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Detection of Lubricant Divulge in Remote Area

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ABSTRACT: The main purpose of this project is to detect and predict the lubricant spill in remote area with the help of machine learning algorithm. This is due to the lubricant spills in the industries in the location where the usage of lubricants is much needed. Also, the gradual increase in the shipping of products through marine which carries products such as lubricants can cause pollution if they are spilled. Here, Deep Neural Network algorithm of Machine learning is used in this project with help of MATLAB. They give accuracy in predicting oil spill from remote location and effectively distinguish an oil spill from a biogenic slick.

KEYWORDS: Remote sensing, Deep Neural Network, Lubricant, Lubricant divulge, MATLAB.

I. INTRODUCTION

Lubricants helps in reducing the friction between machinery surfaces along with generating electricity by heating or cooling them. They are not only oils used in car engines, but also transformer oils, metalworking fluids, and hydraulic oils and helps in transmission of particles in the industries. Lubricants are used in many industries and some of their applications are in Medical industry where they are used in ultrasound examination, in bio-applications on humans (e.g., lubricants for artificial joints). As the usage of Lubricants are higher, it is estimated that about 50% of all lubricants are released into the environment. Few of the common disposal methods are recycling, burning of lubricant, landfill and discharge into water. This disposal methods are strictly regulated in most of the countries as even small amount of lubricant divulge will contaminate the water resources as well as cause airborne pollutants if the disposal is burned.

The disposal of most of the lubricant is caused by the general public by discharging them into drains, ground and throwing them as trash. The direct contamination of the environment also takes place by accidental spillages in both land as well as water resources, pipeline leakages and some natural or mam-made disasters. Release of such lubricants in our environment affects the growth of flora and fauna as they are toxic. Sometimes the used lubricant may be toxic to human is it is not disposed safely and securely. So, it is very much important to identify the divulge of lubricants in the environment.

The project is used to identify and predict the lubricant divulge in the area (land as well as water resources) with the help of captured image of the spill. We use Deep Neural Networking to predict the lubricant divulge. Deep Neural Network is one of the categories of machine learning algorithms which is a implementation of stacking layers of neural networks. The Deep Neural Network is interpreted by terms of probabilistic interference or Universal approximation theorem. DNN concerns about the capacity of bounding the width of the network and allowing the depth to grow in Universal approximation theorem. In Probabilistic interference they feature interference as well as training, testing of the networks. DNN is beneficial to complete autonomous work without compromising its accuracy and efficiency. DNN is a layered organization of connecting of neurons to other neurons. They form a complex network by the signals passed within the neurons as input. They use feed-forward network which passes data without looping from input to output. It trains and test the data by Pre-processing, compressing, extracting, training and testing.

II. RELATED WORK

Dongmei Song, Zongjin Zhen, Bin Wang, Xiaofeng Li, Le Gao, Ning Wang, Tao Xie and Ting Zhang, "A Novel Marine Oil Spillage Identification Scheme Based on Convolution Neural Network Feature Extraction from Fully Polarimetric SAR Imagery", IEEE Access (Volume: 8), 30 March 2020, pp. 2169-3536.

Lubricant spill pollution has caused various significant impact on ecological environment, ecological resources and economy. Synthetic Aperture Radar (SAR), specially polarimetric SAR (PolSAR), has been proven to be an efficient

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tool for marine lubricant divulge detection. traditionally, lubricant divulge detection methods mainly rely on artificially extracted polarization characters and the detection accuracy is limited by the qualities of feature extraction. Recently proposed Convolutional neural network (CNN) has capacity to mine spatial feature from large data set automatically. Set off by these, in this paper we proposed a novel lubricant divulge identification method based on multi-layer deep feature extraction by CNN. PolSAR data are categorized into a 9-channel data block to feed the CNN. After which a 5-layer CNN architecture is devel6 to extract two high-level features from the original data. The features are fused after the procedure of dimension reduction via principal component analysis (PCA). At last, the support vector machine method with radial basis function kernel (RBF-SVM) is utilized for classification. Three sets of RADARSAT- 2 fully polarimetric SAR data were used in this analysis to validate the proposed method. The obtained results says that the proposed method provides competitive results in overall classification accuracy and kappa coefficient. Also, this method can improve the accuracy of lubricant divulge detection, reduce the false alarm rate, and effectively distinguish a lubricant divulge from a biogenic slick.

