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Underground Oil Pipeline Leak Detection Using CNN and SVM

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Abstract:

Oil leaks on land and water surfaces from pipeline cracks cause severe damage to the environment. Pipeline leak detection is an essential step for pipeline safety management. This paper presents synthetic aperture radar (SAR) images as an approximate representation of the target scenes due to their expansive field of view and capacity to gather data at any time, irrespective of weather conditions. The present study presents a transfer learning framework that uses deep learning convolutional neural networks (CNNs) for pipeline leak detection. Where we worked on image SAR data that was spilt into 80% training data and 20% test data. The investigation of CNN transfer learning is carried out using two distinct approaches: parameter-based CNN transfer learning and hybrid feature-based mechanisms. The optimal transfer learning model is selected using ResNet-50, Xception and AlexNet algorithms pre-trained on ImagNet. The results demonstrate that the feature-based CNN transfer learning approach the Xception model, combined with an SVM classifier proposed in this study exhibits superior performance compared to parameter-based CNN transfer learning methods. The method the Xception model, combined with an SVM classifier achieved highest accuracy of 99.6%, recall 99.7%, precision 99.5 %and F1scor 99.6%.

Keywords: Oil Leak Detection; Convolution Neural Networks(CNN) ; Feature Transfer Learning .

1-Introduction

Pipelines have become the most economical and reliable means for transporting oil and gas due to them in simplicity, cost-effectiveness, and operational reliability. However, pipelines are vulnerable to leakage caused by natural deterioration, corrosion, climate change, and human activities. Pipeline leakage can lead to significant economic losses and severe environmental contamination and pose serious risks to human health and safety [1].

Oil leaks, in particular, result in considerable environmental damage. A notable example is the 2010 British Petroleum Deepwater Horizon oil spill, which caused a widespread marine disaster, illustrating the severe environmental risks associated with the transport of crude oil [2].

In recent years, machine learning (ML) models have been increasingly utilized to enhance object recognition, a critical capability across various industries in the information technology era. Integrating of ML and deep learning (DL) has significantly improved the accuracy and efficiency of object detection, playing a vital role in advancing computer technologies [3].

One of the most effective techniques in deep learning is transfer learning, where pre-trained models, particularly convolutional neural networks (CNNs) trained on large datasets like ImageNet, are fine-tuned for specific tasks [4].

This study proposes a novel approach to pipeline leak detection using CNNs and transfer learning. The methodology employs two distinct techniques: feature-based transfer learning and parameter-based transfer learning. The effectiveness of the proposed method is demonstrated through an analysis of leak detection on synthetic aperture radar (SAR) image datasets. The remainder of this paper is structured as follows: Section 2 reviews related work; Section 3 outlines the methodologies, including the SAR dataset and the proposed leak detection technique; Section 4 presents performance metrics and discusses the results; and Section 5 concludes with suggestions for future research.

2- Related Work

Oil leak detection systems have advanced significantly over the years, with researchers combining several technologies to enhance accuracy and efficiency.

Starting with Sharafutdinov et al. in 2020 [5], the researchers proposed using multiple devices on unmanned aerial vehicles (UAVs) for oil leak detection, including microwave radiometers, infrared, radar, laser radar, and ultraviolet spectrometers. Remote spectral analysis was used to identify oil spills and determine their location and size. The goal was to develop an efficient method for monitoring fires and accidental spills, enhancing environmental and industrial safety in oil operations. A software package developed in C++ automated the spill area determination, improving measurement accuracy and reducing setup time.

In 2022, Jabbar et al. [6] introduced a smart, automated method for detecting oil spills and water pollution using image processing techniques in Iraqi rivers. The system focused on spills in locations such as Khor Al-Amaya and Shatt Al-Arab River. The method utilized deep convolutional neural networks (DCNNs) combined with image processing algorithms. The approach, which operated in two stages (training and operational models), achieved an accuracy of 83.54%, demonstrating a balance between precision and recall.

