# Detection of Pipeline using Machine Learning Algorithm and Analysing the Effect of Resolution Enhancement on Object Recognition Accuracy

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***Abstract*— Evaluation of defects in pipeline installed in underwater demands smart engineered solutions. Burying the large pipelines in underwater facilitated for the purpose of petroleum, LPG, potable water and other gaseous requirements are increasing every decade. Underwater pipeline route tracking during leakage or any emergency conditions is necessary and is challenging. The detection of pipelines in underwater is made easy through SONAR imaging and is evaluated through state-of-the-art technology. So heuristic approach is formulated here using the emerging machine learning technique. The research framework is focused on design and analysis using efficient machine learning algorithm, which can detect buried pipelines. Various statistical parameters are selected here for the comparison of highly compete algorithms named convolutional neural networks (CNN), Fuzzy C means clustering and Apriori Algorithm. The system design is adopted using MATLAB IDE tool and simulated results are validated and tested.**

**Keywords*:* Pipeline detection, apriori algorithm, convolutional neural network, Machine learning , segmentation**
.

## I. INTRODUCTION

Underwater imaging finds it applications in Cable and Pipeline Survey, Search and recovery, Land Mines detection, sub-bottom oil and gas surveys, Target verification and location, Archaeological Surveys, Geological/Geophysical Surveys, Marine Construction Surveys, Scour/Erosions Surveys for Rivers and Streams, Sediment Classification etc. The surveillance and inspection of the pipelines for gas leakage or potable water leakage is achieved by underwater image processing. The underwater image and seabed is captured by acoustic based instruments carried by remotely operated vehicle(Andrew Bagnitsky et al)[1].

Image processing in underwater is achieved through Acoustic based instruments such as side scan sonar equipment, with frequency 200 KHz. Side scan sonar equipment captures image upto a depth of 75 m. Pipeline sometimes get buried underneath the sediments such as rock, sand, clay, etc, so subbottom profile equipment with frequency 10-12 KHz is used. Sub bottom profiler capture image upto a depth of 20 m. In this work image captured by both sidescan and sub-bottom profile equipment is used. The attempt is made to detect pipeline which is buried by sediments.

Due to several constraints the resolution is limited. Object recognition and classification accuracy is less for image which is at low resolution (Pailhas et al., 2010)[2]. Hence the underwater sonar image demands post processing to enhance the resolution and thereby improve the classification accuracy.

The study here focuses on pipeline detection with suitable post processing algorithm to detect the pipeline automatically. In this study we trained the image using Apriori algorithm, convolution neural network and Fuzzy C Means algorithm to detect pipeline. By using the image processing method, firstly the images are binned and Region of Interest is extracted through super pixel segmentaion. Through this technique ROI showing pipeline is extracted. The extracted pipeline will have some missing pixels due to ambient noise. So the image is enhanced and passed on to edge detection algorithm[10]. Finally the statistical features of the pipeline are extracted and the detected pipeline is classified.

## II. LITERATURE SURVEY

In 2009 Wu Xue-Feii et al., presented work [3] entitled "Design Automated evaluation of covered pipeline' by picture handling and found that many clandestine water pipelines are old. With the advancement of technology proficient method to analyse deformity of damaged pipelines is considered. In light of the picture handling, deformity is highlighted using HSV technique. QFCM (Quick Fuzzy C-Mean clustering) [3]region strategy is applied to remove remarkable parameters. Significant highlights like region, edge, estimation and width of defects is structured. Nhat-Duc Hoang et al., examined [4] Corrosion in pipes appliying Texture Analysis and Meta-heuristic Optimized Machine Learning Approach, in . The traditional process performed by Man is a tedious work. Subsequently, this investigation involves picture handling employed with HSV channel separation, extracting GLCM and GLRL features. A dataset comprising of 2000 images is trained and tested. Support vector machine (SVM) combined with differential flower pollination technique is applied to differentiate corrosion and non corrosion. This result is supported by Wilcoxon rank test model with outcome 92.81%.

Vision-Based Pipe Checking Robot For Crack Detection is presented utilizing Canny Edge Detection Method in 2017 by Syahrian et al.[5]. The Piping arrangement is essential for ensuring security in the industrial setup. The pipe checking robot captures the image inside pipe where human intervention is not possible. The image is then programmed for detection of cracks using canny edge detection technique.

