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CORROSION DETECTION AND PREDICTION USING IOT AND MACHINE LEANING

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Abstract -Pipelines are used as a medium to transport the oil, however, low maintenance causing not only the loss of the material itself but as well to the surrounding people and environment. In order to tackle the incidents, experts are assigned and experiments are conducted to analyze the source of the leakage. The leakage is frequently triggered by moreover natural disaster such as earthquake or person carelessness such as near to the earth preservation of oil tube. Natural disaster is unpredictable and it is difficult to prevent; therefore, researches are carried out in detecting corrosion of transmission pipelines. A new oil pipeline corrosion prediction model is proposed in this article. An associative categorization method named categorization based on manifold connection rules is practical in the planned forecast model. This proposed prediction model named pipeline leakage detection which carried out by using Machine Learning (ML) algorithms in order to build an optimum decision tree. The decision tree is said to be optimum in terms of the genetic algorithm is used to examine the correlation between a group of association rules instead of using one single rule in predicting a case.

Key Words*:Corrosion detection, IoT, Machine Learning.*

1. INTRODUCTION

Corrosion is defined as the deterioration of a material, usually a metal, because of reaction with its surrounding environment. That response can be recognized as electrochemical procedure, which contains a variety of hard and liquid substances. The types of substances may differ as they depend on the environmental individuality on anywhere the pipelines are situated. On the whole, present are four rudiments that must act in response to lead the incidence of corrosion such as

1) Anode (oxidation reaction) Corrosion

2) Cathode (reduction reaction) No corrosion

3) Electrolyte (cautions and anions)

4) External path (usually metallic)

If any of the on top of rudiments is not obtainable, the pipelines will not decay or rust. Otherwise, corrosion will occur and decrease the width of the pipe partition to a number of degrees. If such a reaction is not terminated, the pipeline may form a rough gap (pitting), cracks on its surface and even ruptures.

Basically, corrosion can occur since of response of anode, cathode, and electrolyte on the metal outside of pipelines. To administer corrosion, the factors so as to be able to be those rudiments must be figured exposed. They are able to be recognized from two parts, which are the susceptibility of the pipes fabric and the surroundings that can start decay on the pipelines wall inside and outwardly. However, identifying causes will be intense on the ecological aspect because it is the factors so as to can guide corrosion might happen from a variety of factors. In this part, the surroundings that will be investigated are :

1) Atmospheric corrosion

2) Internal corrosion

3) Sub-surface corrosion.

Fig -1:Corrosion in pipelines

Owing to decay can shape leakage in the outside of pipelines, present are a number of penalty that can occur. Fluid let go, fire, and explosions are the belongings of such incident. In this case, the fluids release will be an initial impact that can occur when present is a hole on the tube wall. If it is linked with the flammable source, the explosion can occur. The inflammable source can be powder, haze, air combination, heat and burning surfaces, frictional sparks, auto ignition. If the ignition is not handled appropriately, the accidents can be extended to the fire and/or explosion. Fire and/or explosion are the most unwanted consequences. The exposure of fire and explosion can create smoke that may toxic human's health and any organisms in the surrounding area. The worst case is that it could produce thermal radiation that may majorly destroy the environment and properties also lose human lives.

2. LITERATURE SURVEY

Red-dark channels were previously defined and removed for background light and estimation the outbreak of this disease. Visualization compensation for object-camera distance retrieval Background and color of objects by analyzing the physical properties of We developed a simple but efficient low-pass filter to debug the point spread function, Debiler Underwater imagery. Different types of water surface images were used under different conditions For experiments. The experimental results indicate that the proposed algorithm effectively Underwater images were recovered while absorbing and dispersing effects. [1]

The reason for damaging the surface image of the water is to survey sophisticated intelligence algorithms. As a sophisticated method of deicing and refining underwater images, Underwater image decorating performance and color restoration in various ways, The underwater image identifies color evaluation metrics and provides an overview of the key Underwater image applications. Underwater environment, which contains numerous organisms Resources and energy are the main factors needed to sustain sustainability Human development. Underwater imagery is the enhancement of contrast widely used techniques for color correction. Contrast is an enhancement of contrast has attracted a lot of attention in recent years. [2]