In 2023, S. Dehghani-Dehcheshmeh et al. [7] explored the use of CNNs and Vision Transformers (ViT) to detect and locate oil spills in open water using Sentinel-1 SAR C-band images from 2015 to 2017. Various models, including CNN, ViT, DeepLabV3+, FC-DenseNet, U-Net, and architectures, the DenseNet were employed, yielding the highest accuracy of 95.56%, recall of 68.75%precision 79.99%and f1-score 73.94%.

Later in 2023, D. Wang et al. [8] introduced the DRSNet model, integrating ResNet-50 within the DeepLabV3+ framework and SVM classifiers. Tested on SAR images from the RADARSAT-2 satellite, including data from the Deepwater Horizon spill, DRSNet outperformed accuracy 76% other semantic segmentation models, demonstrating significant advancements in oil spill detection.

Also in 2023, Ali et al. [9] developed an automated UAV-based visual inspection system for detecting rust on oil tanks. Using sequential fuzzy logic and threshold algorithms combined with image processing, the system achieved an accuracy of 83% on a dataset of 180 samples, highlighting its effectiveness in detecting surface defects.

3- Methodology Section

In this study, we propose a transfer learning based convolutional neural network approach for image-based pipeline leak detection as shown in Figure 1. After obtaining the image data, it is pre-processed. Then the pre-processed data is fed into the proposed models and finally the proposed models are compared to obtain the best results.

3.1. Data acquisition

The dataset used in this study consists (2007) synthetic aperture radar images collected from the Sentinel-1 satellite, where the leak detection on a pipeline in India was studied year 2020. The images cover a variety of environmental conditions, including desert, remote, and rugged areas, as well as different weather conditions of heat, rain, and wind. The dataset includes 1010 images of oil leaks and 997 images without oil leaks. Leaks vary in size, shape, and thickness, and represent a variety of real-world scenarios. The length of this pipeline is 5 km and the diameter of the pipe is 13 inches (33.02 cm) with a three-phase structure. A mass flow of 375,000 kg/h (104.1667 kg/s) at a pressure of 198 bar (19.8 MPa) enters the pipeline. According to the pipeline profile, the maximum variation in the pipeline geometry (throughout the pipeline) is about 45 meters. The number of images is about 2007 images with size (640 * 640) obtained from the attached link [https://universe.roboflow.com/daisycat1008-outlook-com/oil-spill-detection-q6qid]. This dataset is used in the field of oil leak research on the ground.

3.2 Pre-processing of Data

Preprocessing is a critical step in improving model performance by transforming raw data into a standard, manageable format suitable for training. The Figure1 illustrates the preprocessing techniques used in this study including data augmentation using ImageDataAugmenter, and resize all image.