Oil Pipeline detection by Mobile Robots Replacing Digital Cameras and applying Sobel Edge Detection method in 2015 is experimented by A.Prema et al [6]. The authors expressed in their examination work with higher-order Neural units showing cracks, This method improves computational features in data handling. This paper presents neural units with high order synaptic methodology for image data handling applications. Edge recognition methodology are performed out by high request synaptic schedules and the outcomes are seen through Hough transforms. The results show that the accuracy for crack detection for K means clustering is 89% and high compared to the existing methods top down search, bottom up search, defays clink method.

Through literature survey it is inferred that most of the research work is done for pipelines installed in industries and building, very little research is done for pipelines laid in underwater so attempts is made for pipeline detection through emerging machine learning platform.

The development of SONAR instrument has raised query of resolution need. The shortcomings of the SONAR technology and the necessity for high resolution image plot are emphasized. Finding the resolution for recognizing the target is still a difficult job. The attempt has been made by most scientists (Kessel 2002)[7]; (Florin et al. 2003)[8]; (Myers and Pinto 2007)[9], looking for the least resolution and distinguishing the figure of the mine target like cone or cylinder (Pailhas et al.2010)[2] is still not solved. So development of super resolution technique to analyse the necessity for resolution vs object recognisation accuracy is focused in this research work.

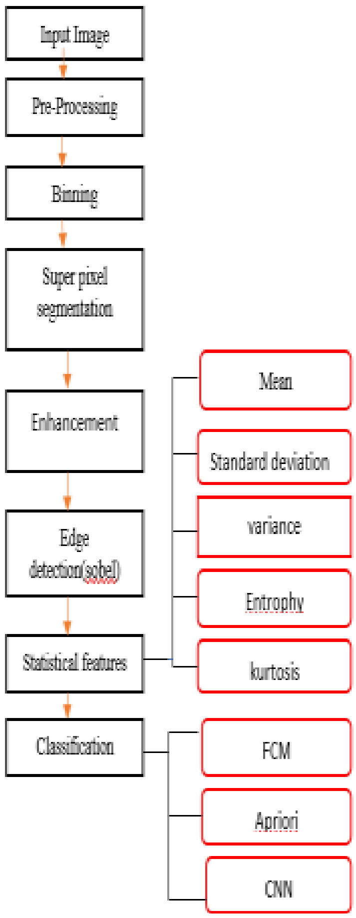



**Fig 1 Block Diagram for pipeline detection**

## III. DESIGN METHODOLOGY

### *A. Material and Methods*

The raw sonar data is collected from Indomer Coastal Hydraulics Pvt Ltd. The data was recorded using BENTHOS SIS-1600 side scan sonar with frequency of 200 KHz.

The design methodology is illustrated in Fig 1 where each module is described below.

### *B. Preprocessing*

The underwater pipeline image under test shown in Fig 3 is read using imread() command, and converted from RGB color scale to gray scale. The image is further resized to 100 X 100 to handle the image pixels in a fixed scale.

### *C. Binning*

The images under test normally contain the noise information which is converted into smoothing data through binning technique[10]. To handle the noisy data, to extract the useful pixel information from the test data, binning will be used. In this method, the data is first sorted and then the organized values are disseminated into a number of heaps or bins. As binning methods consult the locality of values, they perform local pressing.

*D. Maximum intensity Measurement*

From the given test image the maximum intensity can be extracted through X and Y axis intensity pixel values and can be used to find out the variance between the neighborhood pixels.

*E. Super pixel Segmentation*

Super pixel segmentation [11]is an art of machine learning process in which the image is being divided into several segments in order to simplify the image analysis. During machine learning classification, the segmented super pixels act as a parametric object to be considered for iterative analysis.

*F. Edge Detection*

Edge detection is the process of finding the minute variance between the pixel intensities to create the boundary between the pixel differences. The most familiar edge detection principle such as Sobel filter [6][12] are used here to extract the edges of the super pixel segmented image objects clearly.

