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A DEEP LEARNING BASED ANALYSIS OF OIL SPILLED IMAGES TO MINIMIZE POLLUTION IN MARINE ENVIRONMENT

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Abstract

The rising demand for oil and increased shipping capacity are significant contributors to the pollution of the world seas and oceans that is caused by human activity. Oil spills on the world waterways are another major cause of this pollution. Because of the growing demand for oil and the capability of the maritime transport industry, oil spills on seas and oceans have become a significant source of pollution in recent years. It is of the utmost importance that oil spills are constantly monitored and that measures are taken to clean them up as quickly as is humanly possible. This is since oil spills can have devastating effects not only on the local ecosystem but also on the economies of states that are located along the shore. Because of the ongoing threats that are posed to marine life, biodiversity, and habitats, it is of the utmost importance to be able to keep a watch on oil spills from a distance, recognise them, and take action to clean them up. This is essential. In the past ten years, developments in remote sensing data collection, computing capability, cloud computing infrastructure, and cutting-edge SqueezeNet algorithms have led to significant advancements in oil spill detection. These developments have been responsible for most of the progress. These technological advancements have made it possible to identify oil spills more accurately.

Keywords:
Oil Spill, Shipping, Pollution, SqueezeNet

1. INTRODUCTION

Oil spills can be the result of activities that take place on land, or they can be the result of activities that take place at water. Ships and offshore structures are two common examples of sources of pollution that make their way from land into the water. Oil spills in the water can be brought on by either carelessness or malice on the part of the person responsible. The decrease in the number of marine accidents as well as the amount of oil that has been unintentionally spilled is some welcome good news. In addition, the amount of oil that has been accidentally spilled has also decreased. On the other hand, normal tanker activities may still result in the discharge of oily ballast water and leftovers from tank cleaning.

Furthermore, the engine room detritus, fuel oil sludge, and toxic bilge water from all ships will eventually make their way out to sea. The seafaring industry has demonstrated persistent expansion throughout the course of the past decade. If there were a greater number of ships, there would probably be a corresponding increase in the quantity of unlawful oil spills. It has been hypothesised that illegal discharges could have been caused by a broad range of different types of ships, including oil tankers [1].

Oil spills can be located and monitored using a wide variety of aeroplanes, boats, and satellites. Ships that are fitted with specialised radars may be able to detect oil in the water; however, these radars are only able to monitor a small portion of the surrounding area. Despite this, having the ship on standby in case it becomes necessary to acquire samples of hydrocarbons is essential. The radar systems onboard aeroplanes and spacecraft equipped with synthetic aperture radar (SAR) are the primary instruments for monitoring oil spills at sea [2].

A radioactive sensor known as SAR is only capable of taking images in a plane that is two-dimensional. The characteristics of the surface being measured are reflected in the picture brightness because it was captured before the measurements were taken (the target). An oil spill can be recognised in a SAR image because the oil film reduces the backscattering of the sea surface, resulting in the formation of a dark formation that is in stark contrast to the brightness of the surrounding sea, which has not been contaminated by the spill. This allows the oil spill to be located more easily. Because of this, it is now feasible to determine the exact location of an oil spill. Synthetic Aperture Radar (SAR) sensors that are based in space offer several advantages over airborne patrols when it comes to locating oil spills in the ocean. These advantages include the fact that they are not limited by daylight, that they can see through clouds, that they can survey vast areas, and that they cost less [3].

A dark formation can be seen on SAR images because of oil films having the effect of reducing the backscattering of the water surface. There is a significant connection between the incidence angle of a radar sensor and the mechanisms that are accountable for radar backscattering from the surface of the water. This connection exists because the incidence angle of a radar sensor is measured in degrees. Brief gravity-capillary waves that are caused by the wind are the primary agent of radar backscattering over a large range of angles, approximately ranging from 20° to 50°. Because of the existence of the hydrocarbon layer, these waves go through a process called local attenuation, which leads to a reduction in the amount of backscattering that they do [4].

When one attempts to produce brief gravity-capillary waves, it is implicitly believed that a weak wind field is already present. In actuality, the wind speed at its lowest point will vary depending not only on how frequently measurements are taken, but also on the angle at which those observations are taken. Within this frequency range, the oil layer can be observed if the wind speed is between 2 and 3m/s.