Deals for using Side Scan Sonar (SSS) for underwater testing Objects (cables and pipelines). It is suggested to use an autonomous body of water Purpose. The problem is in processing acoustic images to find communication lines fixed c-bottom and underwater robot control function. The actual cable search results and Pipeline tracking modeling experiments are discussed. A mind or tethered device The case is limited due to their radius of work area and the need for supporting characters (it grows) Cost of inspection work). Effect of processing actual SSS-images (meanwhile obtained via AUV) Cable detection) and pipeline-tracking modeling experiments allow us to conclude that this Methods can be used in acoustic vision movement control systems of underwater robots for investigation Underwater communications. [3]

Events in visual and hydro acoustic tracking are discussed, such as theoretical and Practical Concerns This review also describes the methods and tools for finding communication At the end of the Kinoff, it is necessary to create a simple reliable system Subia cables must be in place to estimate the position of the subta transmission line and the depth of burial Regular maintenance and movement are monitored, regardless of their location and burial room. This task is difficult due to the dynamic environment on the ocean floor, which can be caused Access to position, depth, visibility and utilities. With technological advancement, The task of visual inspection can now be performed by operator-controlled ROV Before processing the surface they give instructions on processing the image The cable must have localization and direction [4].

Introduced two vision-based erosion detection algorithms developed in MINOAS European Project Reference. Both are based on the idea of combining algorithms Weak classifier to achieve good global performance. After evaluating their performance, the Obtaining a percentage of the wrong category is not zero for both algorithms. These results Misclassification can be explained by analyzing what kind and area they look. On the one hand, the FN percentage is not zero as detectors mark the rust the center of the unsafe area; the boundaries are usually not completely labeled. On the other hand, the FP percentage is not even zero due to the presence of different compositions Images are categorized according to faults [5].

Describes the process of automated analysis of the inside surface of a pipeline by Digital Image Processing (DIP). The entire platform includes inspection mobile robots there is a line-laser and CCTV camera to detect defects in the internal pipeline structure it is not readily available to human observers. A simple algorithm is enabled Detecting cracks in the inner surface of pipes with approximately 80 percent accuracy the end result shows the main purpose of the vision system and the use of the DIP technique. Pipe Investigation is not a new topic in the field of education, industry. There are many different methods the proposed but remote environment for direct human observation is still one to investigate Favorite topic [6].

A novel systematic approach to enhance underwater imagery by damaging algorithms Consequences of attention, inconsistency, and transmission the possible presence of an artificial light source in consideration. Once a room map that is Distance between objects and camera, foreground and background is approximate a scene is divided. The light intensity of the foreground and background are compared to determine whether an artificial light source is working during the image capture process. Later Side effects of artificial light, opacity and brightness the camera needs to focus on the underwater transmission path. Next, the water the depth of appearance in the image is determined by the residual energy ratio of the different colors existing channel in background light. Based on the relative capacity scale for each light wavelength, color change compensation is taken to restore the color balance. Performance of the proposed algorithm for wavelength compensation and image debasing (WCID) is objectively and subjectively evaluated using geo-truth color patches and the video was downloaded from the YouTube website [7].

In the criterion, the corrosion rate can be calculated using any industrially accepted internal corrosion prediction model (ICPM), such as the Norsok model [8]. Though, the consequences of the individual ICPMs may diverge from the sensible corrosion charge at what time the internal environmental parameter of the examination segments are not inside the range of the forecast model. Then, the chosen dig points based on the ICPM's consequences may not give an effectual income for identifying areas that are "on top of standard" in terms of heaviness defeat. The internal corrosion rate of wet gas gathering pipelines is influenced by the fluid composition, temperature, pressure, flow velocity and many other factors [9].

It is hard to expand a hypothetical model that is able of telling the association flanked by all of these factors and the linked decay rates. Though, a diversity of method can be second-hand to forecast prospect data based on the past data of the organization; these methods comprise the arithmetical forecast method, artificial neural networks (ANNs) and fuzzy logic methods [10].

