponding to each piece of contextual information into a value that would be used to indicate situations that poses danger and the one that does not.

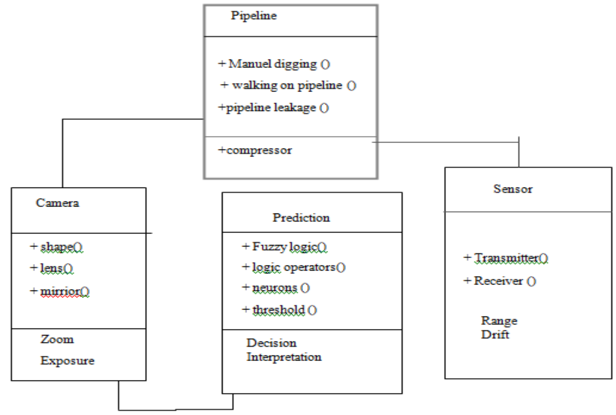

Fig 3: Concept-level design

The deployment interface includes the following parts:
Random Source: this part is made up of;

- Predicted Parameters sensor blocks: This converts the real time parameters like pressure, leakage in pipeline, manual digging and walking on the pipeline, etc. into electrical signal
- Display Sensor block: Displays the numerical state of the sensed data iii. Multiplexer block; this concatenates the entire sensed signal and synchronizes them through a transmission line to the CNN subsystem.
- CNN Subsystem: The CNN subsystem passes these signals through different signal line (transmission line) to the control subsystem.
- Control Subsystem: the control subsystem predicts the sensor output based on the signal it received from the CNN subsystem and displays a 1 to any predicted activity that poses threat and 0 to the activity that poses no threat

V. RESULTS AND DISCUSSION

Values are entered for each parameter, and a particular threshold is set for the system used in checking when an intrusion occurs in the pipeline. Table 4.1 Show the value data used in testing the system for an intrusion.

Crude oil pipelines are essentially transmission pipelines with large lines of about 6-48 inches in diameter that move gas through long distances and at high pressures between 200 – 1500 pressure per square inch (psi). But in the proposed system, the threshold for an intrusion is set to be any value below 18.0 Psi.

A deep learning technique for oil and gas pipeline surveillance consists of four main phases: Convolution layer,

feature extraction, classification and pooling layers in which the most crucial phase is the feature extraction phase.
Simulation experiments have been performed with the pipeline field dataset gotten from EPCL. The data obtained from EPCL comprises of three parameters: walking on the pipeline, manual digging and leakage in the pipeline. The numeric target attribute (labelled as 1 or 0) is intentionally embedded in each pattern to indicate the presence (indicated by a 1) or absence (indicated by a 0) of a threat.

Table 1: Simulation Result

Time (hrs)	Manual digging (cm)	Leakage (cm)	Walking On pipeline (kg)	Pressure (Psi)	Label
1:am	10.00	2	9	21.0	Ok
2:am	14	1	13	28.0	Ok
3:am	11	4	14	29.0	Ok
4:am	13	1	10	24.0	Ok
5:am	9	15	3	27.0	Ok
6:am	16	1	2	17.0	DANGER
7:am	14	5	13	32.0	Ok
8:am	4	11	14	29.0	Ok
9:am	12	8	10	30.0	Ok
10:a	10	6	12	24	NIL
11:am	1	16	1	19	Ok
00.0pm	15	12	10	37	Ok

Table 2. Threat Events Prediction Table based on simulation Result.

Input Parameters		***Label***	***Output***		***Label***
Manual Digging	***0-18***	***Normal***	***Pressure***	***0-18***	***1 (Intrusion)***
	19 - Above	***Danger***		***19-Above***	***0 (Normal)***
Pipeline Leakage	***0-17***	***Normal***			
	18 – Above	***Danger***			
Walking on the Pipeline	***0-16***	***Normal***			
	17 – Above	***Danger***			

Table 2.Is a breakdown of the prediction output of table 1.with the traffic-ability data and the labels. The traffic-ability are values between zero and one, where zero indicates no threat and one indicate threat.

A. Graphical Representation

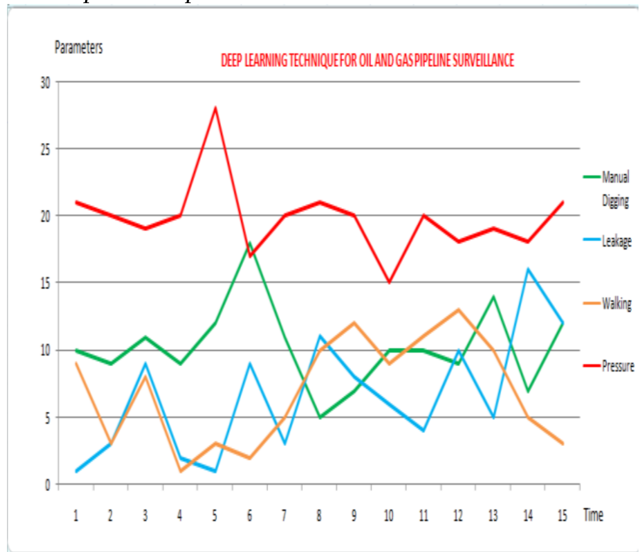

Fig.4. Graph of the Predicted Parameters against Time

The red line indicates the rising and dropping of pressure wave at different time intervals, at 1:00am the pressure wave is 21.1Psi,while the manual digging is 10.0cm ;leakage at 1.0cm and walking on pipeline at 9.0kg which indicates no threat because it is above the set point. At 2.0am the pressure dropped to 20.1Psi indicating no threat. At 5.0am there was a great increase in the pressure to 28.1 Psi while at 6am an intrusion occurred caused by manual digging, the pressure dropped to 17.0 Psi.

The green line indicate manual digging .At 1:00am, manual digging was at 10.0cm; at 5am it rose to12.0cm. At 6am it got to an intrusion point of 18.0cm, the system predicted danger. At 10am the pressure dropped to 15.0 Psi but there was no intrusion because all the parameters were below the set points. The blue line indicate leakage in pipeline, At 3am the reading was at 11cm indicating no threat while at 2pm it rose to 16cm causing the pressure drop to 18.0 Psi in the system, predicting a threat. The orange line indicates walking on the pipeline, all indicating no threat to the system.

VI. CONCLUSION

In conclusion, the Oil and Gas AI Pipeline monitoring system based on deep learning holds great promises as a future neural network model if properly planned. Using functional object-oriented approach, the ideas of advanced machine learning in deep learning such as the one proposed here can lead to better neural models for diverse kinds of tasks. Thus, it is desirable that researchers shift from using existing simple neural network architectures to more sophisticated ones.

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