On the other hand, the discharge will be cleared by the wind if the breeze is strong enough. To begin, the amount of energy that is provided to the short pulses is sufficient to combat the effect that is caused by the dumping of the oil film. Then, once the waves have built up, the turbulence in the top sea layer could cause the spill or a portion of it to break apart and sink. This could happen after the waves have built up. After the waves have grown up to their full height, this may take place.

The intensity of gravity-capillary short waves that are caused by wind is reduced by a variety of natural and artificial occurrences in the ocean. These occurrences can be either natural or man-made. When compared to the ocean that is in the vicinity, certain landmasses come across as having a significantly darker colour on SAR images. Dark formation is a word that can be used to refer to any portion of an image that is significantly darker than its surroundings, and the term can be used to describe any element that fits this description.

This presents a particularly difficult challenge because the available research does not contain a well-defined standard that stipulates how much darker a location must be. This lack of a standard makes it difficult to determine how much darker a location needs to be. Even within the confines of a single image, there is a wide range of necessary levels of blackness and contrast for accurately depicting the gloomy areas of the scene.

2. LITERATURE SURVEY

Deep learning algorithms are used in machine learning and artificial intelligence. All these algorithms derive their fundamental principles from the make-up and operations of the human brain. These deep neural networks have excelled in a wide range of geoscience and remote sensing applications, where they have displayed extraordinary capabilities and achieved remarkable levels of success [5].

In contrast to more traditional approaches to machine learning (ML), deep learning (DL) is driven entirely by the data it processes to determine how features should be represented and how to comprehend the data it is given in the most efficient way possible. As a direct result of this, the step of feature extraction that relied on the expertise of individuals in the construction of handcrafted features is not necessary any longer prior to the phase in which the classification of the oil spill will take place. to differentiate between oil spills and other events with comparable appearances, several distinct DL models automatically retrieved discriminative learned features.

The fact that these models can be applied to a wide range of situations makes it possible to consider both the case-specific quality of traditional approaches and the problem at hand. Since 2017, there has been an increase in the number of studies that investigate oil accidents by using DL models. This trend is expected to continue in the foreseeable future. These models were used for a wide range of applications. Different DL models can have different architectures, components, and tasks because different neural network architectures require different combinations of elements. This is since different architectures of neural networks require different combinations of components to be used [6].

2.1 CONVOLUTIONAL NEURAL NETWORK

CNNs are among the most widely used deep learning techniques for image recognition. Due to the design of this structure, it is now feasible to feed images directly into the deep neural network. Traditional feedforward DNN architectures, such as CNNs allows these architectures to learn highly abstract features from the images. The term feedforward learning refers to the architecture used in this form of learning system.

The process of extracting features from unprocessed data makes use of convolutional layers. to generate the features, these layers combine the outputs of several trainable convolutional kernels or filters and apply them to a specific section of the data. To generate nonlinear convolved features, also known as feature maps, the output of each convolutional function is nonlinearly transformed by an activation function (such as a rectified linear unit, sigmoid, hyperbolic tangent, or softmax), which results in the production of nonlinear convolved features. CNN capacity to model unpredictable data is boosted because of this improvement (i.e., multiple maps of neurons) [7].

The output sizes that are produced by the initial picture as well as those produced by the feature maps are equivalent to one another. Additional pooling layers, such as maximum and average pooling layers, reduce the dimensionality of feature maps. This enables the network to acquire usable features while maintaining its insensitivity to the precise locations of targets.

To improve the abstraction of the features that have been extracted while also conserving the processing resources that are available and preventing overfitting by reducing the number of learnable parameters, feature maps are typically down sampled by half using pooling layers. This is done to improve the quality of the features that have been extracted. This is possible because of how these layers work together [8].

At the very top of the construction is a layer that is totally interconnected with all the other layers. This layer, which is itself comprised of many hidden layers, is the one that decides the overall score for each category by combining features from lower layers. It is also the layer that determines whether a layer is hidden. The very top level of a network is referred to as the categorization layer, and it is the only level in the network that is fully connected from top to bottom. The presence or absence of an oil spill) and softmax are utilised as decision-making tools in the process of determining the classification results.

