Oil spill detection and classification system

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***Abstract-* Oil spills are a serious environmental issue since they can seriously damage ecosystems and marine life. To respond quickly and effectively to an oil spill, early detection and classification are crucial. In recent years, numerous methods for identifying and categorizing oil spills have been developed utilizing remote sensing data. These methods, however, frequently have limited accuracy and are computationally expensive. In this research, we propose a machine learning-based method for classifying and detecting oil spills. To identify and categorize oil spills, the system combines spectral and textural information that are retrieved from satellite photos. To eliminate the influence of air and ocean surface conditions on the satellite images, we use a pre-processing stage. Then, we use a variety of machine learning techniques, such as Artificial Neural Network (ANN) and Convolutional Neural Network (CNN), to categorize the discovered oil spills into distinct groups according to their extracted features. On a dataset of satellite photos gathered from diverse parts of the world, we test our method. The testing findings show that our system detects and categorizes oil spills with excellent accuracy, with an overall classification accuracy of 99.6%. Additionally, our approach performs better than a number of cutting-edge methods in terms of precision and computational effectiveness.**

***Keywords*: Oil spills, Remote sensing, Machine learning, ANN, CNN.**

INTRODUCTION:

An important environmental issue, oil spills have the potential to seriously harm marine ecosystems and the way of life of those who depend on them. For a successful response, oil spills must be quickly identified and classified. This can reduce the environmental damage and enable fast action to be taken to contain and mitigate the spill's effects. Systems for detecting and classifying oil spills on the surface of the sea include a variety of remote sensing technologies, such as radar, sonar, and optical sensors [3]. These systems can be used on many different platforms, such as satellites, aircraft, and drones, and they can be used both during the day and at night.

Synthetic aperture radar (SAR) is one of the most widely utilized remote sensing techniques for finding oil spills. SAR is a type of radar that produces sharp images of the earth's surface using a moving antenna. These pictures can be used to spot alterations in the water's surface, including the existence of oil spills. The advantage of SAR is that it can see through clouds and other atmospheric obstructions that can prevent other forms of remote sensing technology from working properly. Optically based sensors, such as multispectral and hyperspectral sensors, are another frequently utilized technology for oil spill detection [1]. These sensors pick up on variations in light's reflectance or absorption at various wavelengths, which can be used to determine whether there is oil on the water's surface. High-resolution images from optical sensors can be used for oil spill detection and classification.

The creation and use of autonomous systems for the detection and classification of oil spills has significantly increased in recent years. These systems analyse the data gathered by remote sensing technologies and apply machine learning and artificial intelligence algorithms to offer real-time information on the location and size of oil spills [9]. Continuous operation of autonomous systems enables near-real-time information on the spill's state and enables quick action. Systems for detecting and classifying oil spills are crucial instruments for environmental monitoring and response, to sum up. They identify and categorize oil spills using a combination of remote sensing technologies and AI algorithms, giving vital information for quick response and mitigation measures [7]. To ensure that the environment and those who depend on it are protected, it is crucial to keep developing and improving these systems as the demand for oil and gas rises.

This study proposes a detection of oil spill on oceans using synthetic aperture radar images utilizing a CNN (Convolutional Neural Network) and ANN (Artificial Neural Networks). A dual setup is used to create a large enough dataset, the dataset undergoes gray scale imaging, preprocessing, and image segmentation. After image segmentation the image undergoes for feature extraction that uses the ANN and CNN to classify the oil spill images. The proposed system is able to obtain the highest success rate in classifying the oil spill images. The system can also have implemented in the drones or any uav projects so that it can detect the oil spill so that it can be cleaned before it can do further damage to the marine systems.

LITERATURE REVIEW:

Oil spill detection and classification is a crucial step in environmental protection and monitoring. Various techniques and technologies have been put forth in recent years for the identification and classification of oil spills. We shall examine some of the most important and recent contributions to the area in this literature assessment.

