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Convolutional Neural Network Approach to Detect Underwater Pipeline Degradation using IOT dataset

Mr. Vaibhav A. Parjane[1] Dr. Tripti Arjariya[2] Prof. (Dr.) Mohit Gangwar[3]

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Abstract: In the offshore petroleum and natural gas industry, corrosion of subsea pipelines is thought to be a significant problem. It has a direct impact on the pipeline's integrity, which in turn results in gaps and leaks. Subsea visual examination and surveillance are carried out by trained human divers at the present time; moreover, offshore facilities are migrating from shallow seas to deep oceans as a result of the depletion of fossil fuels. Accordingly, for visual surveillance and inspection of subsea pipelines, an imaging-based robotic solution is required as an alternative due to the inhospitable underwater environmental factors that human divers must operate in. Absorption and light scattering which further results to blurring, colour attenuation, and low contrast, is a challenging issue for underwater imaging-based surveillance and inspection operations. This problem is caused by an unfriendly medium. As a result, a system that has been proposed could make it possible for an unmanned underwater vehicle to identify damaged pipelines in a series of images. Transfer learning from Convolutional Neural Networks (CNN) that had been previously trained was the foundation for the classifiers (CNN). Because of this, it is possible to achieve favourable results in spite of the limited number of damaging training scenarios which are faced. The method that has been suggested has been put through its paces by utilising IOT data taken from a real pipeline inspection. When estimating the amount of corrosion, a reasonable level of accuracy was achieved, which assisted in differentiating between the corrosion and non-corroded surface of corroded pipelines? The both qualitative and quantitative studies both show encouraging results, which motivate the integration of the proposed technique into a robotic system that is capable of performing underwater pipeline corrosion investigation in real time.

Keywords: *Under Water Pipeline Degradation Detection, CNN, MobileNet, VGGNET, Shallow Net, IOT*

1. Introduction

Pipelines that run beneath the sea must be thoroughly checked at regular intervals. It may take several days to finish these inspections, which are typically carried out with the assistance of remotely operated underwater vehicles (ROVs) as well as autonomous underwater vehicles (AUVs). The photographs of the pipeline need to have handwritten annotations added to them, and key characteristics of the pipe like anodes, connections, and damage, are required to be identified and noted. The possibility of automating this detection either as a supplement to the human annotation or to substitute the human altogether would save a significant lot of time and resources, as well as possibly both money and time. The online identification of damage by an AUV might even enable it to return back around and examine the area in greater detail.

[1]*Ph.D. Research Scholar, Department of Computer Science and Engineering, Bhabha University, Bhopal, Madhya Pradesh, India*
[2]*Head, Department of Computer Science and Engineering, Bhabha University, Bhopal, Madhya Pradesh, India*
[3]*Director (Alumni Cell), B. N. College of Engineering and Technology, Lucknow*
[3]*mohitgangwar@gmail.com*

The majority of the challenges involved in mechanising this process are similar to those encountered by underwater robots when attempting to classify images [16, 17]. Droplets in the water can cause a variety of optical effects, including a deterioration of focus, colour, and contrast. Training the classes of interest is made more difficult by the presence of imbalance data sets, which contain a large number of negative examples but only a small number of positive instances, and very vague characteristics that serve to differentiate the classes.

Concrete is prone to deterioration and impact, two factors that should be considered during structural examinations. The appearance of cracks in the exterior is an early warning sign of damage to the structure [18, 19, 20]. Because they are extremely reliant on the skills and experience of the investigator, manual inspection approaches generally lose objectivity in quantification [21, 22, 23]. This is due to the fact that manual inspections are performed by hand. Because of this, automatic damage detection techniques, particularly those based on images, are of particular interest. Transfer learning strategies are utilised because, most of the time, there are not sufficient amounts of positive examples for training. Transfer learning has become a well-known method for the classification of images. Because of this, it is possible to harness the power of quite large image data sets and apply it to the classification of information from other realms. According to the strategy that was proposed, there were only 80 out of 10,805 IOT photographs that consist of damaged pipelines.

The IOT data set was obtained as high definition still pictures captured at close range to strobe lighting. Despite this, the quality of the photographs can vary depending on the state of the water. A system similar to the one depicted in Figure 2 has been suggested as a way to reliably detect damage as well as localise the damage within the photograph. This includes a full image, 4-way classification algorithm as well as a separate channel that becomes active when damage is identified and localises the area of the image where damage has occurred. The Contribution of this paper is as follows

• An assessment of several classification methods for whole images utilising convolutional neural nets is one of the contributions made by this work.

• An evaluation of the networks, which, by visually representing the pixels that are significant to the classification, provides insights into the processes that are carried out by the networks.

• A straightforward method for identifying specific areas where damage has occurred.

This paper is segmented into five sections. In section 2, related work of detecting subsea corrosion of pipeline using various techniques is discussed in detail. In section 3 and section 4, framework of proposed system and experimental finding is discussed in detailed. Lastly, the proposed system is concluded in section 5.