Both the forward and the backward propagation processes are utilised to train and learn the relative weights of the variables that exist between the input and the output of the network. This is done to maximise the accuracy of the training and learning process. Forward propagation involves minimising the value of a predefined cost function by continually backpropagating updates to the weights of the network learnable parameters. This process occurs as new identifying information is accumulated over the course of the network learning process.

In the sections that are to come, we will talk about the numerous CNN tasks and architectures that can be utilised in the process of identifying oil spills. These are accessible for use.

2.2 PATCH-BASED IMAGE CLASSIFICATION

The models are built from equally distributed selections of remotely sensed pictures, and each tile (patch) in the network corresponds to a different class label. These selections are then used to construct the models. The CNN model can be trained to generate a probability map of each input patch label to display the likelihood of an oil spill happening in a particular tile. This map can display the likelihood of an oil spill occurring in a particular tile.

When a CNN is being use for the purpose of categorization, determining the best place to insert the input patch is necessary to get the best possible results from the network. Because of this, selecting a large input image patch size will result in an increase in both the computational strain placed on the network and the amount of time required for the processing overall. If the study choose a small one, on the other hand, the CNN model might not be able to acquire features that enable it to differentiate between different kinds of objects. Using data acquired through remote detection, multiple CNN architectures were used, and each one was successful in classifying oil spills from different locations.

To differentiate between oil slicks and erroneous positives in the ERS-2 SAR data collected from the China Sea, [5] demonstrated a DenseNet-based CNN network structure. This structure was used to analyse the data. To creating the DenseNet model, we chose 148 images from the ERS-2 data collection to use. These 148 pictures depict a total of 86 oil slicks and 62 samples that are virtually identical to them. Due to the small size of the sample that was examined, the researchers disregarded the probability that oil and oil-like slicks were mixed.

In the [6] adjusted the CNN architecture and hyperparameters with the help of a large dataset that was composed of SAR dark regions. This was done by using the dataset to design and adjust the CNN architecture. They were able to accomplish this by training the CNN with the data collection. First, to train the model, we created 4843 samples of oil slicks and another 18,925 samples that were intended to resemble oil slicks by employing human labelling and data augmentation techniques. Together, these samples numbered 24,843 and were used.

Several studies were conducted with the purpose of determining how the performance of patch-based classification could be enhanced by incorporating optical and parametric SAR characteristics into the analysis. In the article [10] were successful in obtaining SAR polarimetric characteristics by utilising data from the C-band SAR spectrum (i.e., entropy, alpha, and single-bounce eigenvalue relative difference). After gathering this information, a convolutional neural network (CNN) was trained to recognise the differences between petroleum oil, plant oil, and oil emulsion. The CNN model was educated with 5400 unique instances, and it reached an accuracy rate of 91.33% when it was used in the identification process.

To locate oil accidents, implemented a CNN model for the purpose of deriving deep features from SAR polarimetric data. After that, they used principal component analysis to carry out dimensionality reduction, and after that, they used a support vector machine classifier equipped with a radial basis kernel to recognise the spillage.

They were able to independently retrieve oil films from AVIRIS hyperspectral images by utilising spectral indices and a one-dimensional convolutional neural network. Mining information pertaining to deep spectrum features allowed us to achieve this goal. The CNN model performed noticeably better than other machine learning models, such as SVM and RF, which are models that are utilised in machine learning substantially more frequently.

3. BACKGROUND AND RESEARCH GAP

Ease of use, and potential for reproducibility, manual inspection has become the method of choice for detecting oil spills in recent years. On the other hand, since it is dependent on the expertise of the interpreter, it cannot be relied upon very much. This makes it a very unreliable method. In this method, operators receive instruction on how to analyse images to locate oil leaks in their facilities. The first step in getting rid of erroneous positives is to filter out any oil spills that might be visible in a SAR image.

A method of discrimination is utilised to differentiate between actual oil accidents and false positives that have been reported. Some imitators are straightforward to distinguish from oil spills since their shapes and configurations are obviously dissimilar to those of oil spills. This makes it possible to recognise these mimics. A good illustration of this can be seen in the dark regions that appear after the formation of internal wave areas, eddies, or rain cells. When working with more involved situations, on the other hand, a cursory examination is not appropriate.