III. EXISTING SYSTEM

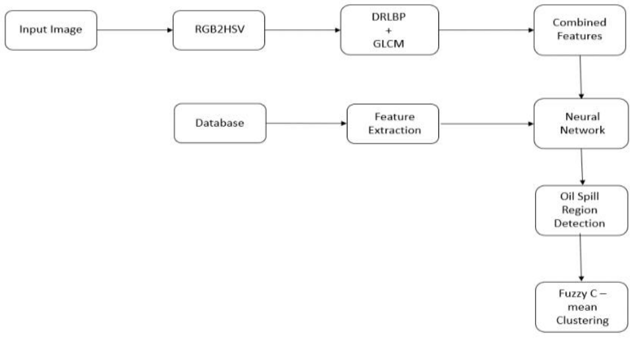
First, Traditional detection of oil spills such as field investigation will take large amount of time, expensive as well as failed to achieve the efficient identification of lubricant spills in area. In the past few years, remote sensing and machine learning algorithms plays a vital role in detecting, predicting and monitoring oil spill slicks. Remote sensing the data and various components of machine learningclassification systems are used in reviewing and analysing, the lubricant spills. There are different methods used for this purpose.

One of this method is to detect the spill in wide range of area cause frequency of acquiring the multisensory data of SAR images using machine learning algorithms. They are to be done by data processing, feature extraction and classification using ML techniques for identifying lubricant spills. Though this is method is implemented the usage of satellite-based images have their unique spectral characteristics and they use different sensors such as Laser fluoro-Sensors, UV light in lubricant spills is limited. So, we in our project we use the captured images instead of SAR images and deep neural network which is time saving as well as efficient in accuracy.

IV. PROPOSED SYSTEM

Lubricant divulges in marine leads to the demise of various marine mammals. The lubricants which are spilled on the ocean spread all over the surface of the water thereby marine animals such as whales and dolphins' blowholes gets clogged making it difficult to breathe. The oil also coats the fur of the marine animal such as otter and seal making them vulnerable to hypothermia. Small fishes that consume the food covered by these oils can become poisonous sometimes. Therefore, the marine animal that consume the oil spilled fish or other food may be poisoned by oil or may experience other problems.

Massive oil spill leads to ecological disruption and it also affects the economy of the people who depends on fishing as a source of income. Lubricant divulge in industrial areas causes harm to the local environment. In humans it causes breathing and neurological problems, skin and eye irritation. Based on the amount and type of lubricant spilled the effect of the oil spill varies. When lubricant gets mixed with water, they form a pudding like consistency. This process is known as emulsification. Emulsified oil is arduous to separate leading to greater inconvenient for marine habitats.



In proposed system, the detection and conjecture the lubricant divulge in remote area with the help of machine learning algorithm. The use of deep neural network algorithm in machine learning for the conjecture of lubricant divulge implemented using MATLAB R2018a. Lubricant divulge can occur by various reasons and in various places.

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In marine oceans, great lakes, rivers, and even on shores it occurs due to accident or improper containment. In industries it occurs due to pipeline damage. Using this project, it very much convenient to detect the lubricant divulge from another biogenic slick.

A. *MATLAB:*

In MATLAB implementation and testing algorithm are convenient. For image processing, MATLAB is for best for implementation. MATLAB has the ability to read both common and domain – specific image format in wide variety. MATLAB has various features such as High – level language, Interactive Environment, Handling Graphics, Mathematical Functional Library, Application Program Interface (API), Toolboxes, Accessing Data, Interfacing with Other Languages.