2. Literature Survey

According to A. Mensah et al. [1] conversing corrosion defects in pipelines typically take place in a cluster in a way that the failure stresses is not influenced by a single defect. This is the case even when the defects are caused by the same thing. These metal loss deformities have the possibility of reducing the serviceability of the pipeline, which may result in a breach of containment as well as potential damage to the facilities and the atmosphere. Therefore, in order to plan inspections, carry out repairs, or substitute pipeline segments in the event that an event of this nature takes place, operators of pipelines conduct predictive and probabilistic integrity assessments to investigate corrosion deformities. Moreover, the huge proportions of conversing metal loss deformities that are acquired by in-line inspection equipment are typically evaluated by conservative physics-based compositions. These compositions are generally centered on the composite solitary defect methodology, which is utilized to decide the burst pressures. The requirement to predict exactly the failure stress of the substantial quantity of clustered corrosion faults in the pipeline necessitates a method of machine learning that is both algorithmically efficient and capable of effectively accommodating variability in the input data. As a result, categorical machine learning algorithms are trained, evaluated, and assessed using existing experimental burst pressure of rust clusters that have the same defect detail for a preliminary test. This is done as part of this research. In the paper, this methodology is presented, in which the anticipated pipeline failure stress of the rust clusters acquired by real in-line inspection are evaluated by produced artificial neural networks as well as non-linear regression models. These models provide an overall average deviation percent of 2.5% and 9.4% respectively, which is better than the models that are currently available in the literature. This method provides a framework for efficient decision-making by pipeline operators, with the end goal of lowering the costs of pipeline maintenance and operation in a responsible manner.

A comparison of different models used to determine the remaining strength of rusted pipelines is carried out by Xian-Kui Zhu et al. [2]. First, a concise review of burst estimation techniques for defect-free pipes is presented. This review covers topics such as the strength alternatives and flow strategies of burst pressure, in addition to experimental evaluations. A summary of corrosion assessment system is presented next, and these models are divided into three generations according to the source stress that is used in every model. After that, those corrosion methods are assessed in relation to the full-scale burst data, with the primary goal being the validation of the recently developed third-generation models. Following this, a discussion of recent developments, such as the PRCI corrosion evaluation projects, the constraint impact, the bulging aspect, and the deformity width effect, will take place. Eventually, the major technical difficulties that must be overcome in order to enhance the corrosion model are addressed. These difficulties include material failure mechanism, full-scale testing, numerical modelling, and real corrosion deformities.

In accordance with Rafael Amaya-Gómez et al. [3] defects caused by corrosion have an effect on the resistance of hydrocarbon pipelines because they raise the likelihood that the pipelines will fail, which would lead to a Loss of Containment (LOC). It has been suggested that this probability of failure can be estimated using a variety of methods, some of which focus on empirical methods, while others center on probabilistic evaluations. Despite this, there are not many works that focus on the variation of corrosion faults and how fragmentation may influence intervention choices. The information that is acquired from in-line inspections (ILI) is utilized in this paper to construct a corrosion deterioration model underneath a pressure-stress failure criterion. This framework is then used to generate a dynamic method. The goal of this strategy is to determine the best times and places for carrying out interventions. According to the findings, the conventional reliability evaluations, are suboptimal and may conceal critical zones. This result is demonstrated by a real-world example in which rust progression is more accurately estimated, and the challenges associated with traditional static segmentation are emphasized.

According to Ram K et al. [4] failure risk assessment of pipeline networks is necessary for the efficient management of these networks. The analysis of a large amount of pipelines is typically labor and time intensive due to the typically expansive and intricate nature of pipeline networks. This research makes use of recent developments in machine learning to devise a feasible alternative to analytical methods that require a significant amount of computational resources in order to ascertain the potential for failure of steel pipelines for oil and gas. The potential for rupture in pipelines that are experiencing active corrosion deformities is assessed by taking into account the pipelines' remaining power after corrosion pitting. In the first part of the research, a thorough dataset of pipelines is created based on the information that is retrieved from the literature, and a prediction of the true failure pressure is made taking into consideration the variability between the anticipated burst failure stress and the exploratory burst test results. Estimation of the actual burst failure tension is carried out in a probabilistic fashion using a variety of design codes. The DNV RP-F101 model offers the least amount of variability in its prediction of the failure pressure when compared to the other models that can predict burst failure. As a result, the model is put to use to calculate the likelihood that pipelines will fail when they are operating at their burst limits. A scale that ranges from low to extreme failure risk is used to categorize pipelines according to the likelihood of failures that they may experience. After that, eight different machine learning methods are tested using the newly generated dataset in order to determine which one produces the most accurate failure prediction model. When evaluating the effectiveness of machine learning techniques, both the confusion matrix as well as the computational efficiency is taken into consideration. It demonstrates that XGBoost is the best algorithm for predicting malfunction, and it is suggested that this algorithm be used for any future study. In addition, the computational effectiveness of the physics-based model and the machine-learning algorithm are evaluated by comparing with one another. It has been discovered that algorithms for machine learning can accomplish a failure risk evaluation of pipelines with increasing processing efficiency than the method that relies on physics. The physics-based model is approximately 12 times slower than the algorithms for machine learning that is considered to be the weakest.

Internal corrosion is a problem that affects pipeline infrastructures throughout their entire life cycle, as stated by G. Canonaco et al. [5]. These pipelines are responsible for transporting gas or oil from one location to another. This effect has the potential to pose significant threats to both the environment and individuals. The former is caused by the possibility of fluids performed by the facilities itself leaking, while the latter is caused by accidents that may spontaneously ignite due to the existence of gas leaks. As a result, the development of predictive mechanisms that are capable of enhancing the prevention and management of this phenomenon is of the utmost importance. Unfortunately, the rusting of pipelines is not understood well enough to create a mechanism that would fix the prevention and monitoring needs associated with the administration of these infrastructures. This would be a significant step forward. In addition, the phenomenon is sufficiently complicated to make it impossible for semi-empirical models to accurately reproduce its behaviour. Recently, Machine Learning methods have shown that they are capable of modelling complex phenomena given sufficient and relevant data. As a result, these techniques have become an intriguing potential option for corrosion forecasting. Regretfully, the proposed solutions in the existing research are based on inadequate data sets, and the performance measures are not carried out in an adequate manner, which undermines both the allegations made and the results that are obtained. In light of these considerations, the purpose of this paper is to present an ML-based approach to modelling the corrosion occurrence. This approach includes the generation of a data set, the concept of the ML-based model, and its assessment.