It is particularly challenging to differentiate between objects when there are natural oil slicks present or when the winds are not blowing. In such a situation, it is essential to carry out a more in-depth analysis that takes into consideration several distinct aspects of the problem at hand. When it comes to the study of oil slicks, there are many different factors that must be considered; however, the ones that are of the utmost significance are the following: the speed and direction of the wind, the time of year, the shape analysis, the size of the slick, and the overall morphology of the region that is being observed.

It is important to pay attention to the conditions of the wind because low wind speeds (two to three metres per second) result in many dark formations, and high wind speeds (eight to ten metres per second) render the oil undetectable. The time of year can be helpful in differentiating between naturally occurring slicks, such as an algae growth, and grease ice, which typically forms in the summer. In addition, the size of the slick is considered to eliminate low-wind regions and even massive natural slicks as potential sources of the oil spill. When travelling from one region with no wind to another region with wind blowing, it is necessary to have a general understanding of the morphology of the area in question to recognise the dark formations that are generated because of the transition.

These shady features are frequently produced because of the shielding effect of the topography that lies all around them. The boundaries between water masses that have distinct properties, such as two water masses of varying densities, fronts add a complexity layer. This is because fronts mark the boundaries between two water masses that have distinct properties. The addition of fronts can significantly complicate the situation in a variety of different ways. Within these shaded structures, a bewildering variety of sizes and shapes, arranged in a myriad of different patterns, may be found.

Oil leaks and the many natural phenomena that imitate their appearance can be easily differentiated from one another by using shape analysis due to the distinctive characteristics that they share. When conducting an analysis of shape, each characteristic of the black shapes, including the borders, tails, and roundness of the shapes, are taken into consideration. The backscattering values at the border of the spill typically differ significantly from one another, creating a clear line of demarcation between the area that was affected by the spill and the area that was immediately adjacent to it. On the other hand, natural occurrences typically have clearer boundaries to identify their limits than man-made phenomena do. On the other hand, the construction of the borders of an older spill is substantially more complicated than that of a more recent one. The tails of a look-alike can be thin and straight or slightly curved in the case of oil spills; however, the illustration depicts the natural behaviour of a look-alike as having softer curves than the example shows. Identical-looking features, which are frequently associated with natural structures such as eddies, can stretch for a significant distance in one direction or another.

If the study notice a lengthy, dark formation, regardless of whether it is curved, the study can be certain that there has been a recent release of hazardous materials. On the other hand, most natural occurrences take the form of a circle, whereas the shapes that man-made spills typically take are horizontal. Because it is difficult to quantify roundness, one typically depends instead on the experience and judgement of the photo-interpreter.

When an oil spill detection service is performed manually, the general practise is to also identify the potential spill location as part of the service. This is because manual detection methods are less accurate than their automated counterparts. In general, spills are categorised as high, medium, or low according to the probability of oil contamination.

The background to understand the nature of the image manifestations, become of the utmost importance in the translation process. Researchers are putting in a lot of effort to develop fully automated or at least semi-automated systems to make up for the lack of employees who have the necessary knowledge. These systems will be able to recognise and identify mysterious dark formations such as oil spills.

4. PROPOSED METHOD

For the categorization process to work properly, it is essential that the algorithm be provided with certain characteristics as inputs. The accuracy of the classifier as well as the method heavily depends on a collection of characteristics that can differentiate the oil spill from its close relatives in an effective fashion.

This collection of characteristics is essential to the success of the classification. Conventional methods for detecting oil spills classify dark objects in SAR images as oil spills or phenomena that appear to be oil spills based on a set of statistical features that are chosen at random. These conventional methods classify dark objects as oil spills or phenomena that appear to be oil spills. This is done on the presumption that these dark objects are oil spills or occurrences that give the impression that they are oil spills.

One of these three overarching classes can be assigned to each of the characteristics that are typically utilised in the process of oil spill identification. Features that capture the physical behaviour of oil spills (such as mean or maximum backscatter values, standard deviation of the dark formation, or a larger surrounding area); features that refer to the geometrical characteristics of oil spills (such as area, perimeter, and complexity); features that refer to the context of the oil spill in the image; features that refer to the geometrical characteristics of oil spills; and features that refer to the context of the oil spill in the image (e.g., number of other dark formations in the image; presence of ships).

