RESEARCH PAPER

Using deep learning to identify the severity of pipeline dents

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ABSTRACT

With the advent of machine learning, data-based models can be used to increase efficiency and reduce cost for the characterization of various anomalies in pipelines. In this work, artificial intelligence is used to classify pipeline dents directly from the in-line inspection (ILI) data according to their risk categories. A deep neural network model is built with available ILI data, and the resulting machine learning model requires only the ILI data as an input to classify dents in different risk categories. Using a machine learning based model eliminates the need for conducting detailed engineering analysis to determine the effects of dents on the integrity of the pipeline. Concepts from computer vision are used to build the deep neural network using the available data. The deep neural network model is then trained on a sub set of the available ILI data and the model is tested for accuracy on a previously unseen set of the available data. The developed model predicts risk factors associated with a dent with 94% accuracy for a previously unseen data set.

Key words: Deep learning, in-line inspection, pipeline, finite element analysis.

INTRODUCTION

Dents, gouges, and other anomalies in pipelines are very common and can be formed at various stages in the life of a pipeline. Dents can form during manufacturing, installation, or any time during the service life due to third-party damage. Dents in a pipeline [1] are identified as a local area with some depression where the radius of curvature has the opposite sign than the radius of curvature of the pipe. Extensive research has been conducted in the 1990s on the effects of dents on the integrity of the pipelines. The effect of a dent on the strength of a pipeline (how it affects burst pressure) or the fatigue life of a pipeline has been studied in detail [2]. Research has shown that plain smooth dents without an accompanied metal loss (gouge) do not have a significant effect on the burst pressure of a pipe [1]. However, the presence of a dent can significantly affect the fatigue life of a pipeline as the dent area acts as a local imperfection to facilitate a stress concentration as the pipeline is cyclically pressurized during its regular course of operation. The higher stress at the dent area can lead to a reduction in the fatigue life of the pipeline. For pipelines experiencing large numbers of pressure fluctuations (liquid pipelines), dents are routinely categorized by the stress concentration factor (SCF).

Dents are identified from in-line inspection (ILI) calliper data. The dents in the ILI data are obtained in the form of a point-cloud format of the depth of the inner radius of the pipeline in an R-θ-z co-ordinate system. The stress concentration factor of a pipeline can be numerically determined by conducting a finite element analysis (FEA) of a pipeline model built from the calliper data. The SCF then can be directly related to remaining life calculation for the pipeline. This method is frequently used to assess the integrity of dented pipelines and the details can be found in [3].

In this work, a deep learning algorithm [4] is developed to classify the dents according to their respective categories directly from the ILI data. The model is developed by training on a large data set of ILI data of which the SCF is already known from FEA. A neural network model is fit on the data to predict a pre-defined risk category based on its SCF. This