According to the findings of Giuseppe Canonaco et al. [6], over the past few years, due to the continuously rising available data, ML techniques have become a standard de facto in a wide variety of applications. If these methods were utilized in the domain of pipeline corrosion in the appropriate manner, it would lead the way for a considerable improvement in the control and prevention of this potentially hazardous problem. Because pipeline facilities do not come equipped with fluid-dynamical detectors, it is not possible to obtain an essential family of descriptors for this potentially hazardous occurrence without first resorting to simulation models. Because of this issue, there is an issue with incorporating and verifying simulated data with real data of other identifiers of the phenomenon. Specifically, this problem arises because of this issue. Therefore, the purpose of this paper is to demonstrate how these two distinct data sources can be combined to produce a comprehensive dataset that accurately describes the corrosion event that takes place in pipeline infrastructure.

Isotonic regression is a powerful ML model that was presented by A. A. Alqarni et al. [7] to anticipate the corrosion expansion in oil and gas pipelines. The primary objective of this paper is to demonstrate how accurate this model is at estimating the level of corrosion present in the pipeline. In this particular research project, the isotonic regression model was chosen as it is a non-parametric prototype that has the capability of being freely shaped without making any assumptions about the shape of the target function. This was done in order to circumvent the highly chaotic behavior of the corrosion formation mechanism. The other reason for this is that the isotonic regression analysis is also intended to be able to predict monotonically increasing degradation mechanisms like rusting. Using the actual corrosion depth information recorded from five sensors are attached to the studied pipeline, this paper also analyses three machine learning algorithms used in regression evaluation namely: linear, isotonic and power regression. The Jupiter notebook is utilized throughout the process of assessing the effectiveness of every ML model. Calculating the prediction performance of each machine learning model requires the utilization of four distinct types of prediction performance measures.

A hybrid intelligent technique was proposed by Shanbi Peng et al. [8] to anticipate the rate of corrosion of the multiphase flow pipeline. The model that is being proposed utilizes a combination of Chaos Particle Swarm Optimization (CPSO), Support Vector Regression (SVR) and Principal Component Analysis (PCA). The model is being referred to as PCA-CPSO-SVR. PCA is capable of reducing the data dimension as well as screen out the primary variables that influence corrosion factors. CPSO is utilized in order to optimize the hyperfine specifications in SVR, which ultimately results in an improvement to the prediction accuracy provided by the prediction model. The proposed model has a mean absolute error of 0.083, which is 18.6 percentage points lower than the SVR model's value. The suggested framework has higher prediction accuracy when compared to five benchmark models, including linear regression, artificial neural network, PCA-genetic algorithm-SVR, and PCA-PSO-SVR. In light of the findings presented above, it appears that the PCA-CPSO-SVR model is capable of producing accurate forecasts of the corrosion rate along the multiphase flow pipeline.

For the purpose of determining the time-dependent CDD expansion of corroded pipelines using ML, Chinedu I. Ossai et al. [9] utilize the historical operating characteristics. This data-driven ML technique tends to rely on Subspace Clustered Neural Network (SSCN) as well as Particle Swarm Optimization (PSO) to approximate the CDDs of a single-SSCN. This is accomplished by going to treat the first Subspace Cluster (SSC) like a regression model that incorporates of the concealed and bias layers in addition to the input variables. Across individual value decoupling, transitions, and adjustments of the hyperspace of the deeper levels in the SSCN framework, the multi-SSCN prototype is connected to the single-SSCN model. In order to calculate the authenticity of the pipelines at distinct classes, the CDDs that were approximated with the SSCN frameworks were put to use. These CDDs were used to calculate a Weibull distribution relying leak and burst failure probability assessment. The results that were obtained show that this method has potential applications for the inspection of corroded and aged pipelines.

The research conducted by Yiming Liu et al. [10] examines the use of machine learning techniques to identify, categorize, locate, and quantify pipeline anomalies. These techniques are based on the intelligent analysis of routine operations and services, non - destructive testing data, as well as machine vision data. It has examined the statistics and ambiguities surrounding the performance measures of various machine learning methodologies. A SWOT analysis, which examines a company's strengths, flaws, possibilities, and threats, is carried out. It is recommended that practitioners make use of guides in order to carry out automated pipeline condition assessments. This review offers some new perspectives on how ML can be applied to the process of automatically assessing pipeline conditions. The pipeline industry will benefit from using the SWOT analysis to support decision making. Afzal Ahmed Soomro et al. [11] aim to assess the present state of the Bayesian network strategy, which incorporates approach, influential criteria, and datasets for risk evaluation. Additionally, they intend to provide industry experts and scholars with ideas for future improvements using content analysis. These goals will be accomplished by evaluating the current state of the Bayesian network methodology. Even though the focus of the study is on corroded oil pipelines, the expertise that is gained can potentially be applied to a variety of other industries.