Table.1. Feature used in the Study

Major Features	Minor Features
Area	Mean Haralick texture
Background mean value	Object mean value
Background power to mean ratio	Object power to mean ratio
Background standard deviation	Object standard deviation
Complexity	Perimeter to area ratio
Local area contrast ratio	Ratio of the power to mean ratios
Max border gradient	Shape factor I
Max contrast	Shape factor II
Mean border gradient	Shape texture
Mean contrast	Spectral texture
Mean contrast ratio	Standard deviation border gradient
Mean Difference to Neighbors	Standard deviation contrast ratio

5. SQUEEZENET

SqueezeNet is a variant on the standard CNN architecture that makes use of fewer nodes. Although it maintains a high level of precision, it does so use a smaller number of variables than a traditional CNN. The construction of the SqueezeNet makes use of several procedures that are developed from those of the CNN. These procedures include the following: The first thing the study need to do is switch the filters so that they are 1x1 rather than 3x3. The next thing to do is cut the amount of input channels down to three sets of three.

In the third phase of the process, the study will downsample the network at a late stage to increase the size of the activation maps of the convolution layers. The preponderance of the SqueezeNet is made up of Fire modules, which are layers of squeeze convolution and only have a single filter in each. Following that, the findings of the layers that came before it are transferred to an expand layer, which contains a combination of 1x1 and 3x3 convolution filters (as shown in Fig.1).

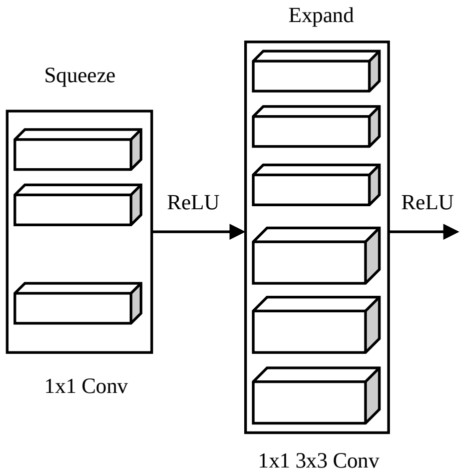

Fig.1. SqueezeNet Architecture

The first convolutional layer of the network architectures that have been discussed has received a considerable quantity of attention and thought from researchers and developers. Min made the decision to use a multilayer perceptron, which is more commonly referred to as an MLP, in order to increase the expressive capability of the network. This was done rather than using the traditional linear convolution kernel. This research also describes how a multi-layer perceptron, also known as an MLP, is comparable to a cascaded cross-channel parametric pooling layer that is positioned behind a conventional convolution kernel. This analogy objective is to accomplish the incorporation of information across multiple channels as well as the linear combination of several different feature maps.

Because the size of the convolution kernel value grows in proportion to the number of input and output channels, the performance of this technique is at its peak when working with a restricted number of channels on both the input and output sides of the equation. The complexity of the convolution kernel parameters and procedures, as well as the number of input channels, were both reduced of the addition of a 1×1 convolution to each inception module. The structure is finished off with an additional 1+1 convolution that is appended to enhance feature extraction and make the most of the overall number of channels. This helps make the most of the overall number of channels.

A pooling layer and a fire module are two of the novel building blocks that we suggest introducing into the network to improve its convergence. The structure of ResNet, which acted as a model for us to model our concepts after, was the primary source of motivation for us. It is then connected to the convolutional layer that comes after it, which occurs after the combination of the two layers that came before it. When a convolution stack is connected to ResNet by way of its shortcut connection, a process known as identity mapping takes place. This is a procedure in which the input to the stack is simply appended to its output. We let the stacked nonlinear layers correspond to a different mapping of $F(x)$: $H(x)$-x, where $H(x)$ is the intended underlying mapping in a formal sense. We do this by letting the nonlinear layers stack on top of one another.

This guarantees that the layers will build in the correct order. The initial transformation can be represented as an expression of the form $F(x)+x.F(x) + x$. When available, the expedited link will almost always go directly through instead of stopping at any of the intermediate levels. We look to the residual structure of ResNet as a possible solution as a beginning point for combating the problem of vanishing gradients and degradation without increasing the number of network parameters. This is important because it allows us to avoid increasing the complexity of the network.