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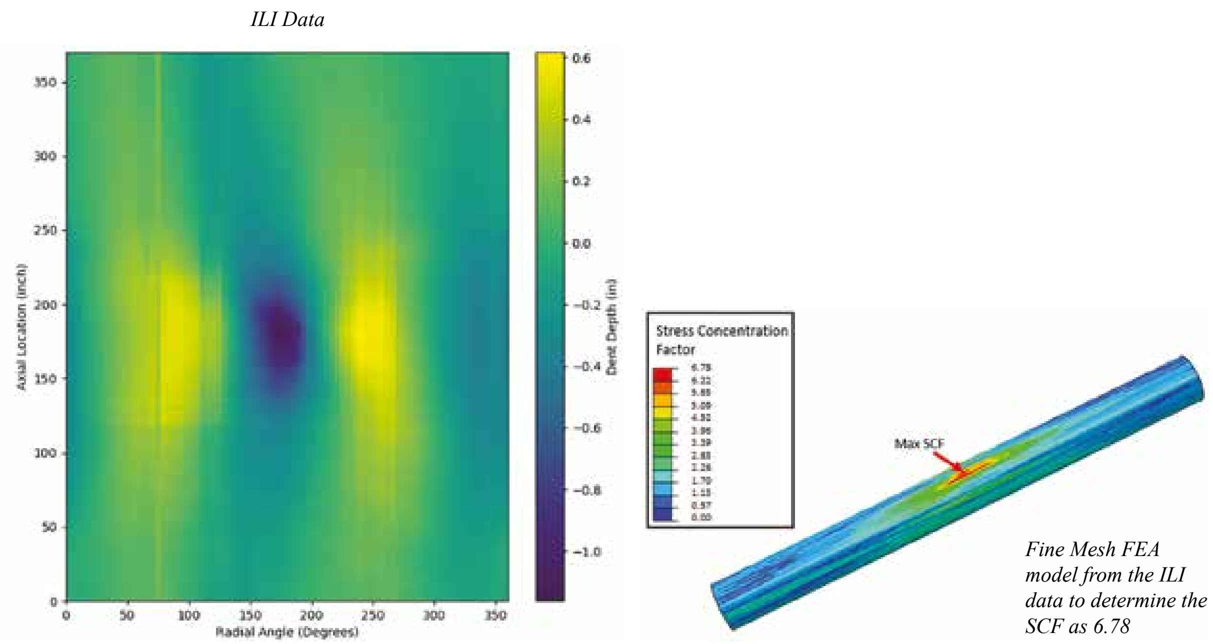

Figure 1. *Colormap of ILI data of dent depth on the left. FEA model of the dented pipe on the right.*

approach treats the ILI data as an image and builds an image classifier which can classify the dent based on its risk category. The concepts of computer vision are used here to build a deep learning model that can classify dents solely from the ILI data. Using this data-based model will eliminate the need of conducting a detailed finite element analysis to estimate the SCF. This fast and easy-to-use model can be deployed in real-time in an edge device or as a cloud-based service.

The predictive model described in the current work is a neural network with multiple hidden layers, which is also known as deep learning (DL). Deep learning is a subset of the broader topic of machine learning (ML).

SCF	Category
Less than 2.5	**Low**
Between 2.5 and 4	**Med-Low**
Between 4 and 6	**Med-High**
Greater than 6	**High**

Table 1. *Categories of dents defined from the calculated SCFs.*

ILI data and risk categories

In this section, the procedure of labelling the risk categories of the pipeline dent data is outlined. The deep learning model is based on a pre-labelled data set, and the predictive model will learn from this data set. The SCF of each dent was determined from conducting an FEA. The details of the method of analysis can be found elsewhere [3]. FEA is conducted in ABAQUS (version 6.14) software [6] after building models (with refined mesh) of the dented pipes using the ILI data. Linear elastic analyses were carried out on the pipe models after adding appropriate boundary conditions. An internal pressure was applied to generate a nominal hoop stress equivalent to 25% of the specified yield strength. The SCF was determined as the ratio between the maximum principal stress and the nominal hoop stress of the undented pipe. For unconstrained dents, the fatigue cracks initiate at the outer surface of the pipe. The SCF at the outer diameter of the pipe is used for classifying the dents.

An example of ILI data from a dented pipeline and the corresponding FEA model to determine the SCF is shown in Fig. 1. The ILI data consists of the radial deformation (depth) from the nominal radius of the pipe. In Fig. 1, a dent with a maximum depth of around 1.20 inches is located around the middle of the inspected pipe. The FEA reveals the SCF to be 6.78 for this dent outer surface.

The data-based predictive model will predict the risk category of a dent. In the parlance of machine learning, this type of problem is known as “classification” problems, since these models predict a “class” or a “category” rather than a numerical value. In order to label different risk categories based on SCF, different SCF values are classified into four different risk categories – Low, Medium-Low, Medium-High, and High. The corresponding SCF values associated with these categories are shown in Table 1. It should be noted that the risk categories can be adjusted based on pipeline operation.

Current work has been conducted on data based on 155 dents. The histogram distribution of the dent categories is shown in Fig 2. It is observed that most of the dents fall in the categories of Medium-Low and Medium-High risk. This is expected in a database, since the low risk dents generally will not be analysed as they will have a low depth of dent. Also, many dents which are very severe might have already been replaced, so high-risk dents are also less common.