*G. APRIORI Algorithm*

The major technique in machine learning APRIORI algorithm [12] is one of the flexible and accepted algorithm in data mining for target recognition and classification. APRIORI algorithm utilizes the close relationship between the concurrent sample inputs and predefined analyzed targets present in the database. APRIORI algorithm uses the most awaited item sets extracted from the relational database, when the database is scanty, subsequently frequent item set will be short. APRIORI algorithm and similar algorithm can get favorable properties under this condition. This algorithm has been accomplished into two steps where,

1) Frequent items in a database should be selected first.

2)The recurrent item sets and self-reliance constriction are used to form Rules .

*H. Convolution Neural Networks CNN*

Machine learning is one of the strongest technique growing rapidly for numerous classification, and prediction process, one such technique uses Convolutional Networks (ConvNets) [13] are formerly the most competent for classifying image data.

Their various levels of layers and architectures (Fig 2) are inspired from the science of biology. Through these models, utilizes invariant features are selected in hierarchical order. They first recognize low level topographies and then learn to identify and association of these features to learn more difficult patterns. The dissimilar features derived from dissimilar layers are also distinguished. And each layer has detailed number of neurons and presented in 3 extents: height, width, depth [11].

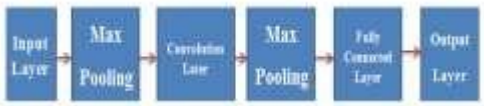



**Fig 2 CNN**

## IV. RESULTS & DISCUSSIONS

*A. Input under Test*

**Fig 3 Input** SONAR **Image**

To test the proposed model, a set of SONAR images shown in Fig 3 are taken for analysis and testing.

*B. Binning*

**Fig 4 Binning**

The above Fig 4 shows the Bining process of input test image. In machine learning process binning is a process used to extract features through tuning out the continous variables into catagorial information. The grouping of catagories is accomplished thorugh a set of predefined bins.

*C. Super Pixel Segmentation*

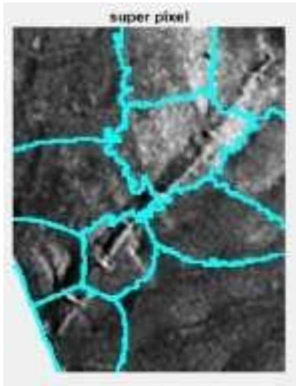



**Fig 5 Super pixel Segmentation**

The above Fig 5. Depicts the simulated result of Super pixel segmentation which actually seggregates the input pixels into small divisions. As a result of segmentation some of the pixels are lost. Hence the segmented image is enhanced using sparse representation algorithm discussed(kumudham et al)[14]. This technique helps to interpolate the pixels and highlight the boundaries.

*D. Edge Detection Process*

Fig 6 shows the edge detection process and its result eventually with suppressed noise. The processed image obtained for sobel edge detection models [10] is shown below.

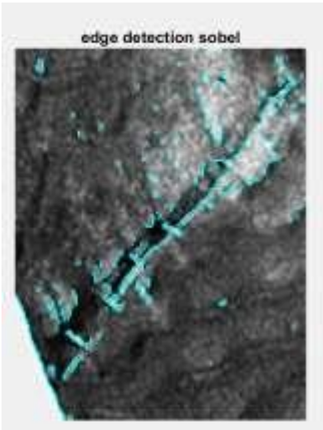



**Fig 6 Sobel Edge detector**

*E. Statistical Parameters*


**Fig 7 Statiscal Parameters**

Statistical features which helps to recognise and classify the targets are shown in Fig 7. They are described below.

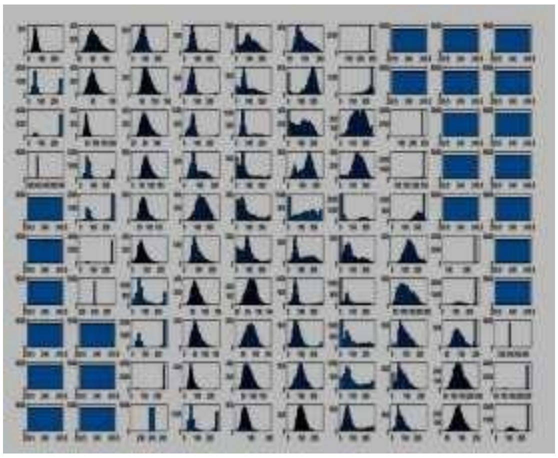


**Fig 8 Intensity Histogram**

Fig 8 illustrates the histogram of pixel intensities with which first order histogram statistical features such as mean, variance, standard deviation, skewness and kurtosis are derived.