A.Mohammed et al. [12] use a variety of machine learning techniques, such as Support Vector Machine, Random Forest, k-Nearest Neighbor, fully connected Artificial Neural Network and Long Short-Term Memory (LSTM), to make predictions about the wall thickness of pipes at various locations. In the course of carrying out this study's data processing and analysis, a total of six distinct process variables as well as the pipe wall thickness at three distinct locations within a downstream oil and gas sector were taken into consideration. The results of the study illustrated that LSTM outperformed the other methodologies that were utilized and successfully identified the pipe wall width trend. The test Root Mean Squared Errors for the three selected locations were 0.019 mm, 0.015 mm, and 0.017 mm, respectively. H. Zhang et al. [13] propose a revolutionary technique for predicting the internal corrosive depths of oil and gas pipelines utilizing Extreme Learning Machine (ELM) that utilizes historical In-Line Inspection (ILI) data, which was first goes through Mutual Information Principal Component Analysis (MIPCA) for selecting features. This technique which relies on Extreme Learning Machine (ELM) utilizes historical In-Line Inspection (ILI) information. As a study case for evaluating the usefulness of the proposed framework, an in-service pipe segment in the province of Qinghai in China that is 170 kilometers long and has 241 recorded instances of internal corrosion faults is utilized. The distance from the elbow, the distance from the upstream girth weld, the initial defect intensity, pipeline stress, and elevation were some of the features that were identified and utilized as predictors. The findings indicate that when compared to commonly used machine learning methodologies like Back Propagation (BP) neural networks as well as Random Forest, the suggested technique enhances the accuracy & calculation pace of the forecasting model more than the methodologies that are presently being used. This is due to the fact that the suggested technique is free parameters. Improved forecasting enables more accurate maintenance planning, which in turn reduces the likelihood of pipeline failure and the associated costs.

According to the findings of K. Mera et al. [14] the corrosion of Ecuador's oil and gas pipelines not only results in financial losses for the country, but it also has a negative impact on both the health of the population and the environment. This study used Machine Learning technique to determine the level of corrosion utilizing data gathered manufacturing products and the chemical processes that take place in oil pipelines. The findings of this study were based on the findings of another study that collected information concerning chemical processes. Following the implementation and evaluation of Support Vector Machine, Random Forest and XGBoost classification techniques based on a set of metrics, like accuracy, precision as well as f1-measure, a chosen model to tune the hyper - parameters of in in order to enhance the accuracy of it. Furthermore, a features extraction stage was taken into account. This stage includes normalizing the data, removing variables that have a high correlation, and ensuring that the variables in the data set are balanced. In addition to that, a 10-fold cross-validation was carried out. Because the findings of the analysis had shown that the Random Forest model had improved performance than the other models, the Random Forest was chosen for the hyperparameters tuning. For example, the accuracy of the Random Forest model was approximately 20% preferable than that of the Supper Vector Machine classifier and 5% stronger than that of the XGBoost model. In addition to that, a web application called a dashboard was established so that the end user could perform the forecasting in an approachable manner. F. Hassan et al. [15] used a technique called machine learning to correctly classify and localise the corrosion defect. Studies were carried out on a steel pipeline with a diameter of 10 inches in order to demonstrate the connection between the precise location of a corrosion flaw as well as the acoustic emission sensor. According to the findings, a corrosion defect can be identified and localized with the help of SVR. This method has the potential to provide a reference point for the real-time surveillance that is functional and has a wide range of application possibilities.

3. Research Methodology

In order to develop the proposed framework, several different standard methodologies were utilised. The IOT dataset is preprocessed in the beginning so that issues such as colour distortion, an absence of detail, and the issue of unbalanced data sets can be resolved. After that came the testing of the three different frameworks and training methods. In the final part of this article, the visualisation technique that was utilized to help understand and authenticate that the selected network utilized the data contained in the images as one might anticipate is mentioned.

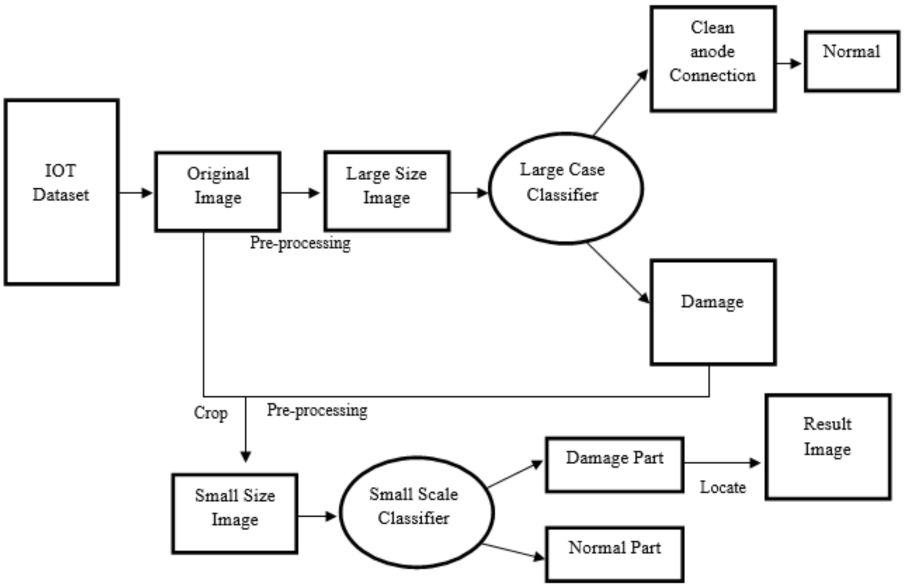

Fig. 1: Proposed System Framework for Detecting Undersea Pipeline Corrosion

The diagram for the proposed model for damage assessment can be found in figure 1. The upper channel divides the entire image into four distinct categories. Class 0, 1, 2, and 3 indicate a clean, anode, connection, and damage respectively. Damage detection in the top channel will activate the reduced small scale classifier, which will then be used to pinpoint the location of the damage within a picture. The detailed description of each structure that makes up the proposed framework is discussed as follows.