The ILI data is presented in a cylindrical coordinate system. However, the grid spacing of the data is not the same for all dents. In order to build a deep learning model, all the input data need to be of same dimension. The incoming data corresponding to a single dent is first pre-processed to be cast in a predefined spatial grid, which is same for all dents. Linear interpolation is conducted for intermediate locations between the measurement points. Standard data cleaning processes, such as the removal of outliers and smoothing are used on the data.

Neural network model

Image classification is a very common problem in computer vision, and it is generally solved by using deep neural networks. The ILI data from the dented pipeline can be considered as an image, as shown in Fig. 1. The output of the pipeline dent image classification model is a category (such as 'high risk' or 'low risk'). There exists a separate category of machine learning models known as regression models, which predict a numerical value instead of a category. Here is a brief description of the neural network model trained to predict the risk associated with a pipeline dent.

A neural network is a type of machine learning model where multiple interconnected layers and nonlinearities map an input to an output. The neural network model is fit on a set of prelabelled data, which is known as the training data. After the model is trained on the training data, its performance will be evaluated on another set of unseen images. This unseen set of images is called a 'test' set. The available data set will be randomly divided in training and test set. A good model will have an optimum performance on both the training and test data sets. This type of problems is also called 'supervised' machine learning since it uses training data that has a labelled output.

Fig. 3 shows a typical ILI data obtained from an ILI vendor. It is represented as a colormap with respect to radial angle in the horizontal axis and axial location on the vertical axis. There is a dent located toward the middle of this data oriented in the circumferential direction of the pipe. The stress concentration due to the presence of the dent is a localized phenomenon. Instead of fitting a large predictive model to the full image, which includes data from 30 ft long

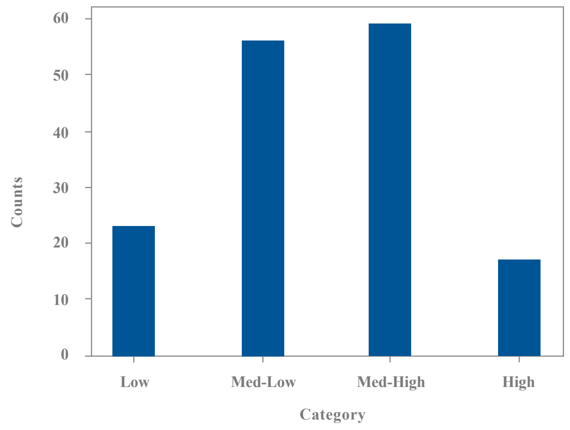

Figure 2. Histogram of the different dent categories in the data.

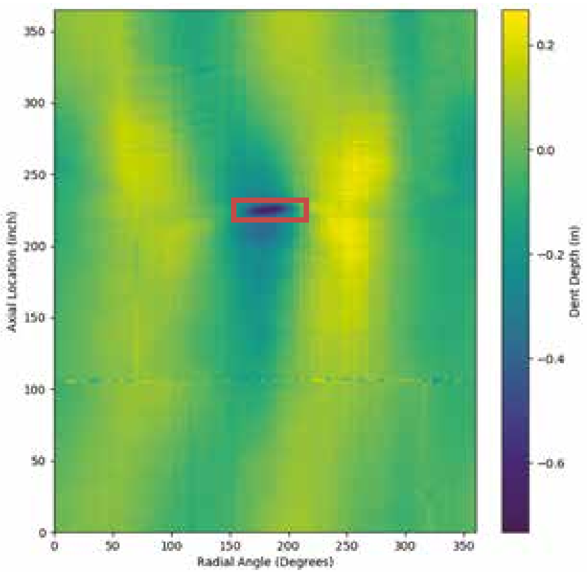

Figure 3. ILI data containing a dent. Local image of the dent outlined in the red box.

pipe over the full 360 degrees circumference, a local image is captured around the dent.