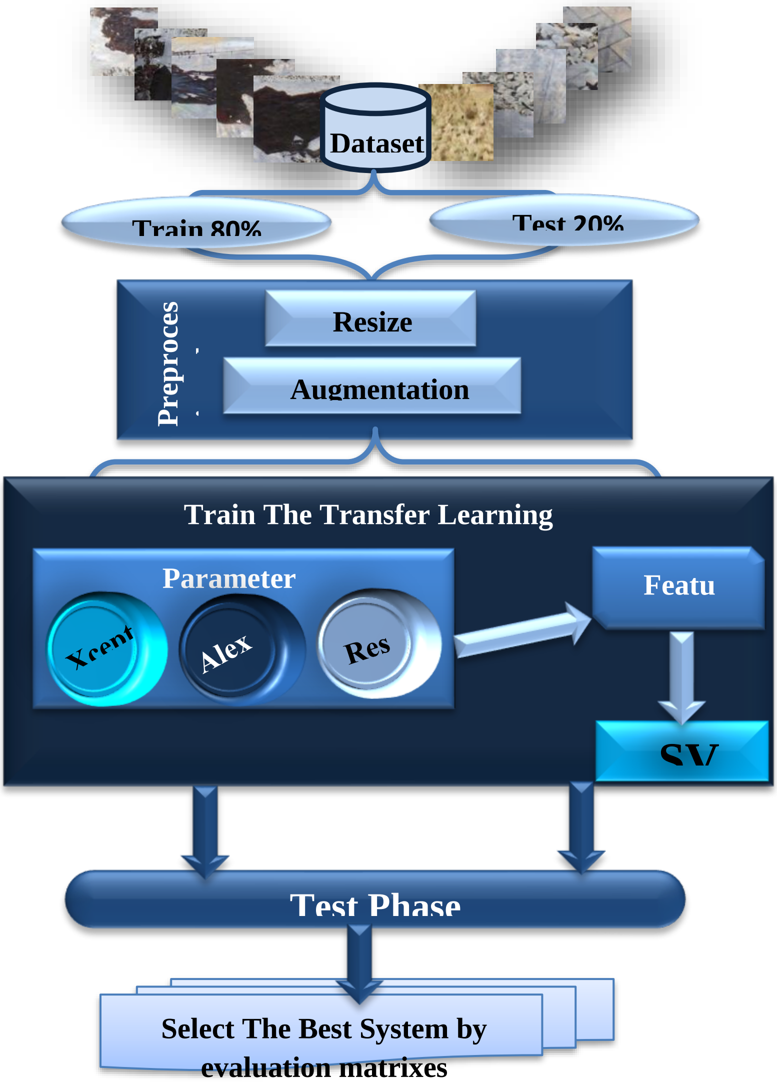

Figure1. Methodology the

3.2.1 Data Augmentation (ImageDataAugmenter)

Data augmentation is a vital technique used to artificially expand the training dataset by applying various transformations to the existing images. This method enhances the model's generalization ability, reduces the risk of overfitting, and ultimately improves accuracy. ImageDataAugmenter applies transformations such as rotation, flipping, zooming, and shifting, which simulate variations that the model might encounter in real-world scenarios. By introducing these variations, the model becomes more robust and less likely to memorize the training data, a problem commonly associated with overfitting [10].

In this study, various data augmentation techniques, including flipping, gradient adjustments, and color oscillations, were systematically applied to enrich the dataset Figure2. Specific augmentation operations, such as rotations at angles of 7, 17, 27, 37, and 47 degrees, shifts along the horizontal and vertical axes, scaling adjustments in the horizontal and vertical directions, and inversions along the horizontal, vertical, and combined axes, were meticulously implemented. These operations were carefully chosen to diversify the dataset and enhance its variability.

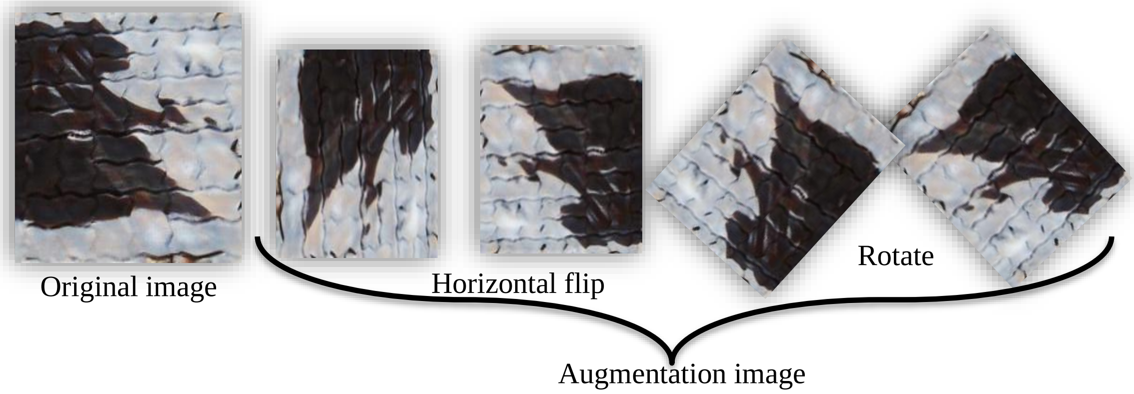

Figure 2. Sample Result Data Augmentation.

3.2.2 Image Resizing

Resizing images is another essential pre-processing technique, particularly for CNNs. Standardizing image dimensions improves computational efficiency, reduces memory usage, and accelerates the training process. Moreover, resizing ensures compatibility with the architectural requirements of deep learning algorithms, as each algorithm typically demands images of specific dimensions [11]. This step not only facilitates faster processing but also ensures that the model can effectively learn from the input data without being overwhelmed by large image sizes.