Data Preparation: The clean, anode, connection and damaged image classes can be found within the IOT picture data set. There are 7383, 4140, 2299, and 80 images found within every class, respectively. The ratios are grossly out of imbalanced with one another. As a result, several additional operations were utilized in to enhance the learning, such as augmenting in to produce additional evidence of the damage class as well as down-sampling in order to reduce the number of illustrations of the other classes. At the end of the process, a balanced training data set consisting of 830 images from each of the four categories is created. In addition, the performance of the model is evaluated using 290 examples from each category.

In addition to the large scale images that serve as the feedback to the four-way classification model, the small regions of the large image is obtained and cropped in order to pinpoint the area of the larger image that contains the damage. The cropping section will get into the specifics at a later point. There are 6000 training images for the small - sized binary classifier that are split between class 0 and class 3, and the test dataset has 600 images split evenly between the two classes.

Data Pre-Processing: In this phase, first, the grouping of the dataset into training and validation is conducted by manually verifying that overlapping, tightly consecutive, images were clustered together either in training dataset or testing datasets to prevent training using the same damage instance as assessed with. This is done to prevent training using the same instance of damage as was tested with. Secondly, by converting all of the pictures to grayscale, the effect of colour distortion can be removed. This is because colour itself does not contain any information that is useful in the classification process. Thirdly, the pipe is cut out of each image using a segmentation tool. Since the pipe is always oriented in the same direction across all of the images, this process is carried out as a one-dimensional segmentation. The vertical fragmentation of an image is accurate to a sufficient degree if there are two local minima in the average grayscale for every column in the picture. Fourthly, because of the circumstances of the underwater environment, the images often lack a certain level of acuity. It has been established that applying a modest amount of sharpening aided to define exactly some of the hazy contours of the pipeline characteristics that were present in the images. Fifthly, in order to address the imbalance that was present in the data set, a number of standard methods for image enhancement, including rotation, flipping, shifting, and zooming, were implemented to the images. Last but not least, the wide range of damage samples that can be included in the data set can be enhanced by trimming the damaged image into patches. A data set that successfully contains both damaged and undamaged sections of pipe can be successfully created using cropping. Because the anode class and the connection class appear almost exactly the same as damage regionally, but only differ in full scope, the damage class has been enhanced with patches from both the anode class as well as the connection class here. This is one way to approach the problem of the limited data set and its uneven distribution.

The dimensions of the acquired images are currently 410 pixels wide by 231 pixels elevated. Following the application of image segmentation to remove the pipe areas, their width and height are in the range of 130 to 210. After that, a region measuring 128 by 128 pixels is extracted from every image in order to obtain information of a large size. The large data set is then divided into arbitrary, possibly overlapping patches, which are used to create the small data set.

CNN Architectures: A shallow net, VGG16, and MobileNet V1 are the networks that are put through their paces in this test. The subsequent discussion will cover the specifics of its description:

Shallow Net: The goal of the shallow net was to establish a point of reference against which the transfer learning strategy could be evaluated. It should be mentioned that the data set was insufficient for properly learning the feature space at this location; consequently, the findings for this net should be regarded with some level of caution. A network consisting of three convolutional layers as well as two fully connected layers was developed and then trained for the four-way categorization. This network is depicted in Figure 2.

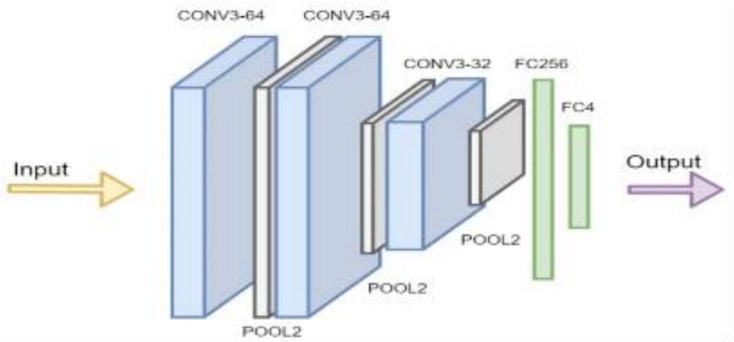

Fig. 2: Framework of Shallow Net.

VGG16: Transfer learning will be applied to the VGG16 network after it has been trained on the IOT dataset. This option was selected. This is a popular option due to its strong efficiency as well as its straightforward construction. There are a total of 41 layers in the VGG16 model, and 16 of those layers have learnable weights. There are 13 convolutional layers, and there are three fully connected layers. During the training process, only the fully connected layers were initialised and re-trained. This was done so that the pre-trained weights could be maintained. It was also tested to determine if, after training the fully connected layers, performance could be enhanced by fine-tuning the final convolutional layer, but the results did not show a considerable improvement.

MobileNet V1: When there is a scarcity of data, it is frequently advantageous to use a model that is less complex and more lightweight. It is the one that will be put through the MobileNet test, which is a group of effective models for mobile as well as embedded vision uses. The simplified architecture that MobileNet is based on makes use of depth-wise distinguishable convolutional for the purpose of improving the network's computational efficiency. In addition to the i.e. notation, the width multiplier and the resolution multiplier are utilised in order to make a further compromise between productivity and precision. When compared to VGG16, which contains 138 million parameters, MobileNet has a significantly smaller number of parameters (4.2 million).