For the identification and classification of oil spills, remote sensing techniques are frequently used. These techniques use sensors on satellites, in the air, or on the ground to collect pictures or other information for finding oil spills. Several researchers have proposed several methods, including synthetic aperture radar (SAR), optical imaging, and hyperspectral imaging, to find oil spills via remote sensing. For instance, Gade et al. (2018) suggested a deep learning-based technique for SAR image-based oil spill

identification. Similar to this, Li et al. (2020) suggested a unique approach for classifying oil spills using hyperspectral photography.
In recent years, the identification and classification of oil spills has seen a rise in the use of machine learning approaches. In order to find oil spills in photos or other types of data, these strategies employ algorithms that can learn from data. Oil spill detection and classification have been applied to a variety of machine learning methods, including deep neural networks, support vector machines, and random forests. For example, Zhang et al. (2021) suggested a deep neural network-based approach for identifying and categorizing oil spills using SAR pictures. Similar to this, Huang et al. (2019) suggested using optical images to detect oil spills using a machine learning-based technique.
Underwater oil spill detection and categorization using acoustic techniques. These methods discover and find oil spills in water by using sonar or other sound sensors. Numerous researchers have suggested using acoustic-based techniques to identify and categorize oil spills. For instance, Deng et al. (2018) suggested an approach for detecting undersea oil spills using acoustic waves. Similar to this, Zhao et al. (2020) suggested a technique for classifying undersea oil spills using passive acoustic monitoring.
IoT and WSNs are cutting-edge technologies that can be used to identify and classify oil spills. These innovations include tiny, wireless sensors that may be positioned in or close to water bodies to keep an eye out for oil leaks. IoT and WSN-based techniques for oil spill detection and categorization have been proposed by a number of researchers. Using wireless sensor networks, Liu et al. (2019) suggested an IoT-based technique for detecting and monitoring oil spills. Similar to this, Chen et al. (2021) suggested utilizing machine learning to identify oil spills using a WSN.
Multi-modal approaches increase the accuracy of oil spill detection and classification by utilizing several sensors or data sources. To increase the accuracy of oil spill detection and classification, for instance, optical and SAR images or optical and hyperspectral images can be combined. Multiple academics have suggested multi-modal techniques for identifying and categorizing oil spills. For instance, Wang et al. (2019) proposed a multi-modal approach using optical and SAR pictures for oil spill detection and classification. Similar to this, Zhou et al. (2021) suggested a multi-modal approach for identifying and categorizing oil spills using optical and hyperspectral pictures.

METHODOLOGY:

1. DATA COLLECTION: Collecting pertinent data is the initial stage in creating an oil spill detection and classification system. Different sensors, such as Synthetic Aperture Radar (SAR), optical sensors, infrared sensors, and hyperspectral sensors, may be used to capture the data. SAR data is especially helpful for finding oil spills because it can see through clouds and find spills in any weather.
2. PREPROCESSING: To eliminate any ambiguities, errors, and noise in the data, preprocessing is necessary. Preprocessing steps could include data normalization, image enhancement, and filtering.
3. FEATURE EXTRACTION: Relevant features are extracted from the data after preprocessing. The characteristics could have a texture, shape, colour, or spectral makeup. The spatial arrangement of pixels in the image is described by texture features. The geometric characteristics of the oil slick are described by shape features.
4. CLASSIFICATION: A classification algorithm is trained to categorize the oil spill after the features are extracted. Classification is accomplished using machine learning methods like Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN). The system is trained on a set of data that has been classified, with the class labels indicating whether or not each image contains an oil spill. Based on the features gleaned from the photographs, the algorithm develops the ability to categorize fresh images.
5. POST PROCESSING: Post processing techniques are used after classification to increase the classification's accuracy. Segmentation, fusion, and spatial and temporal filtering are examples of post processing techniques. Small noise pixels are eliminated.
6. VALIDATION: In order to determine the system's accuracy, independent data is used to validate it. In order to evaluate the resilience of the system, the validation data may be gathered from various sensors or at various periods. Metrics including accuracy, precision, and recall are used to gauge the system's performance.