Each of the algorithms requires a different input image size. For the AlexNet algorithm, the required input size is 227 × 227 pixels; for the ResNet-50 algorithms, the required input size is 224×224 while the Xception algorithm requires 299× 299 pixels. The raw data obtained from the SAR is of size 646 × 646 pixels. Therefore, preprocessing will be performed to resize the data to match the network requirements.

3.3. Convolutions Neural Network

A convolutional neural network (CNN) is the most widely used deep learning algorithm. CNN has the benefit of autonomously recognizing the necessary traits without the need for human interaction, which sets it apart from its predecessors [12].

This approach optimizes the network's training process and enhances its efficiency by minimizing the number of parameters needed. This accurately depicts the processes occurring in the visual cortex of the brain. These cells have the ability to detect just specific changes in their immediate surroundings, rather of perceiving the whole world as a whole. CNN, like MLP, consists of many convolution layers, followed by subsampling (pooling) levels, and ultimately FC layers [13]. The architecture of the CNN for image categorization is shown in Figure 3.
There are many types of common CNN architectures, and a detailed explanation of some CNN architectures is given below:

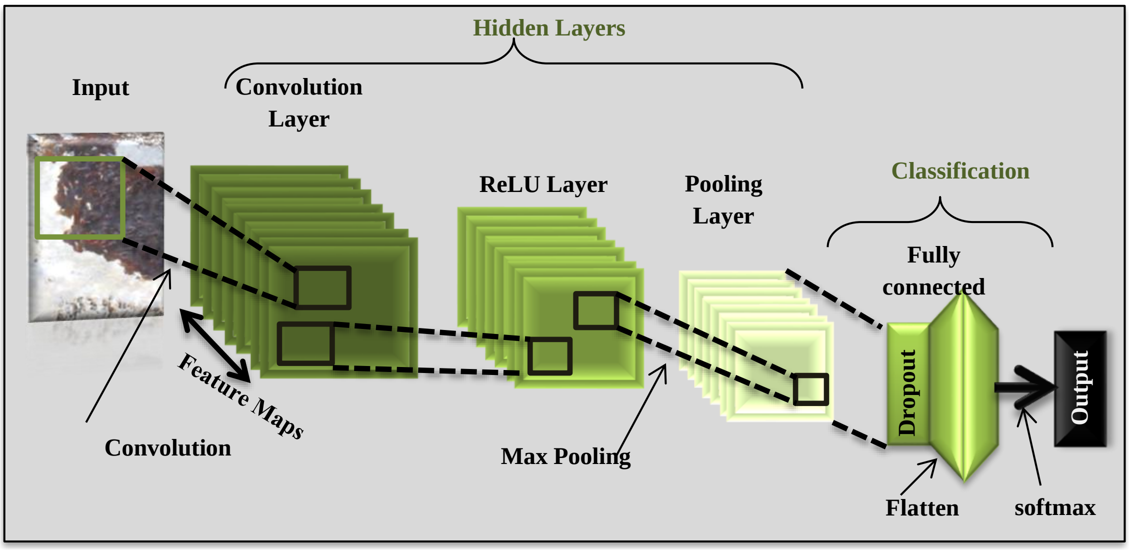

Figure 3. Architecture of a typical convolutional neural network.

3.3.1 ResNet 50

ResNet, also known as residual neural network, is a neural network architecture that incorporates convolutional and pooling layer blocks, together with skip connections or recurrent units. Furthermore, batch normalisation takes place after block. ResNet, similar to the VGG family, has several variations, including ResNet-34 and ResNet-50 with 26 million parameters, ResNet-101 with 44 million parameters, and ResNet-152 with 152 layers [14]. The ResNet-50 and ResNet-101 models are widely used for tasks such as semantic segmentation and object identification.

3.3.2 AlexNet

AlexNet is widely regarded as a highly esteemed model in the world of CNN architecture. It has shown groundbreaking achievements in the areas of image recognition and classification. Krizhevesky et al. first introduced AlexNet, which enhanced the learning capacity of CNNs by increasing their depth and adopting various parameter optimisation procedures [16].