4. Result and Discussion

When evaluating the efficacy of these networks, metrics such as precision, recall, F1-score, and Receiver Operating Characteristic (ROC) are taken into consideration. The ROC curves of three different networks are displayed in Figure 10, and an overview of the statistics can be found in Tables I and II, respectively. On both small and large scales, it is observed that MobileNet performs considerably better than VGG16 and shallow network. The ROC curves for each of the individual classes are depicted in figure 3. It shouldn't be a revelation that the damage class is responsible for handling the performance cap. The connection class and anode class, characterised by their geometric straight lines, are able to be differentiated from random noise in a simpler manner.

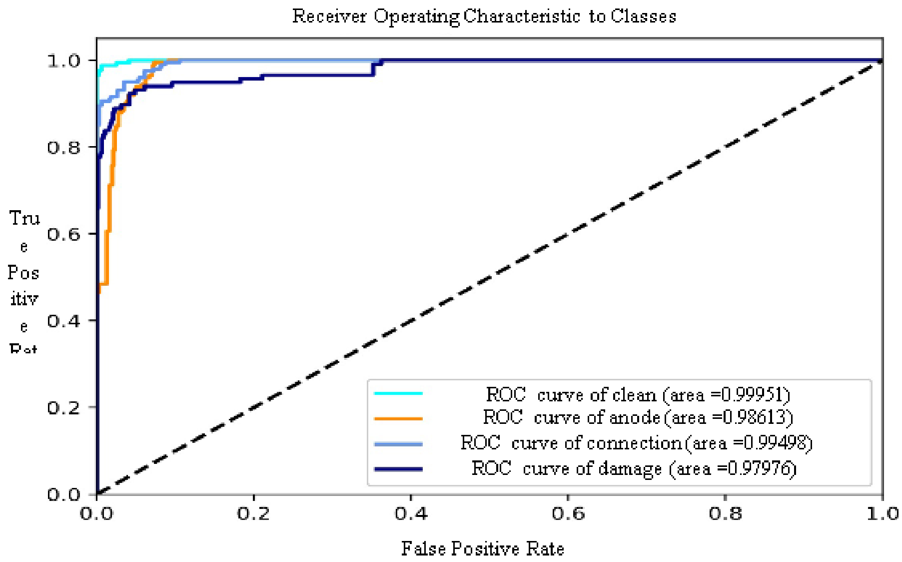

Fig. 3: Individual class ROC curves for mobile nets applied to large scale images

Figure 3 presents an illustration of individual class ROC curves for mobile nets applied to large scale images. Classes 0 through 3 are designated as clean, anode, connection, and damage, in the sequence.

Table I: A comparison of the performance of MobileNet, ShallowNet and VGG16 networks with regard to large images

Technique	Class	Precision	Recall	F1-Score	ROC
MobileNet	Class 0	1.0001	0.9598	0.9795	0.9996
	Class 1	0.8469	0.9495	0.8953	0.9862
	Class 2	0.8986	0.9208	0.9096	0.9948
	Class 3	0.9435	0.8548	0.8969	0.9798
VGG16	Class 0	0.3616	0.9828	0.5286	0.9782
	Class 1	0.9737	0.5607	0.7116	0.9252
	Class 2	0.8969	0.5595	0.6891	0.9209
	Class 3	0.9474	0.3847	0.5472	0.9432
Shallow	Class 0	0.8828	0.8219	0.8512	0.9772
	Class 1	0.5447	0.9546	0.6936	0.9526
	Class 2	0.6952	0.8467	0.7634	0.9317
	Class 3	0.7548	0.1706	0.2788	0.8315

The performance comparison of MobileNet, VGG16 and Shallow Net using large scale image is performed using metrics precision, F1-score, recall and ROC is illustrated in table 1.

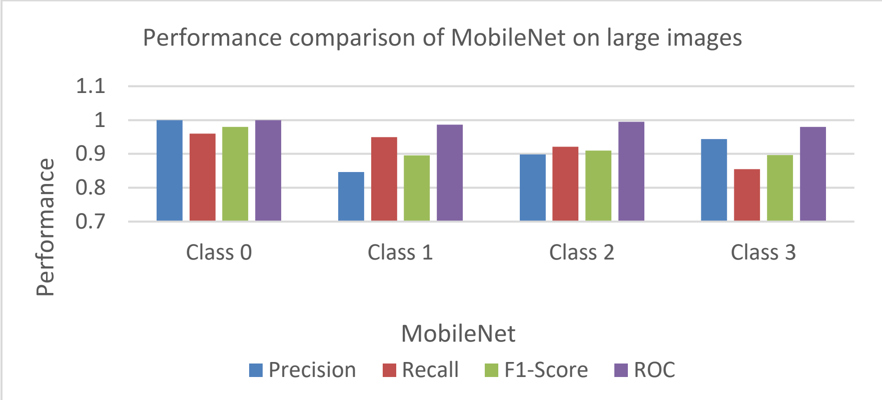

Fig. 4: Performance Comparison of MobileNet on large Scale Images

Figure 4, 5 and 6 depicts the performance comparison of Mobile Net, VGG16 and ShalloeNet using large scale images