**Mean**

Mean will give absolute value when 1st dimension is not equal to one.The size of the other dimension become same if the size of the dimension becomes same.

$$\mu = \frac{1}{N} \sum_{a=i}^{N} A_i \qquad (1)$$

**Variance**

The variance var($v$) is same as mean but by default one is observed and normalized by the variance.

$$v = \frac{1}{N-1} \sum_{a=i}^{N} |A_i - \mu|^2 ) \qquad \textbf{(2)}$$

**Entropy**

Texture of the image is calculated through the process of Entropy.

$$Ent = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-j)^2 \mathrm{M(i,j)} \qquad \textbf{(3)}$$

**Standard deviation**

The dispersion and variation are calculated through standard deviation.

$$S = \sqrt{\frac{1}{N-1}\sum_{a=i}^{N} |A_i - \mu|^2} \qquad (4)$$

**Skewness**

If Mean is great, median and mode or equal which will let skewness greater than 0.

$$s = \frac{E(x-\mu)^3}{\sigma^3} \qquad (5)$$

**Kurtosis**

The peakness distribution and flatness are calculated and characterized by skewness.

$$k = \frac{E(x-\mu)^4}{\sigma^4} \qquad (6s)$$

The above Fig 7 shows the performance measure as statistical parameters such as mean, standard deviation, variance, skewness and kurtosis results .

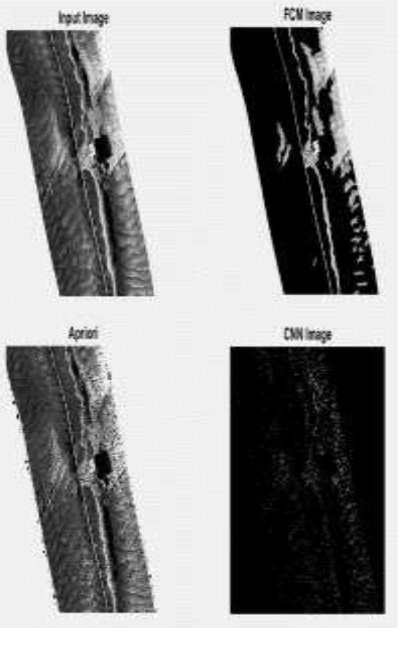



**Fig 9 Result of APRIORI, FCM and CNN technique**

*F. Comparison of APRIORI, FCM and CNN algorithm*

The FCM algorithm is highly matching the features of the input image under test. The algorithms are compared and finally prediction results are accurate as depicted below. As many surveys [15][16] implies FCM is more accurate and created a standard model on prediction of various image classification techniques in practice.


**Fig 9 Accuracy measurement**

**Performance measures**

The above Fig 9 clearly shows the output of major algorithms like Apriori, FCM and CNN in which the FCM shows better result after resolution enhancement interms of accuracy of 92.5% whearas the apriori and CNN with resulted 71.8% AND 73.5% . The accuracy of images with pipeline and without pipeline is shown in Table 1. It is found that after resolution enhancement the accuracy is increased.

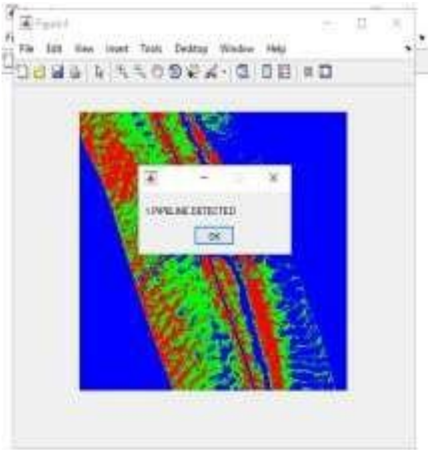


**Fig 10 Pipeline detection**

**Fig 10 illustrates the detection of pipeline using machine learning algorithm.**

The same technique is applied for real time image data collected and the output is shown in Fig 11.