3.3.3 Xception

Xception is a convolutional neural network architecture introduced by Francois Chollet in 2016 for deep learning tasks [17]. The model is named "Extreme Inception" because it expands and improves upon the architecture of the Inception model. The Xception model uses depthwise separable convolutions instead of the conventional convolutional procedures used in the Inception model. This substitution enhances the efficiency and performance of the parameters [18]. The Xception model is often used as a foundational paradigm for transfer learning in practical applications. Due to its pre-training on extensive datasets such as ImageNet, the model already contains specific image processing skills [19].

3.4. Support Vector Machine (SVM)

One of the widely recognized and frequently utilized machine learning algorithms is the Support Vector Machine (SVM). Known for its effectiveness in classification tasks, SVM is particularly valued for its ability to handle both linear and non-linear data through the use of various kernel functions, making it a versatile tool in supervised learning [20].

3.5. Transfer Learning

The objective of this work is to achieve efficient and precise detection of pipeline leaks by utilizing transfer learning. Transfer learning can be categorized into two types: feature and parameter-based transfer learning. Feature-based transfer learning is the process of transferring the representation of features from the original data to the designated target data. The classic machine learning method is more effective in achieving the objective job, thanks to the newly generated features [21].

Parameter-based transfer learning, also known as model-based transfer learning, involves transferring knowledge at the model level. It presupposes that the parameters (weights) or previous knowledge acquired from the source data may be applied to the target data. The primary utilization of transfer learning is in its feature extraction capability and past knowledge rather than focusing on reweighting and relationship mining[22] . Hence, the CNN transfer learning method for pipeline leak detection is investigated using parameter and feature-based transfer learning.

3.5.1. Parameter- Based Transfer Learning

The most straightforward and best-used parameter-based learning method is to modify the pre-trained CNN to acquire knowledge of the new task. A parameter-based CNN transfer learning framework is proposed for oil spill detection using images, as shown in Figure 4. The work is as follows:

1- After obtaining the image dataset from SAR, the data pre-processing is performed as mentioned above.
2- Divide the image dataset into a training and a test)80% and 20% respectively).
3- The pre-trained CNN model that we want to work on is selected. Here we choose three models, which are ResNet-50, Xception and AlexNet.
4- We substitute the final three levels with layers that correspond to the SAR image collection.
5- We define the training parameters, including optimizer, mini-batch size, number of epochs, validation data, learning rate and validation frequency.
6- The CNN model is trained using the training dataset.
7- We employ a fine-tuned CNN model to classify the test dataset and compute the classification accuracy.

The optimal model was determined using the root mean square propagation (rmsprop) optimizer. The learning rate of each CNN model was adjusted to 1e-4 during training and all models were trained for 20 epochs. Although this method contributed to better model performance, one drawback was the extended training time, with some models requiring more than four hours to complete the training process.