V. METHODS

Image is a matrix of pixels. Each location in the matrix is filled with different pixel values to produce an image. The process of converting an image to digital format for performing certain actions on it is known as Image Processing. These processed images can be used to train and predict the forthcoming values of a model. There are four preliminary steps for creating a model using images. They include: 1) Extraction, 2) Pre – processing, 3) Compression, 4) Training, 5) Testing.

A) Pre – processing

Pre – processing is a data extracting technique which is used to transform raw data into processable data. They help in removing noise, reduces the size of data, transform it for further processing. The steps involved in data pre – processing are as follows: 1) Data Cleaning, 2) Data Transformation, 3) Data Reduction.

1) Data Cleaning: Data cleaning is a process in which unwanted, irrelevant or missing data parts are either removed or filled. It handles missing data, noisy data, etc. In case of missing data, the data parts can be either neglected or filled in. Missing data is mostly filled either using mean value or most probable value. It is most advisable to fill the missing data, since real time data sets may have large amount of missing data. When a model is developed based on these data sets, it may lead to unreliable prediction. The noisy or error data are mostly meaningless data that cannot be interpreted by machines. They unnecessarily increase the amount of storage space required. These data can be handles by binding, regression or clustering methods.
2) Data Transformation: Data transformation is the second step in data Pre – processing. It helps in transforming collected data into more suitable data sets for mining process. It involves four processes: 1) Normalization, 2) Attribute selection, 3) Discretization, 4) Hierarchy generation. Normalization usually scales the given values based on specified range. It helps to regulate and regularize the data points that highly vary from other. Attribute selection creates new attributes to the data which helps in mining process.
3) Data Reduction: Final step of Pre – processing is Data reduction. Since data mining is done with huge amount of data, it becomes hard to process efficiently. Thus, to avoid this situation, data reduction is used. By doing this, we can get increased storage efficiency, reduced data storage and processing cost. There are various steps involved in data reduction. They are: 1) Data cube aggregation, 2) Attribute subset selection, 3) Dimensionality reduction.

B) Compression

Compression is an important step in image processing before starting to process large images. It is mainly used to reduce the storage, computation cost and increase computational speed. Compression process is done with the help of encoder. It relays on the type of mathematical transform used. Compression helps us by reducing the number of pixels required without reducing the quality of the image. Three basic steps involved in image compression are: 1) Image transformation, 2) Quantization, 3) Encoding.

1) Transformation: In compression, transformation of the image is required to transform the data from one domain to another, that is from one format to another. In this transformation, the mathematical transfer function used plays a vital role. In this module we have used DWT (Discrete Wavelet Transform). DWT is used to separate image to pixel. It is especially used for lossless image compression. It can also be used for lossy image compression. It compresses images in grey level format. It can be used for several image standards such as JPEG, MPEG, PNG, etc. Image tiling is first done before giving it as an input for transformation. The image is transformed to wavelet coefficient data.

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2) Quantization: Quantization is a process in which various level of intensity and data is grouped into a particular level. This is also done based on mathematical functions that are defined based on pixels. Quantization is a vital step in compression. New levels in quantization are found with the help of fixed filter size. Using the fixed filter size, each terms of the filter divided and then rounded to the closest integer value.
3) Encoding: Finally, the quantized values are encoded using one of the two popular encoding mechanism. They are: 1) Huffman variable – length encoding, 2) Run – length encoding. During decoding and reconstruction process, the reverse of the transform function, quantization mechanism and encoding scheme is used.

C) Extraction

GLCM (Grey Level Co – occurrence Matrix) feature extraction is used for holding the co – occurring intensity pattern at a given offset for a given image. The texture features we have extracted using GLCM are: 1) Contrast, 2) Correlation, 3) Entropy, 4) Energy, 5) Homogeneity.

1) *Energy:* Energy is a measure of the homogeneousness of the image. It can be calculated from the normalized COM. It is a suitable measure for detecting the disorder in texture image is a suitable measure of energy.
2) *Entropy:* Entropy is a feature which gives us the measure of complexity of the image. Complex textures tend to have higher entropy.
3) *Contrast:* Contrast is used to measure the local variations and texture of shadow depth in the gray level co-occurrence matrix.
4) *Correlation:* Correlation coefficient helps to measure the joint probability occurrence of the specified pixel pairs.
5) *Homogeneity*: Homogeneity is used to measure the closeness of the elements distributed in the GLCM to the GLCM diagonal.