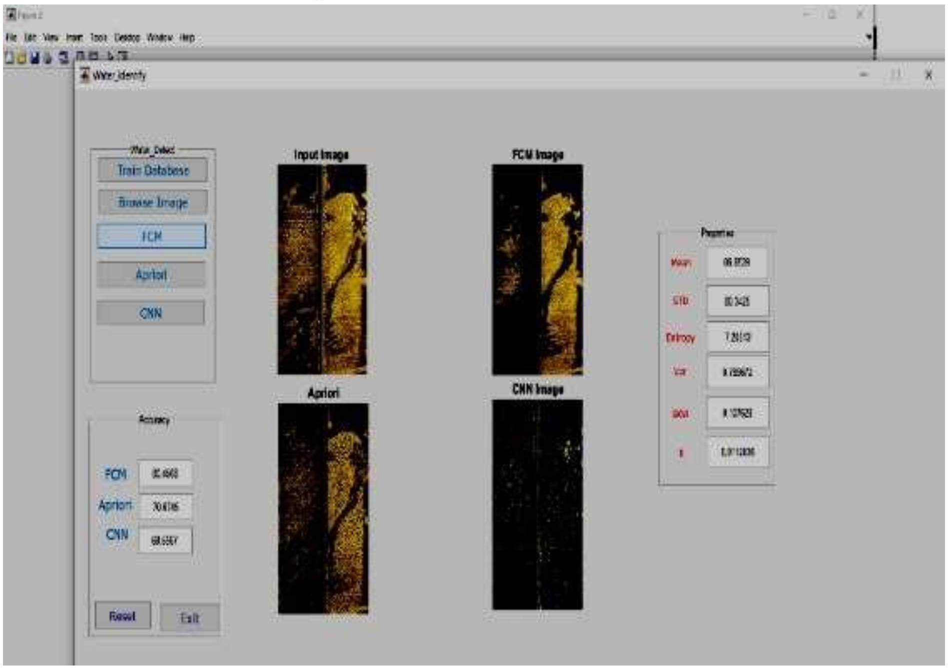
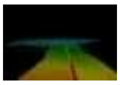
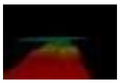



**Fig 11 Indomer Image**

TABLE 1. **CLASSIFICATION ACCURACY VS RESOLUTION ENHANCEMENT**

| Sl.No | Sonar Image | FCM Algorithm (%) | | Apriori Algorithm (%) | | Convolution Neural Network Algorithm (%) | |
|---|---|---|---|---|---|---|---|
| | | Without resolution enhancement | With resolution enhancement | Without resolution enhancement | With resolution enhancement | Without resolution enhancement | With resolution enhancement |
| 1 |  | 83.4 | 92.5 | 62.5 | 71.8 | 68.9 | 73.5 |
| 2 |  | 84.4 | 92.6 | 63.8 | 72.0 | 69.2 | 73.4 |
| 3 |  | 85.3 | 94.1 | 70.2 | 71.7 | 68.1 | 75.3 |
| 4 |  | 86.7 | 94.6 | 61.5 | 71.9 | 66.7 | 73.7 |
| 5 |  | 83.3 | 94.4 | 61.5 | 72.3 | 67.9 | 72.4 |
| 6 |  | 84.8 | 92.3 | 62.6 | 73.2 | 65.4 | 74.8 |

## V. CONCLUSION

Evaluation of a heuristic model for pipeline detection is experimented in this research work. The proposed model is implemented using the MATLAB IDE 2018 version, machine learning toolbox. The image processing techniques are most helpful for detecting the information from the raw SONAR image. The comparative study of machine learning algorithms FCM, Apriori, and CNN model is eventually implemented here, resulting Apriori is achieved with 71.8- 72.3% of accuracy, that CNN provides 73.5 – 75.3% accuracy and FCM achieved with higher accuracy 92.5 – 94.6%. The future work is to detect the crack or defect in the pipeline using hybrid FCM models and with more number of images.

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**Conflict of Interest: The authors declare that they have no conflict of interest.**

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