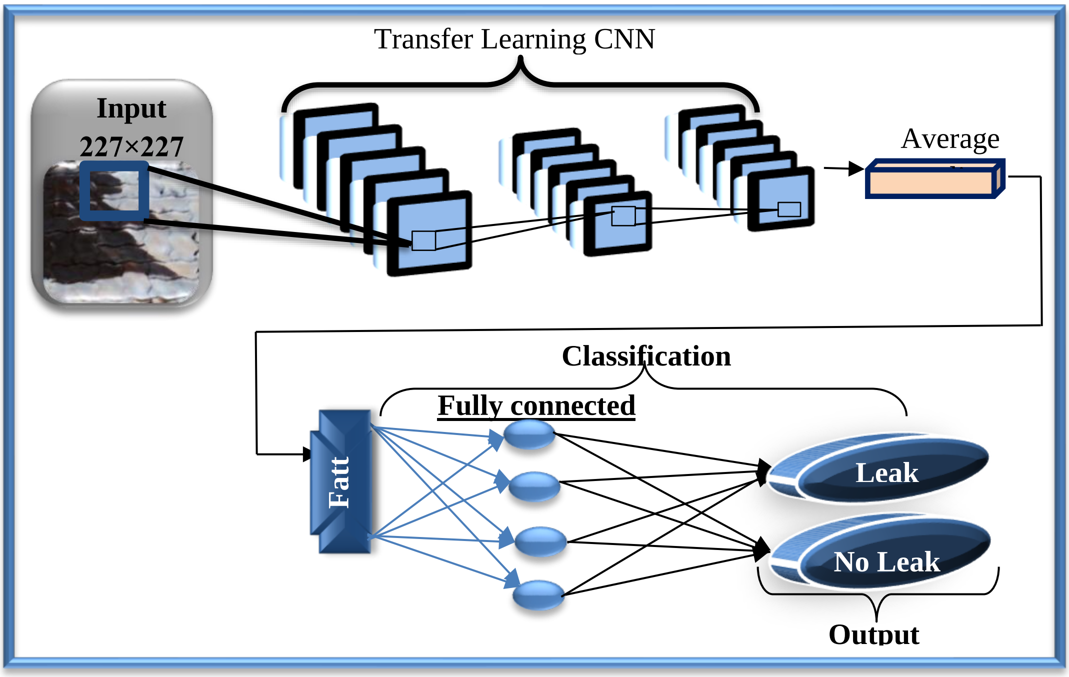

Figure 4. parameter Based Transfer Learning.

3.5.2. Feature –Based Transfer Learning

The dataset used in this study was composed of SAR images. Each image was resized to meet the specific input requirements of the DL algorithms used, as each algorithm demands a particular input format. After resizing image to 224×4224 in the ResNet-50, resize the Xception to 299×299 and AlexNet 227×227the dataset was spilt into training and test sets, with 80% of the data allocated for training and 20% for testing, ensuring that the model's performance could be properly evaluated.

To enhanced the model's accuracy and address the issue of data imbalance where oil leak images are often underrepresented data augmentation techniques were employed. These techniques artificially increased the size and diversity of the dataset by applying transformations such as rotation, scaling, and flipping.

To extract meaningful features from the images, pre trained DL models such as Xception, ResNet-50, and AlexNet were employed. These models, pretrained on large scale datasets, are highly capable of extracting rich and informative features from images. Instead of fine tuning the entire network, the penultimate layers of these models were used for feature extraction. The last classification layers were removed, as they are typically task specific and not relevant to our feature extraction process. For example, in the Xception, features were extracted from the "average pooling" layers, while the AlexNet and ResNet features were extracted from the "fc7" and "pool5" layers respectively, allowing us to capture important image characteristics such as texture, color, and spatial patterns key factors in distinguishing oil leaks from non-leaks areas as show Figure 5.

Once the feature vectors were extracted, they were passed into SVM classifier, which was specifically trained to differentiate between oil leaks and other objects present in images. SVM was chosen due to its strong performance on small, high dimensional datasets an essential requirement for accurate oil leak detection.

In conclusion, the hybrid approach that integrates DL based feature extraction with SVM classification offers highly effective solution for accurately detecting oil leaks in image datasets. In addition to its impressive accuracy, this method is notably efficient in terms of training time, as it does not require the extensive computational resources typically needed in fully finetuned DL models. This makes it a practical and scalable approach for oil leak detection tasks.