BLOCK DIAGRAM :

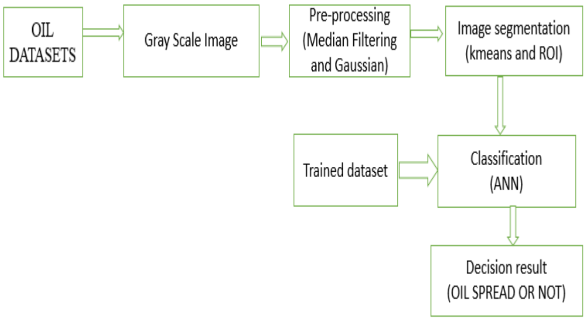

Figure 1: Flow diagram of proposed method

The suggested methodology includes grey scalar imaging of the datasets, median and gaussian filtering, image segmentation using K-means and Region of Intrest (ROI), and CNN for extracting the features from the images. By utilising ANN to categorise the photos based on the extracted features and identify oil slicks or oil slicks that seem similar.

GRAY SCALE IMAGING

When creating a grayscale image, the brightness level of each pixel is represented by a single value. The brightness level is often expressed as a number between zero and 255, where 0 represents black, 255 indicates white, and numbers in between represent different shades of grey. Only intensity information is present in a grayscale image; there is no colour information. This indicates that the image is presented without any colour information in grayscale, ranging from black to white.

Grayscale imaging is frequently utilized in a variety of industries, including digital photography, computer vision, and medical imaging. Additionally, it is frequently used in printing since it allows for the cost-effective reproduction of grayscale images using only black ink. In general, grayscale photography is an effective method for portraying images simply and effectively while preserving crucial visual information.

PRE-PROCESSING

Preprocessing is a crucial step in the detection and classification of oil spills because it improves the quality of the input data and gets rid of any noise or extraneous information that can reduce the system's accuracy. Pre-processing the photos primarily involves two steps: image acquisition, and image enhancement.

Image acquisition:

The process of gathering digital photographs from a variety of sources, such as cameras, drones, satellites, or other imaging equipment, is known as image acquisition. Image capture is a crucial step in the identification and classification of oil spills since it directly influences the clarity and sharpness of the images that will be used for analysis. A number of sensors, each having benefits and limitations of their own, can be used for picture capture. Among the sensors used for image acquisition are those that provide synthetic aperture radar (SAR) images.

SAR photos also offer useful details regarding the scale and scope of an oil spill, which can aid in organizing and setting priorities for response actions. By analyzing the SAR photos over time, it is able to trace the movement and spread of the oil spill and anticipate its potential impact on the ecosystem and marine life.

However, SAR pictures have several limitations. Interference from ships, wind, and other external conditions can cause noise and limit detection accuracy. SAR images also have lesser resolution than optical sensors, making it difficult to identify minor oil spills or distinguish between different types of oil spills.

Image Enhancement:

Image enhancement is the process of increasing the quality and appearance of an image through the use of various techniques that change the image's pixel values. Image enhancement techniques can be employed in the context of oil spill detection and classification to improve image clarity and contrast, making it easier to detect and categorize oil spills.

Image enhancement techniques can be used alone or in combination to increase image quality and clarity. It is crucial to remember, however, that excessive augmentation might result in visual artefacts and false positives, which can reduce the accuracy of oil spill detection and categorization.

Image enhancement is an important stage in oil spill detection and classification because it enhances image quality and clarity, making it easier to differentiate between oil spills and other elements on the ocean surface. Various enhancement techniques can be used to improve the contrast, reduce noise, sharpen features, adjust colour, and improve image resolution, resulting in more accurate and reliable oil spill detection and categorization. The proposed method uses the Gaussian filtering and Median filtering for image enhancement.

A Gaussian distribution-based linear filter called a "Gaussian filter". It is used to blur images by reducing the pixel values. The process by which the Gaussian filter operates is to convolve the picture with a Gaussian kernel, which is a weighted matrix that specifies the strength of the filter at each pixel. Given that it keeps the image's borders and details while decreasing noise, the Gaussian filter is frequently used to smooth out noise in images.

Contrarily, the median filter is a non-linear filter that reduces visual noise by replacing every pixel's value with the median value of its neighboring pixels. The median filter transforms the centre pixel into the median value of the pixel values in a window that is moved over the picture. While retaining the image's edges and details, the median filter effectively gets rid of salt-and-pepper noise.