6. EXPERIMENTAL RESULTS

For FPRs that are less than 106, the TPR for the Faster SqueezeNet technique is greater than 0.9, and the area under the ROC curve for this approach is very close to 1. Following acceleration by TensorRT, the typical amount of time required for 1000 iterations of reasoning is only about 0.68 milliseconds, which is adequate for most applications that are used in the real world. This is the amount of time it takes can be quite substantial, with values varying from 2.57 milliseconds to 4.85 milliseconds. The GTX 1050 graphics card, which has a memory capacity of 2 terabytes, is compatible with a wide variety of computer configurations.

6.1 SAR DATA

Active microwave sensors are a form of remote sensing that are frequently utilised in the process of identifying and keeping track of oil accidents. This is because these sensors have a wide field of vision and can collect data at any time of the day or night, regardless of the weather. Additionally, they can do so regardless of any conditions that may exist. SAR and SLAR systems, which stand for synthetic aperture radar and side-looking airborne radar, respectively, are the two primary types of radar imaging that are utilised in the discovery and monitoring of oil spills.

Both methods use the same image geometry and are based on the same ideas concerning synthetic apertures, such as the concept of a synthetic aperture. The research that was analysed provides evidence that using satellite-based SAR data for monitoring oil spills is both beneficial and efficient. This conclusion was drawn from the findings.

For example, in Fig.4, we can see several oil spill incidents that were captured by SAR images in high-resolution level-1 ground range detected (GRD) format. These images were produced in high-resolution format because they were produced in GRD format. The radar observations are projected onto a standard 10-meter grid using this format. The use of SAR images for the detection of oil spills presents several challenges, one of which is that oil spills are not the only phenomenon that reduce the scattering and appear dark; this applies to both manmade and natural occurrences. Another challenge is that oil spills are not the only phenomenon that can reduce the scattering mechanism and appear dark in SAR images.

6.2 DATASET DESCRIPTION

Maintaining vigilance in the search for oil leaks In addition to jpg images of oil spills and other pertinent occurrences that were extracted from satellite Synthetic Aperture Radar (SAR) data, this dataset includes ground truth masks as well. The original source of SAR data was supplied by the operations of the European Sentinel-1 satellite. This data was collected from the database that was maintained by the Copernicus Open Access Hub of the European Space Agency.

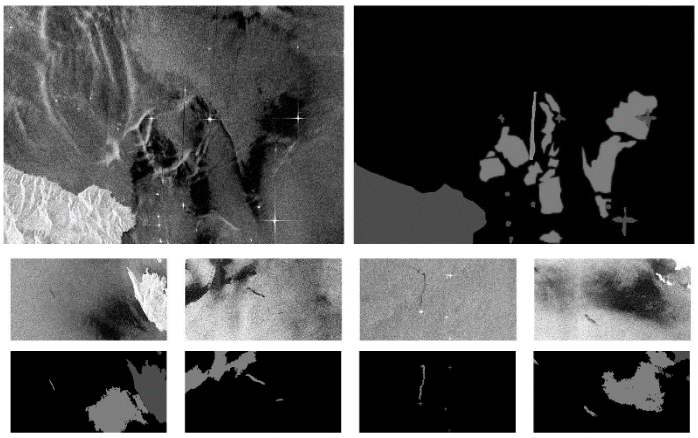

Fig.2. SAR Dataset Image and its Ground Truth

The size of the dataset that was produced, which came to be 400 megabytes, reflects the inclusion of instances drawn from five distinct categories. These categories are referred to as oil spill, look-alike, land, ship, and marine regions, respectively. There are approximately 1000 images in the dataset that can be utilised for training purposes, and another 110 images that can be utilised for testing purposes. We included additional information about the preprocessing, class distribution, and other aspects that were utilised in this research. However, for academics and researchers to be granted access to the Detection Database, there are a few prerequisites that need to be satisfied.