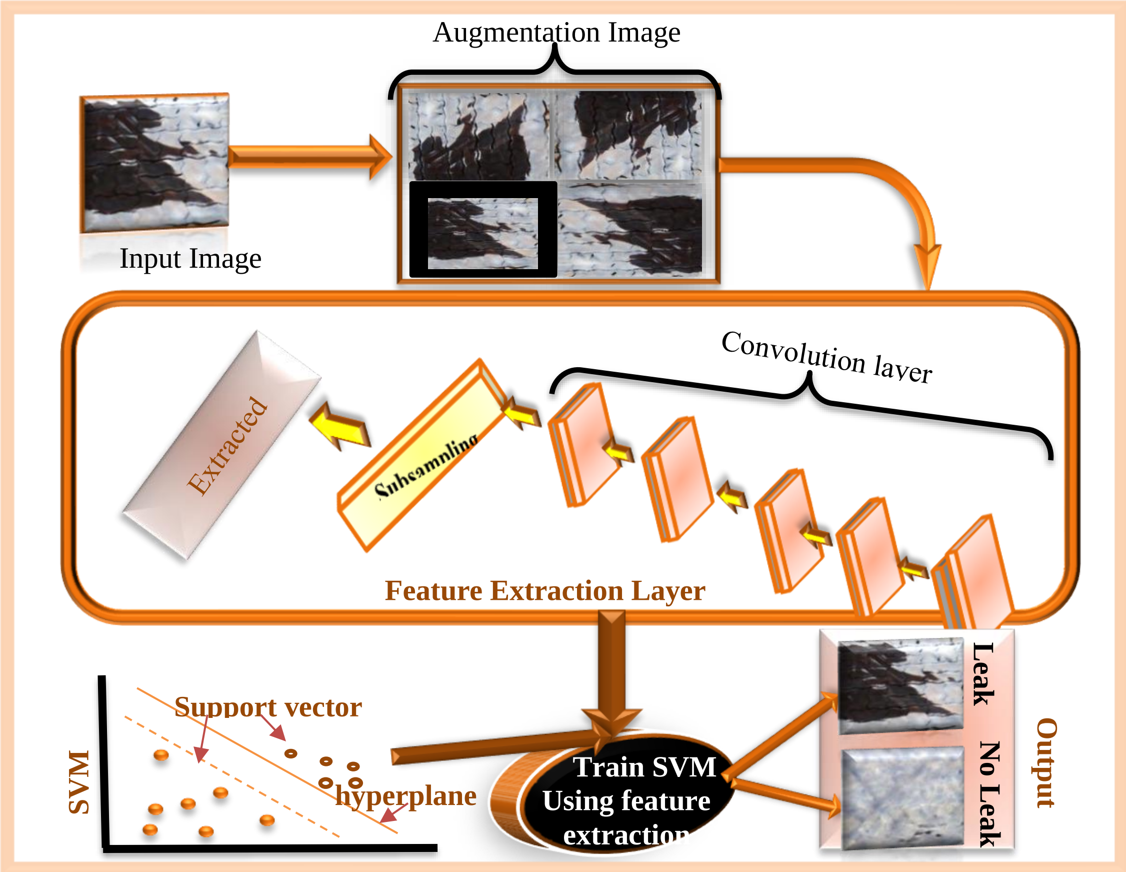

Figure 5. Feature Based Transfer Learning.

4- Evaluation metrics

The confusion matrix is a tabular representation that displays the model's predictions contrasted with the actual assessments of the test data It categorizes the findings into true positives -TP, true negatives -TN, false positives-FP, and false negatives -FN. The division mentioned is crucial for comprehending the model's overall accuracy as well as more particular measures like precision, sensitivity, and specificity as shown in Figure 6. The following equations from the correlation matrix are used to calculate these metrics.

$$Precision = \frac{TP}{(TP+FP)}$$

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)}$$

$$Sensitivity(recall) = \frac{TP}{(TP+FN)}$$

$$F1\_Score = \frac{2\times(Precision\times Sensitivity)}{(Precision+Sensitivity)}$$