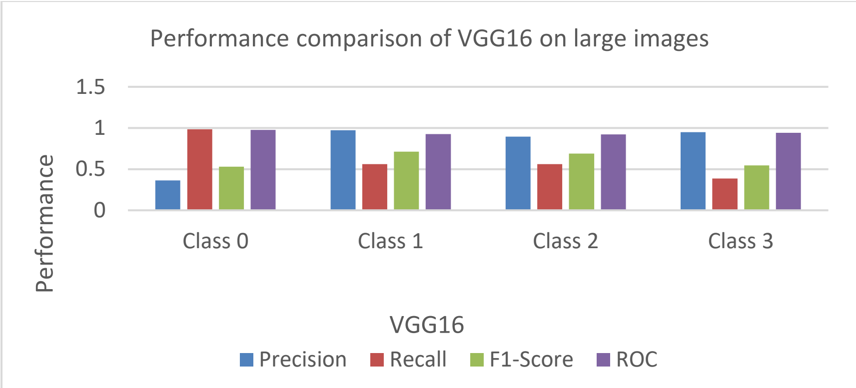

Fig. 5: Performance Comparison of VGG16 on large Scale Images

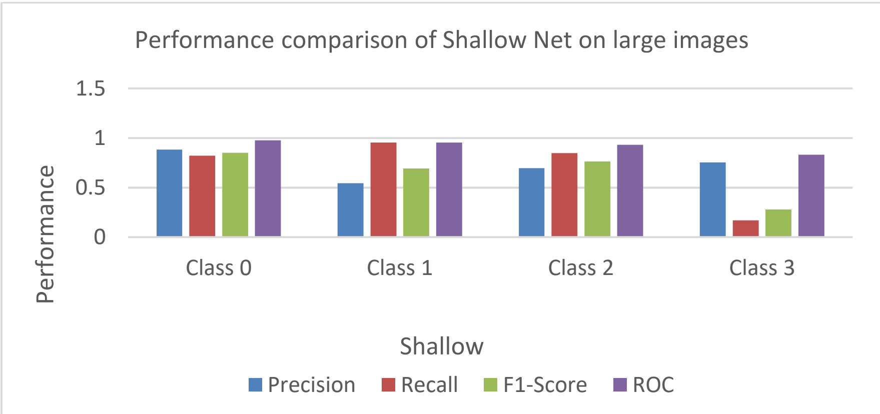

Fig. 6: Performance Comparison of Shallow Net on large Scale Images

Table 2: A comparison of the performance of MobileNet, ShallowNet and VGG16 networks with regard to large images

Method	Class	Precision	Recall	F1-Score
MobileNet	Class 0	0.9414	0.9131	0.9268
	Class 3	0.7878	0.8503	0.8179
VGG16	Class 0	0.9048	0.9231	0.9138
	Class 3	0.7861	0.7445	0.7648
Shallow	Class 0	0.7459	0.5987	0.6642
	Class 3	0.3044	0.4626	0.3672

The performance comparison of MobileNet, VGG16 and Shallow Net using small scale image is performed using metrics precision, F1-score, recall and ROC is illustrated in table 2.

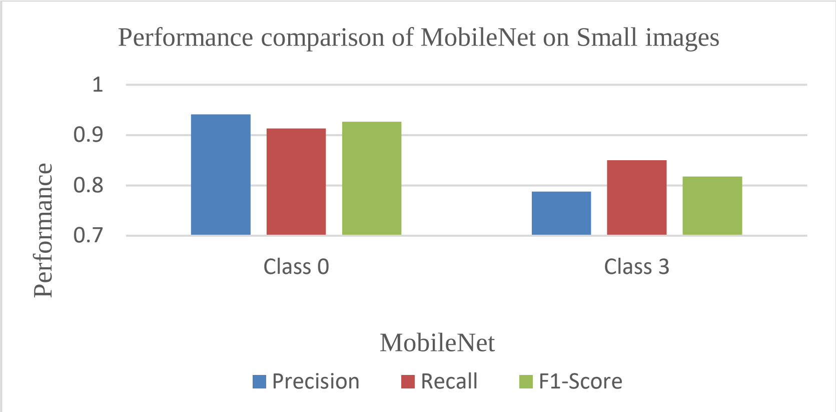

Fig. 7: Performance Comparison of MobileNet on Small Scale Images

Figure 7, 8 and 9 depicts the performance comparison of Mobile Net, VGG16 and ShalloeNet using large scale images.