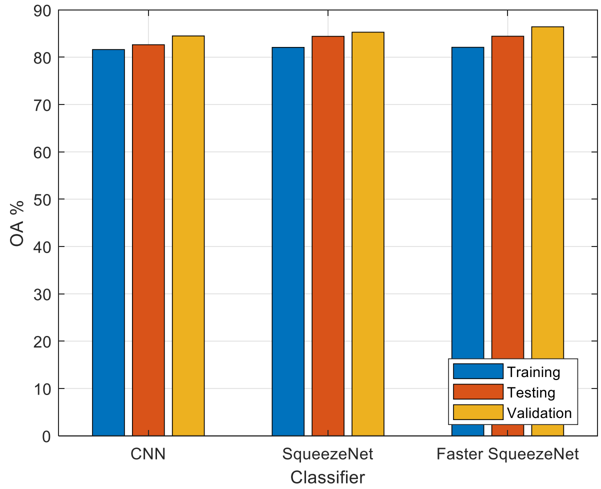

Fig 3. Overall Accuracy (OA)

A cross-validation process was carried out so that it could be determined which combination of input parameters provided the best results for each method. This was accomplished by comparing the outcomes of the two procedures. In terms of its overall performance in terms of OA for a thick oil layer, the proposed SqueezeNet had a superior overall performance than the other models that were compared when they were evaluated over the test samples. It was found that our proposed method required a significantly lower amount of prediction time when compared to other methods in terms of the amount of time that was required for computation.

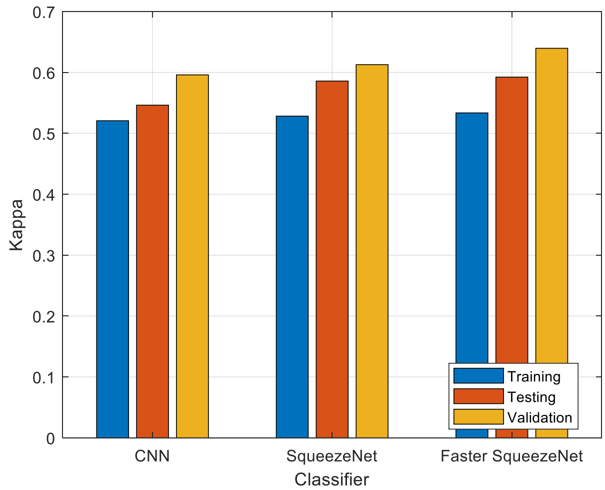

Fig 4. Kappa coefficients

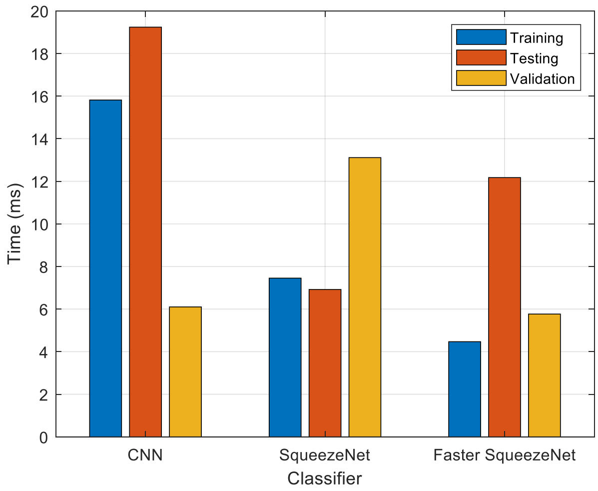

Fig 5. Training/Validation/Testing Time

In addition, a mapping of the distribution of an oil film within an image was created by applying all the methods. Since the findings of this test, our strategy for recognising and categorising oil videos was demonstrated to be effective.

7. CONCLUSION

It is of the utmost significance to evaluate the performance of a classification method using a dataset that was not employed during the process of developing the method. The capability of the SqueezeNet model to generalise around the confines of a training dataset is a solution to the problem that conventional machine learning techniques are unable to generalise beyond the boundaries of a training dataset. The mission of oil discharge categorization was accomplished with flying colours thanks to the application of the SqueezeNet algorithm in all its varied incarnations. The most ideal way to evaluate the efficacy of these classifiers is to conduct a comprehensive comparison of the various classical ML classifiers utilising the preprocessing methods, same data source, training samples, training sample size, chosen features quality, and parameter settings for classification algorithms. Overfitting is a phenomenon that happens when a classification performs well on a training set but struggles to apply its findings to new data. This phenomenon is referred to as overfitting. This issue frequently arises during the process of constructing DL models with insufficient amounts of available data.

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