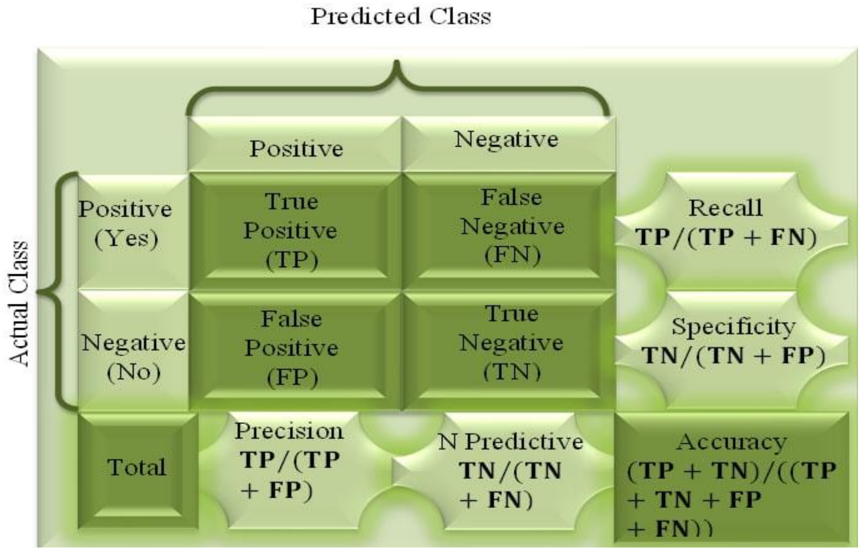

Figure 6. Confusion Matrix.

4.1 Experimental Result

Based on the comparison between the two methodologies, it is evident that the feature-based transfer learning approach outperforms the parameter-based transfer learning method in detecting oil leaks on the ground. The feature-based approach, which combines a CNN for feature extraction with SVM for classification, has demonstrated superior accuracy due to its ability to automatically learn and extract relevant features from the data. The Table 1 below highlights the performance metrics, showing that the feature-based transfer learning method using the Xception model and SVM achieved the best results, with an accuracy of 99.6%, recall of 99.7%, precision of 99.5%, and an F1-score of 99.6%. This clearly demonstrates the effectiveness of the feature-based transfer learning approach in accurately detecting oil leaks compared to the parameter-based approach.

Reviewing Table 1, it is clear that the highest accuracy during the testing phase was achieved by the Xception model combined with SVM.The results confirmed the superiority of the feature-based approach, with the Xception model and SVM achieving the highest accuracy.

Table 1: Compares method CNN Transfer Learning Based Feature and parameter

Algorithm	*Accuracy*	*Sensitivity*	*Precision*	*F1-score*
Method CNN Transfer Learning Based Feature				
ResNet-50 & SVM	98.8	98.5	99	98.7
AlexNet & SVM	99.5	99	100	99.5
Proposed model Xception & SVM	99.6	99.7	99.5	99.6
Method CNN Transfer Learning Based Parameter				
ResNet-50	92.8	99	88.1	93.2
Xception	99.2	98.7	99.7	99.2
AleaxNet	99.3	99.8	98.7	99.3

The table 2 below provides a comparative analysis of methodologies previously used for detecting oil pipeline leaks, as applied to the data in this study. Notably, the proposed system in this study outperformed the other systems in terms of performance.

Author	*Method*	*Accuracy*	*Author*	*Method*	*Accuracy*
Proposed System	Xception&	98.8	98.5	99	98.7
	SVM	99.5	99	100	99.5
	DenseNet-201	99.6	99.7	99.5	99.6
The same Mothed in other Studies					
[8]	DenseNet-201	95.56	68.75	79.99	73.94
[9]	DRSNet (Deeplab + ResNet-50 +SVM	76	---	---	----
[24]	ResNet-50 +SVM	96	80	79	80

5. Conclusion

This paper presents a CNN transfer learning approach for pipeline leak detection in images collected using SAR. The transfer learning approach was implemented using both feature extraction and parameter-based methods. Several advanced models, including ResNet-50, AlexNet, and Xception, were used, all of which were transferred to large datasets. This approach aims to improve the performance of the model by leveraging the strengths of multiple algorithms.

Due to the complexity of the convolutional architecture, especially with the use of the Xception model in combination with a SVM, the highest accuracy was achieved. This highlights the effectiveness of combining deep learning and machine learning for the task of oil leak detection.

Thus, this paper successfully applies a hybrid approach by integrating different methodologies, transfer learning, and advanced deep learning architecture, to develop a highly accurate system for oil leak detection in synthetic aperture radar images. The results demonstrate the potential of such approaches in addressing complex challenges in the field of environmental monitoring and remote sensing.

5.1. Future work

The model can be further developed to receive images from satellites or cameras directly from any location and process them in real-time. This would enable immediate detection of oil spills, providing a faster response mechanism for environmental monitoring and disaster prevention.

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