This local image is later used to build the deep learning model. This approach also ensures that other additional features of the pipeline profile which does not contribute to the stress concentration factor is not included in the model. The dent is identified from the minimum depth (lowest magnitude of the inner radius) of the ILI data. The data is cleaned (outliers are identified and removed) and smoothed (re cast on a grid using linear interpolation) prior to the identification and isolation of dent images. The local dent images are extracted from the available data base.

In general, an image classifier uses the three color channels (red, green, and blue) of a picture. Each of the color channels represent a single two-dimensional array

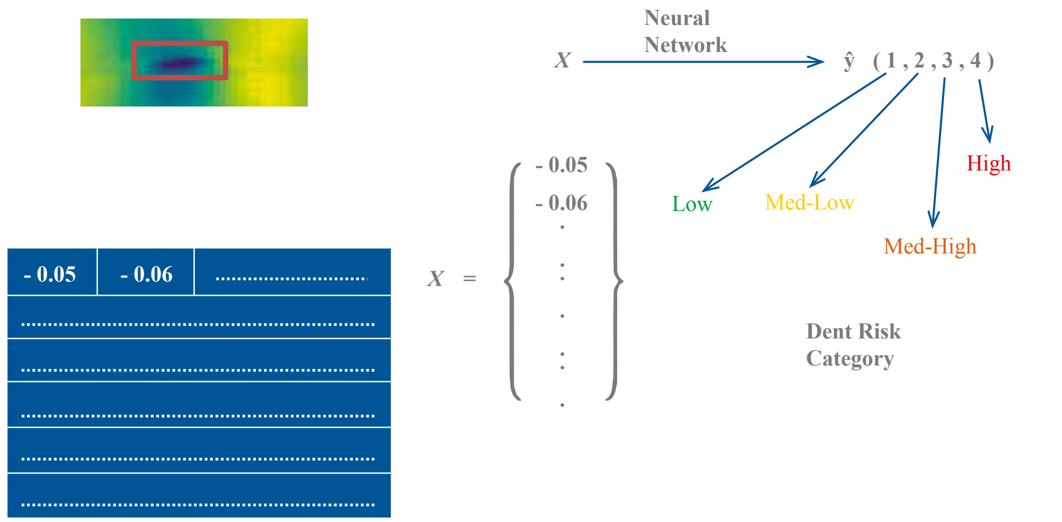

Figure 4. Input and output of proposed neural network.