In this study, noise reduction and image enhancement can both be accomplished using median and Gaussian filters. While a median filter can be used to eliminate salt-and-pepper noise and maintain the edges and features of the oil spill, a Gaussian filter can be used to smooth out noise and enhance the contrast of the image. It is possible to increase the quality and clarity of the photos as well as the precision of oil spill detection and categorization by combining these filters with other image enhancing techniques.

FEATURE EXTRACTION:

The technique that is used in this study for mage segmentation is K-Means algorithm, Region of Interest (ROI) and Convolutional neural network (CNN). It allows the oil spill to be distinguished from other features on the ocean's surface. The oil spill location can be highlighted in a mask or binary picture using the location of Interest (ROI) segmentation technique, which also improves the detection and classification algorithms' precision.

K-Means Algorithm:

The K-means technique is an unsupervised clustering approach that is both simple and efficient. The algorithm attempts to divide a given dataset into K clusters, where K is a user-specified parameter.

The K-means algorithm works like this:

1. The procedure begins by randomly picking K initial cluster centers.
2. Based on the Euclidean distance that lies between each data point and the cluster centre, the closest cluster Centre is allocated to each data point in the dataset.

3. By estimating the mean of all the data points provided to each cluster, cluster centers are updated.
4. Steps 2 and 3 are performed until convergence is reached.

The convergence requirement is satisfied when the positions of the cluster centers do not change between iterations or when the maximum number of iterations is reached.

K is a user-defined parameter denoting the number of clusters to generate, and it is used by the K-means method to split a picture into K clusters. K-means first chooses K arbitrary pixels from the picture as cluster centroids. Each pixel in the picture is then allocated to the closest centroid based on the Euclidean distance between it and the centroid. Until the centroids cease to move or the maximum number of iterations has been reached, this phase is repeated.

The K-means algorithm's key advantage is its simplicity and efficiency, making it a good choice for picture segmentation applications. Furthermore, it can efficiently handle enormous datasets, making it a popular choice for processing large photos. The K-means algorithm can be used to segment images based on attributes such as colour, texture, or brightness. In color-based segmentation, for example, the RGB colour values of each pixel are utilized as features to group similar colors together. Gabor filter responses or gray-level co-occurrence matrices are used in texture-based segmentation to group similar textures together.

The K-means method can be adapted to various data sources and situations. Oil spills can occur in a variety of habitats, including seas, rivers, and lakes, and their characteristics can vary based on factors such as the type of oil and meteorological conditions. The K-means algorithm parameters, such as the number of clusters and the distance metric, can be tuned to the specific conditions of the oil spill detection.

Region of Interest (ROI):

A Region of Interest (ROI) is a portion of an image, video, or signal that is chosen for additional analysis or processing. The ROI is determined by its relevance to the task at hand and can be defined in a variety of ways depending on the application.

ROIs are commonly used in image processing and computer vision for tasks such as object detection, segmentation, and tracking. In object detection, for example, a ROI may be defined as the area of the image that is most likely to contain the object of interest. This can be identified by attributes like colour, texture, or shape, or by using machine learning algorithms that learn to recognize things based on training data.

Region of interest (ROI) is frequently used in Synthetic Aperture Radar (SAR) imaging to identify and analyze certain features within the SAR image. SAR images are created by directing radar waves towards a target and detecting the reflected signals, which can reveal details about the target's surface and attributes. ROIs in SAR imaging can be used for a variety of objectives, including identifying and analyzing specific terrain features, tracking changes over time, and detecting anomalies. An ROI can be used to detect changes in the height of a glacier or ice sheet, for example, or to identify a certain land cover type, such as a forest or wetland.

The use of ROIs in SAR imaging can increase analysis accuracy and efficiency, especially in large-scale investigations with limited processing time and resources. The system can reduce computational needs and avoid false positives generated by other features or noise in the image by focusing on certain areas of interest. Furthermore, when paired with other data sources such as optical imagery or ground truth measurements, the utilization of ROIs can allow for more targeted and detailed analysis of SAR images. This can improve SAR image interpretation and give more usable information for a variety of applications such as environmental monitoring, disaster response, and military reconnaissance.