3. PROPOSED SYSTEM DESIGN

In the system we collect data from data acquisition device and push it on cloud database. Our aim is to detect rate of corrosion in the pipeline. In blast furnace, numerous gases are present which contain several impure particles in it. As a result of these impure particles and exposure of pipelines to hazardous environment causes corrosion. For calculating rate of corrosion we need to know the values of basic parameter of gas in the pipeline such as temperature, shear stress, and pressure of CO_2 and pH value. By using these parameters and putting these values to norsok corrosion calculation programme using ladder logic we will finally calculate corrosion rate in gas pipes . Once the corrosion rate is detected and if the value is much larger than the actual range then the supply will be stopped as all the valves will get closed.

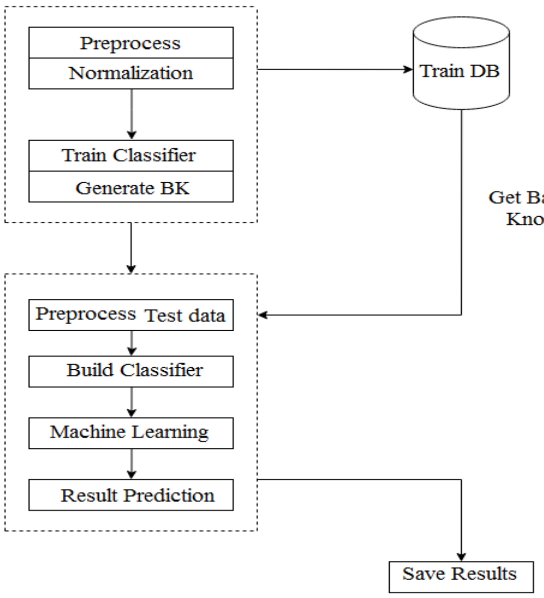

Fig.-2 Proposed system architecture

The BK is nothing but a background knowledge that is generated based on extracted values from sensing systems. According to the proposed algorithm, each event gives reward or penalty respectively, based on that each event changes weight state, and based on that system generates BK rules during the execution.

Algorithm

1: Q-LearningAlgorithm

Input:inp[1.....n]allinputparameterswhichisgeneratedbysensors ,ThresholdgroupTMin[1...n] and TMax[1...n] for all sensor, Desired Threshold Th.

Output: Trigger executed for output device as label.
Step 1 :Read all records from database (R into DB)
Step 2: Parts []←Split(R)
Step 3:
Cval = $\sum$nk=0 Parts[k]
Step 4: check (Cval with Respective threshold of TMin[1...n] and TMax[1...n])
Step 5: T←get current state with timestamp
Step 6: if(T.time > Defined Time)
Read all measure of for penalty TP and reward FN
Else continue. Tot++
Step 7: calculate penalty score = (TP *100 / Tot)
Step 8: if (score≥Th)
Generate event
end for

2: ANN

Input: TrainFeature set which having values of numeric or string of train DB, TrainFeature set which having values of numeric or string of train DB, Threshold T, List L.
Output: classified all instances with weight.
Step 1 : Examine all features as of Test set using below
TestFeature= $\sum$nj=1 (T[j])
Step 2: Examine all features from Trainset using below
TestFeature = $\sum$nk=1(T[k])
Step 3: Read all features from Trainset using below
Step 4: produce weight of together characteristic set
W=(TrainFeature,TestFeature)
Step 5: Verify Threshold
SelectedInstance= result = W > T? 1: 0;
put in each chosen example into L, when n = null
Step 6: Return L

3: SupportVectorMachine:

A supportvectormachineisasupervisedtechniqueinmachinelearning. Inthistechniqueevery data item is represented as a point in a n-dimensional space and hyper plane is constructed that separatesthedatapointsintodifferent classes and thenthis hyper planeissuedforthepurpose of classification. The hyper plane will divide the dataset into two different classes positive and negative in our work. A hyper plane having the maximum distance to the nearest training data item of both the classes is considered to be the most appropriate hyper plane. This distance is called margin. In general, the larger is the margin the lesser is the error in classification. Mathematical model for SVM is as follows:
Input: Train features TF[], Test features Ts[], threshold T,
Output: Classification of weight
Step 1: vector is given as an input
Step 2: Each values in the given vector is extracted
Step 3: The extracted values is searched in the dataset
Step 4: for each (x[] into TF[] when!=null)
Step 5: Get all features x1[]=Ts[]
Step 6: w=CalDistance(x[], x1[])
Step 7: evaluate w with T
Step 8: Classify weight

4. RESULTS AND DISCUSSION

For experiment analysis of proposed system evaluate entire execution in two different open source platforms. First system create network simulator environment to generate sensor nodes, the entire simulation log has used as IoT communication log which is generated by various analogue sensors. The techniques basically define in base approach which is carried out to calculate the various parameter between sensors. For each transaction system automatically calculate some values which is denoted in matrix X. K-means clustering unsupervised learning approach has used to generate the data labels and ANN has used as a supervised learning algorithm. In the Q-Learning the total penalty score is predicted by comparing the present state input with previous

If there is change in state of pipeline parameters then it will be considered as penalty. Otherwise it will be considered as reward. Based on that the reduction of pipeline in 1 year is calculated:

totalpenalty = totalpenalty +(Qstate -previousstate)

In ANN first all the features from test set is read and the all features from train set also read.Then the weight of both feature set is generated

W =(TrainFeature,TestFeature)

The threshold value is verified with W

SelectedInstance = Result = W>T? 1 : 0

Each selected instance is added to L when n is null then the result is returned.

Table-1: Performance evaluation with ANN and Q-LEARNING

	Q-LEARNING	ANN
Accuracy	0.9892	0.9925
Precision	0.9867	0.9897
Recall	0.9933	0.9963
F-Score	0.9899	0.9929

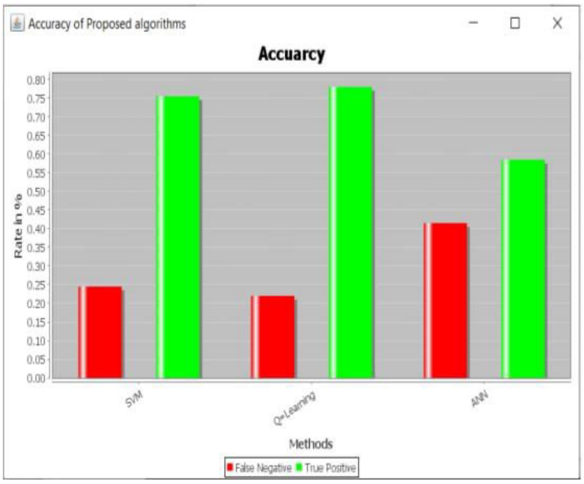

Fig. 3- Accuracy and analysis of proposed system page

5. CONCLUSION AND FUTURE SCOPE

The main purpose was to use underwater image processing techniques For the pipeline network, the same error was found in each file. This paper is presented. The internal as well as external damage by corrosion in gas pipeline is a complex phenomenon, and the integrity of the structure is critical aspect considering the natural gas transport and the corrosion actions factors. Steel damage that occurs on this pipeline system can be identified by careful examination of the corrosion deposits found during pipeline excavation. The mechanism of corrosion is based on the formation of a galvanic couple between microbiologically produced iron sulfides and the steel surface. Using this research we can easily predict the corrosion using Machine learning algorithms. A new image-based method for sub-pipeline corrosion estimation. Image A self-collected inspection of restoration and enhancement was also carried out in a pre-emptive estimation According to the publicly available underwater image dataset, the two have shown promising results. Since the corrosion rate is based on the color information of the carotid shaft, The experiment color was taken in conjunction with the evaluation of the color variation of the traditional image Metrics. The research will provide data for risk assessment models used for maintenance repair And functions of the pipeline system. The bald question asks the rest of the question Some possible perspectives on the safe life of the tube can be applied or developed Studying rust-related cracking and pitting events.

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