D) Training

In DNN, training a network means finding the appropriate neural connection with help of gradient backward propagation which is a feedback loop. Training a dataset means updating them to create a good mapping of output from given inputs. This process involves an optimization algorithm which search through the possible values of space in DNN Model to a set of noise which results in providing a good performance of training the dataset.

The training process is iterative which provides small updates to model for each iteration with step-by-step progress and change the performance for each iteration. This provides a solution for the minimum error or loss occurs in optimization when the training set is evaluated. In training neural networks, we have a challenge which occurs when confronting the General non convex cased dataset. This challenge can be overcome by using gradient descent where each iteration uses back propagation of error algorithm.

E) Testing

Test set is also a part of training set. In testing we split the data, and train, validate with the help of test and test set, in order to find the best noise model and also to prevent over fitting. When a model captures the noise of the data overfitting occurs which may lead to complicated model. In order to have an unbiased evaluation, model is trained with training data set and trained model is evaluated with validation data set for each hyper parameter combination. Based on the validation metrics best model is selected.

DNN have various applications and software employing them which should be thoroughly tested in safety critical domain. To test in a neural network switch to a running operation from leaning operation. In testing we run the same training data in our system if we received an error rate by comparing the neural network output with expected result. While testing the sets, it is very much important that we can't simply use already used for training so, we add some additional data cause in DNN it is about 25% of data used. To get better results the test cases in DNN are generated using symbolic approach and gradient based heuristic search.

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VI. SIMULATION RESULT

1) PRE – PROCESSING:

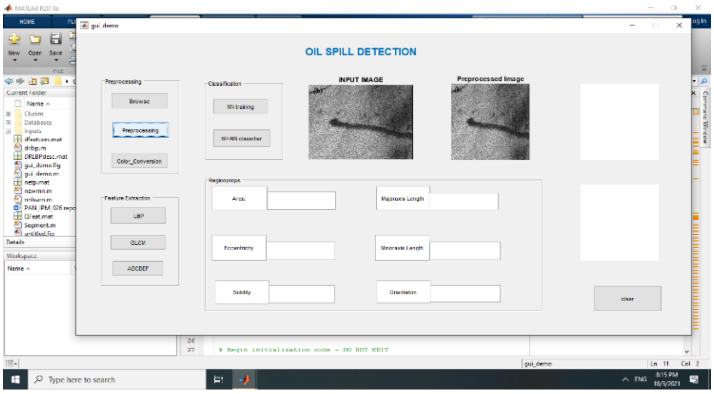

Fig 6.1. Selection and Pre – processing

2) COMPRESSION:

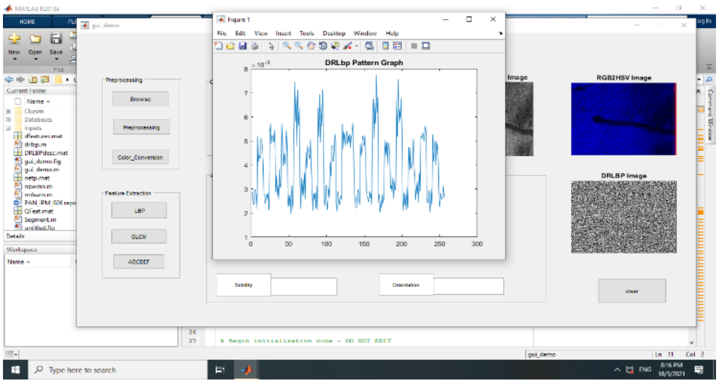

Fig 6.2. Compression and Colour Conversion

3) EXTRACTION:

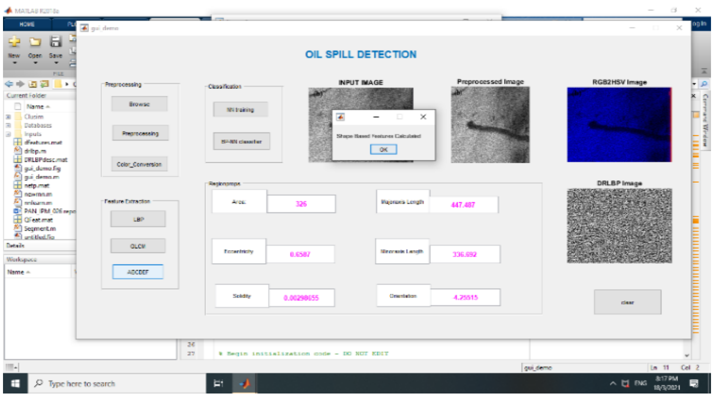

Fig 6.3. GLCM and Feature Extraction

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4) NEURAL NETWORK:

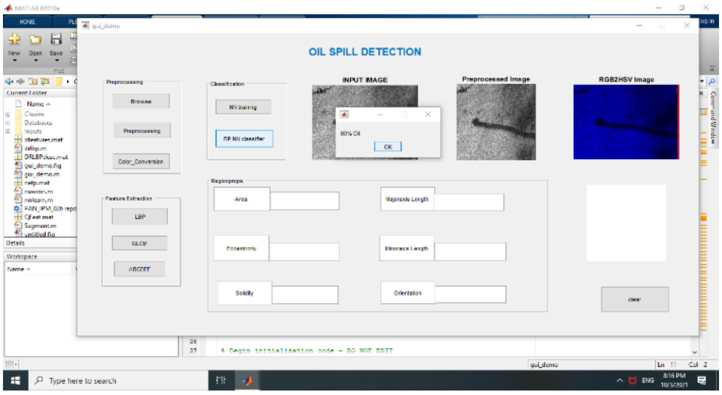

Fig 6.4. Neural Network and Output

VII. CONCLUSION AND FUTURE SCOPE

In view of the drawbacks of previous offshore manually driven oil spill detection strategies with poor or redundant options, we tend to planned associate degree oil spill detection technique primarily based on the fusion of deep learning options. The agenda of this paper are summarized as follows:

1) A NN appropriate for oil spill detection is constructed to mechanically extract recognisable options from the SAR knowledge. visible of the matter that general deep learning strategies cannot fuse multi-layer deep options, we extract high-level options of the CNN network, then reduce the dimension of the high-level options by means that PCA, and eventually fuse the options thus on embrace extensive target feature info. By examination the visual image of high-level options with the normal polarimetric options, we show that the options extracted mechanically by this method exhibit superior representativeness and lustiness.

2) The initial Softmax classifier of the NN network is replaced by the sturdy SVM classifier with associate degree RBF kernel, which enhances the lustiness of the classifier and also the ability to solve non-linear issues. Therefore, we tend to additional improve the classification performance and enhance the power to identify oil spills.

Deep neural network with a certain level of complexity, usually with two and more layers is known as deep neural network. It performs the data processing using trailblazing mathematical models. DNN is performed on priorly existing data, which acts as the fundamental structure. For the process, machine language is used as framework that commences the statistical model through aphoristic code or algorithm which brings results similar to that linear regression in order to obtain better future predictions with high accuracy. The paradigm follows the pattern of a model assimilating machine language, spotting inaccurate predictions, making modification to the fallacy and hence increasing rate of success. Which is why DNN is preferred for this prototype.

Theoretical evolution of these models gave birth to ANN - Artificial Neural Networks. ANN works on the idea that the hidden layers can be used to store data and it decides how the input is co related to output and its correspondence. The information present in the hidden layer puts inputs in combination. DNN then exploits this process and its components, which eventually improves the pattern and its efficiency. As each node in hidden layer determines the evaluation and sectional importance of the input set to that ofoutput. That is practically piling more and more of these layers.

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