Convolutional Neural Network:

CNN is a potent and adaptable deep learning architecture, have completely changed the way computer vision is studied. They show significant potential for a variety of applications, including oil spill detection and classification systems, because to their capacity to autonomously learn and extract features from photos. It is operated by learning progressively more sophisticated information from the input image via a sequence of convolutional layers.

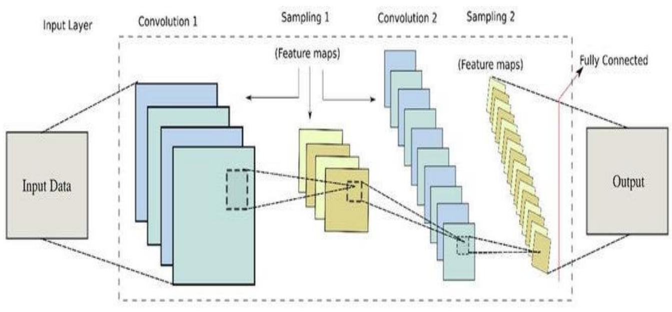

Figure 2 Architecture of CNN

Each convolutional layer is made up of a collection of filters that are used to create a set of feature maps from the input image. The edges, corners, and textures of the image are all captured in these feature maps along with other patterns and features. A sequence of fully connected layers are then used to classify the image using the learnt features after the output of the convolutional layers is input into them. In order to reduce the classification error, the CNN learns to tune the parameters of the fully connected layers and the weights of the filters in the convolutional layers.

CNNs can be used to automatically learn features that are important for differentiating between oil spills and other objects in the image in the context of oil spill detection and classification. On the basis of a sizable collection of labelled training photographs, the CNN, for instance, may learn to recognize the distinctive patterns of oil spills, such as their shape, texture, or color.

The ability of CNNs to learn to recognize features at various scales and orientations, which might be significant for identifying small or irregularly shaped oil spills, is one benefit of utilizing CNNs for feature extraction in oil spill detection and categorization.

Additionally, CNNs may be trained on sizable datasets, which can help to increase the detection and classification algorithms' precision and generalizability.
In terms of feature extraction in oil spill detection and classification systems, CNNs can be an effective tool. They can help to increase the precision and effectiveness of the detection and classification algorithms, resulting in a more effective and prompt reaction to oil spills, by automatically learning pertinent features from the input photos.

CLASSIFICATION:
After characteristics for oil spills and spills that look like them are retrieved from the photographs using CNN. During the training of the system to classify the oil spills, these extracted features are subjected to ANN.
Artificial Neural Network:
The best method to conceptualise artificial neural networks is as weighed directed graphs, where the nodes correspond to artificial neurons and the connections that exist between their inputs and outputs correspond to directed edges with weights. Input from the outside world is accepted by the artificial neural network in the form of vectors representing patterns and images. The notation x(n) for every n inputs then serves as the official designation for these inputs. Next, the weights for each input are compounded. These weights are the details that the artificial neural networks use to specifically address an issue. These weights, in a general sense, frequently represent how tightly coupled neurons are in an artificial neural network. Every weighted input is added collectively inside the computer unit.