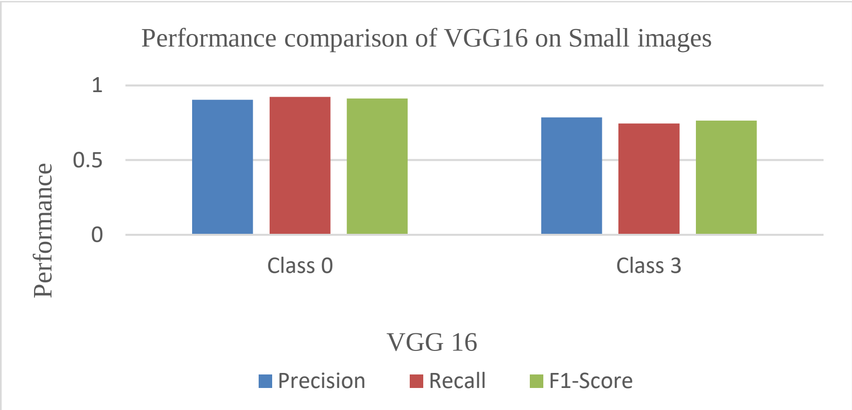

Fig. 8: Performance Comparison of VGG16 on Small Scale Images

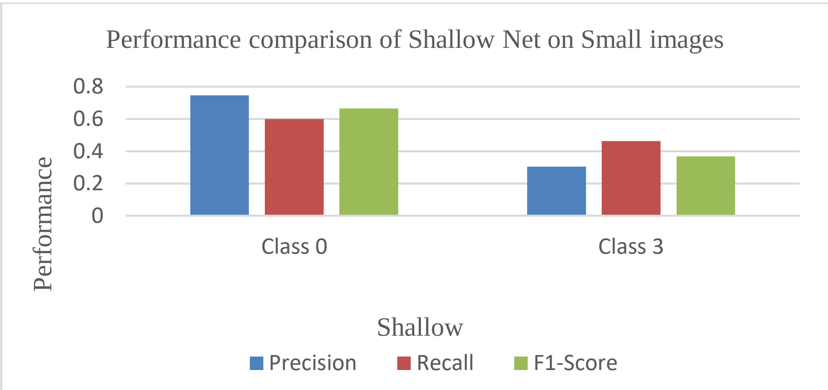

Fig. 9: Performance Comparison of ShallowNet on Small Scale Images

One fact that is worth noting is that despite the fact that both shallow CNN and VGG16 have their own benefits and drawbacks, the performance level of shallow CNN is superior. This is an interesting fact. This is evident from the micro-average ROC curve that is presented in Figure 10.

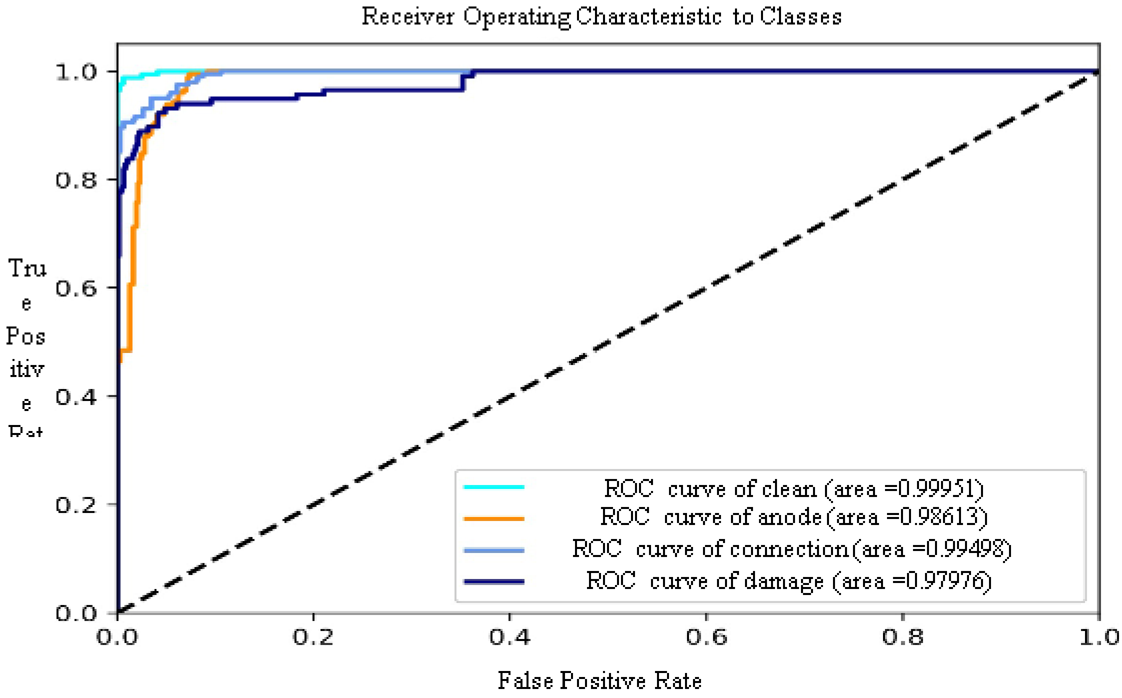

Fig. 10: Micro-average ROC curves of MobileNet, ShallowNet and VGG16 networks on the large scale images

This observation may have an explanation in that the categorization of the four classes is an issue that is fairly simple and can be solved using straightforward models. Due to the limited amount of data available, the shallow CNN is unable to produce a result that is adequate. As a result, in order to prevent training from scratch, another trained network is used that included weights for low-level feature extraction. However, VGG16 is an overly complicated network with a large number of parameters, which in the context of the limited data set can easily cause overfitting. Consequently, transfer learning on MobileNet acts as a compromise by allowing both the utilization of pre-trained weights and the saving of a set of parameters, which both resulted to the optimal outcomes.

5. Conclusion

The proposed system utilises IOT dataset in order to inspect underwater pipelines for cracks and other damage. As a form of input, the process makes use of the image sensor on the autonomous underwater vehicle. These are then fed into a network, where it is preprocessed and categorised into one of four categories. In the event that the problem is determined to be a broken pipe, a second network is utilised to locate the broken area using cropped images. Each of the networks has been trained to begin with pre-trained layers that were obtained from MobileNet. It has been demonstrated that using this method achieves better results than either fully training a shallow CNN structure or using VGG16 as the pre-trained net. It has been illustrated further that the classification algorithm that made use of MobileNet learned more pertinent visual features than the classification model that made use of VGG16 when applied to the IOT data. The forecasting of the intrinsic risk of corrosion for non-piggable pipes is the long-term goal of this study. The recognition of pipeline segments with a greater risk of corrosion will demonstrate where performing localised examinations and direct assessment is necessary.

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