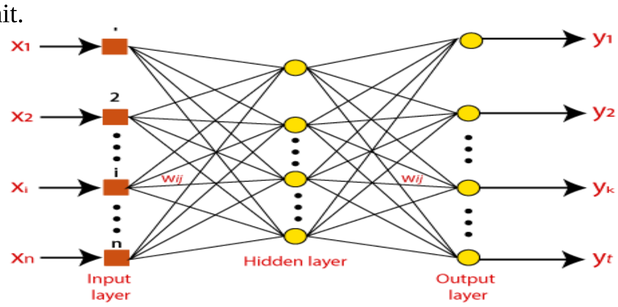

Figure 3 Architecture of ANN

The basic building block of an ANN is a perceptron, which consists of a set of input values, weights, and a bias term. In order to create an output, the values given as input have been multiplied by the respective weights, and the resultant values are then added with the bias term. The perceptron's output is then determined by passing this output via an activation function. An optimization strategy is used during training to alter the weights of the neurons in order to lessen the difference between the predicted output and the actual output. The ANN gains knowledge of the input data patterns and attributes that are most indicative of the desired output.
As part of this study, ANNs can be trained on a set of labelled photos to determine whether they belong in the category of oil spills or other things. The attributes from the pre-processed SAR images, such as the texture, shape, and polarimetric characteristics of the image, would be the input to the ANN. One neuron would make up the ANN's output layer, which would give a binary output indicating whether or not the image represents an oil spill. ANNs can learn to recognize complicated patterns in the input photos that may be challenging to identify using conventional computer vision techniques, which is one advantage of utilizing ANNs for classification in oil spill detection and classification systems. Large datasets can be used to train ANNs, which can enhance the classification algorithm's generalization and accuracy.
In terms of categorization, ANNs can be a useful tool in systems that detect and classify oil spills. ANNs can help to increase the precision and effectiveness of the detection and classification algorithms, resulting in a more effective and prompt response to oil spills. ANNs learn to identify images depending on their attributes.

VALIDATION:
Validation is the process of assessing a machine learning model's performance using data that wasn't used during training. The purpose of validation is to evaluate the model's generalizability to fresh, unexplored data and to spot any over- or under fitting problems. In order to make sure that an oil spill detection and classification system is accurate and dependable, validation is a crucial step in the development process.
Cross-validation, independent validation, and real-world testing are just a few of the methods that can be used to verify the effectiveness of such a system. The technology is deployed in the field for real oil spill detection and classification during real-world testing. This method gives the most accurate and trustworthy estimate of the system's performance, but it can also be difficult because real-world situations are unpredictable and variable. In the context of the study, validation is essential to guaranteeing the precision and dependability of the detection and classification algorithms. We can spot any overfitting or under fitting problems and adjust the algorithms as necessary by measuring how well they perform on a different validation set. This could aid in increasing the algorithms' effectiveness and efficiency, resulting in a quicker and more efficient response to oil spills.
In addition to these methods, it's crucial to assess the system's effectiveness using the right measures, like accuracy, precision, recall, and F1 score. These metrics give a numerical evaluation of the system's performance and can be used to pinpoint problem areas. In building an oil spill detection and categorization system, validation is a key stage. One can verify the system is accurate and dependable and increase the effectiveness of oil spill response activities by validating the system's performance using the right methods and metrics.

RESULTS:

The input image is pre-processed, with features retrieved using the K-means technique and convolutional neural networks, followed by classification using artificial neural networks. The proposed method sample input image is displayed in Figure 4.

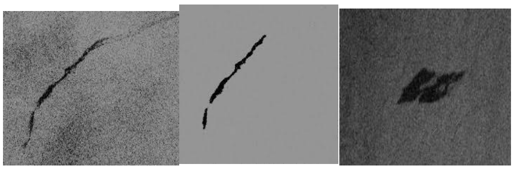

Figure 4 Oil Datasets

In the suggested method, grey scale imaging is first applied to the input images. These grey scale photos are pre-processed using the median and Gaussian filters to get rid of any noise that are present in images as shown in the Figure 5 & Figure 6.

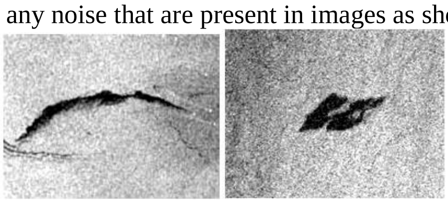

Figure 5 Gray Scale Imaging

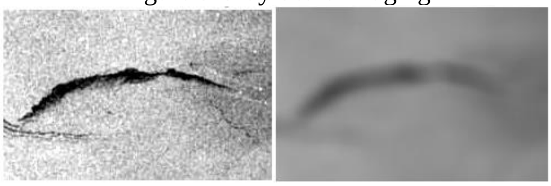

Figure 6 Image Filtering

Images must be segmented using the K-means method and the Region of Interest in order to extract features. The images are sent through CNN after segmentation in order to retrieve their characteristics.

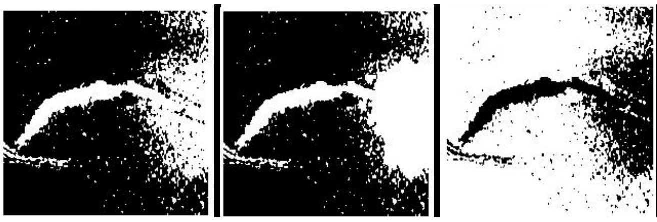

Figure 7 Images After Segmentation

Extracted features	OIL SPILLS	LOOK ALIKE
Contrast	0.7903	0.2397
Correlation	-0.0081	0.1058
Energy	0.9681	0.7592
Mean	0.0081	0.0025
Standard deviation	0.0895	0.0898
Entropy	0.0677	3.5778
RMS	0.0898	0.0898
Variance	0.0081	0.0080
Kurtosis	122.0081	6.7360
Skewness	11.0004	0.4825

Table 1 Extracted Feature using CNN

The overall frequency graph of the proposed method is different from the existing methods for pixel count and gray levels comparison graph for both oil spills and look alike as illustrated in Figure 8.

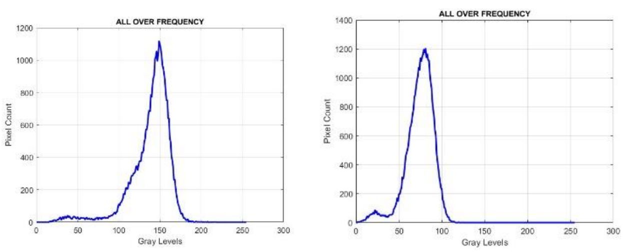

Figure 8 All over Frequency Graph using CNN

We test our strategy using a set of satellite images collected from various regions of the world. With an overall classification accuracy of 99.6% and a success rate of 93.02%, the testing results demonstrate the remarkable precision with which our system identifies and classifies oil spills. In terms of accuracy and computing efficiency, our methodology outperforms a variety of cutting-edge techniques.

CONCLUSION:

In this research, a variety of strategies and methods have been developed, including remote sensing using SAR and optical sensors, image processing, polarimetric analysis, and machine learning algorithms like CNNs and ANNs. These techniques can be used to differentiate oil spills from other objects in an image and extract features from the input data. One of the biggest challenges to identifying and categorizing an oil spill is the considerable range in its characteristics, such as size, form, thickness, and color. Environmental variables including wind, waves, and cloud cover may also have an impact on the detection and classification algorithms' accuracy. It's critical to create dependable systems that work effectively in a variety of environments in order to meet these difficulties. For this, great thought must be given to the system's machine learning algorithms, data processing techniques, and sensor design. In response to oil spills and in reducing their environmental effects, technologies for detecting and classifying them have the potential to be extremely important. These devices can aid in informing response operations and limiting the spread of an oil spill by precisely identifying and categorizing spills. The accuracy and effectiveness of these systems must be improved, as well as the environmental harm brought on by oil spills, by further research and development in this field.

FUTURE WORKS

The majority of oil spill detection and categorization systems now use offline SAR data processing. Real-time monitoring and reaction to oil spills, however, are becoming increasingly important. Future studies might concentrate on creating real-time algorithms that would enable quicker and more efficient responses to oil spills. SAR data is only one of several informational resources that may be utilized to identify and categorize oil spills. To increase the precision and dependability of oil spill detection and categorization, future study may examine the integration of SAR data with other data sources, such as optical images, in situ measurements, and environmental models. Many of the systems used today to detect and categorize oil spills are highly specialized and operate with significant expertise. Future studies may concentrate on creating user-friendly and accessible solutions that will enable a larger variety of stakeholders to use the technology and profit from it. Future research and development in the area of oil spill detection and classification systems has the potential to significantly improve environmental monitoring and protection overall, as well as the protection of marine ecosystems and human health, by addressing these and other issues.

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