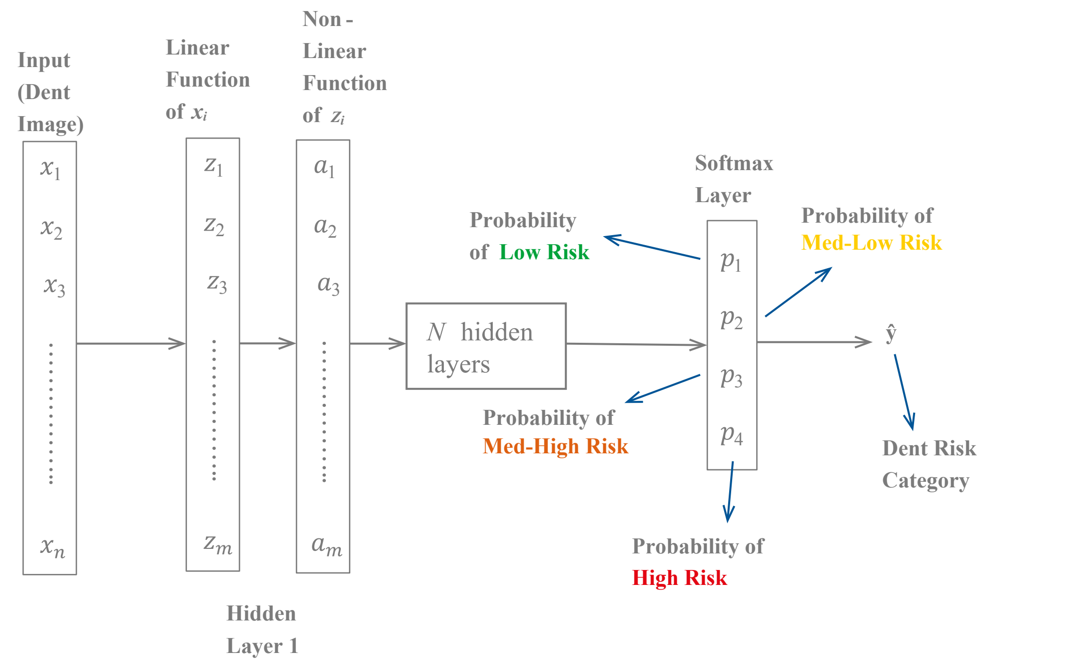

Figure 5. Neural network with n hidden layers for multi-class prediction.

of numbers. As a first step, each of the arrays are flattened and appended at the end of the previous vector to generate a single input vector. So, an image with a three-color channel becomes a one-dimensional array of numbers and is used as input to a neural network. In the current work, the basic concept behind the model is the same as any deep learning-based image classifier. However, instead of using data from multiple channels, the dent profile is obtained from the single ILI data channel.

Fig. 4 shows the input and output for the proposed neural network. The local image of the dent is shown within the red box. This image is an array of numbers which can be represented as a matrix. A part of that matrix is shown in the down-left corner of Fig. 4. This matrix is flattened, and the resulting array X is the input to the neural network. The model will predict an output $\hat{y}$, which can take four values (1, 2, 3, 4) representing the four risk categories of the pipeline dents described in the previous section.

A deep neural network consists of multiple hidden layers each consisting of a linear function and a nonlinear function, that is known as an "activation" layer. The details of the deep neural network are shown in Fig. 5. This neural network has N hidden layers and the output predicts one of the four possible risk categories. For an input vector X of size $n \times 1$ and first hidden layer with m hidden units, the linear function computes the following:

$$Z = WX + b \tag{1}$$

where $Z = \{z_1 \ldots z_m\}^T$ is the output of the linear function, W is the coefficient matrix of size $m \times n$, and b is the bias vector of size $m \times 1$. The variables in W and b will be optimized for each hidden layer to fit the training data set. The subsequent activation layer maps Z to a by a nonlinear function. In this case, the nonlinear activation is a rectified linear function, commonly known as 'relu' [4]. The nonlinear activation computes:

$$a = g(Z) \tag{2}$$

where $a = \{a_1 \ldots a_m\}^T$ is the output of the non-linear activation function. Other than 'relu', there exists a few other nonlinear functions that can be used as an activation function. However, the 'relu' function is one of the most commonly used activation functions. There can be several hidden layers and different number of hidden units in a single hidden layer. The parameters of W and b are optimized for each of the hidden layers. The number of hidden layers and the hidden units are 'hyperparameters' of a deep learning model and needs to be tuned for the optimal performance of the model. For a multi-class classification problem, the final activation layer of the neural network is a 'softmax' layer. Since there are four possible outcomes in the current model, the final layer will have four hidden units. Each of these units will be the probability of the input data being one of the four risk categories. Instead of using a 'relu' activation, this layer normalizes the output from the linear function and maps it to probabilities of each risk categories as shown in Fig. 5. The final output $\hat{y}$ is the risk category that has the highest probability of occurrence.

The parameters at each hidden layer are optimized by minimizing a loss function over all of the training data set. For a single input, the loss function for multi-class classification with four classes is:

$$L(y, p) = -\sum_{i=1}^{4} y_i \log p_i \tag{3}$$

where y_i is the actual probability (which is either 1 or 0) for the input to be classified in i^{th} category, and p_i is the predicted probability. This loss function is minimized over all of the training data set. So, for m training data or dent images, the function to be minimized is:

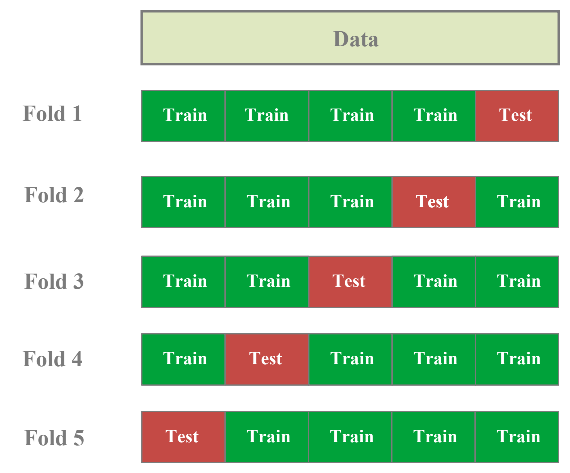

Figure 6. *Five-fold cross validation for hyperparameter tuning.*

$$J(W, b \ldots) = \frac{1}{m} \sum_{j=1}^{m} L(y_j, p_j) \tag{4}$$

The loss function is minimized by a technique known as back propagation [4]. Python's sci-kit learn library [5] is used to build the neural network model. In order to build an optimum model, the hyperparameters need to be tuned. The hyperparameters in this model are: (1) the number of hidden layers, (2) number of hidden units, and (3) the regularization parameter.

A very important aspect of a machine learning model is to build a model that does not overfit the training data. A complex model may fit the training data with 100% accuracy, but it may not be able to predict previously unseen data very well. Some regularization is added to the loss function that will help reduce the overfitting and result in a more regularized model. This is done by introducing an additional term in the loss function in Eq. (4):

$$\lambda \|W\|_2^2$$

where $\|W\|_2$ is the L2 norm of the coefficients W, and λ is a hyperparameter that needs to be optimized.

The hyperparameters are selected by 5-fold cross-validation. The scheme for 5-folds cross validation is shown in Figure 6. The training data is divided in five sets, and a model is trained on four sets of the data for each fold, for a total of five times. Every time a different set is chosen as the test set to evaluate the accuracy in each fold. The accuracy of the model is averaged over these five folds of cross validation, as a hyper parameter is varied. Three hyperparameters are tuned for maximum accuracy over five-fold cross validation: λ, number of hidden layers, number of units in a hidden layer. A deep learning model with optimized hyperparameters is chosen.

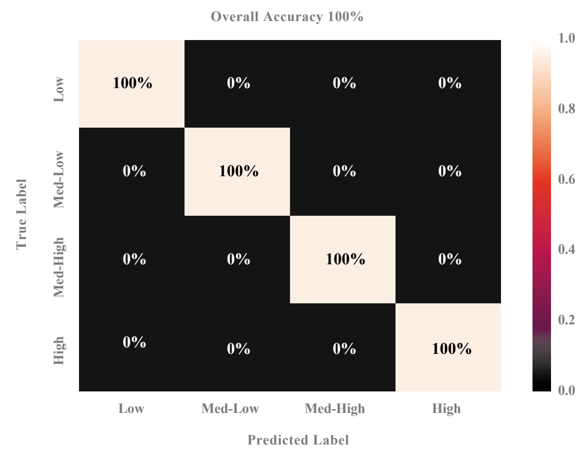

Figure 7. *Confusion matrix for training set.*

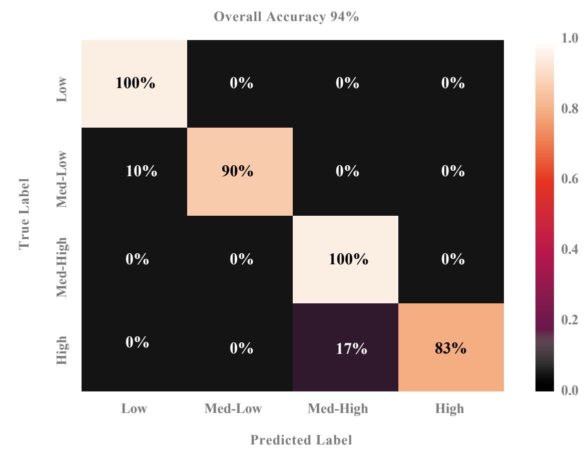

Figure 8. *Confusion matrix for the test set.*

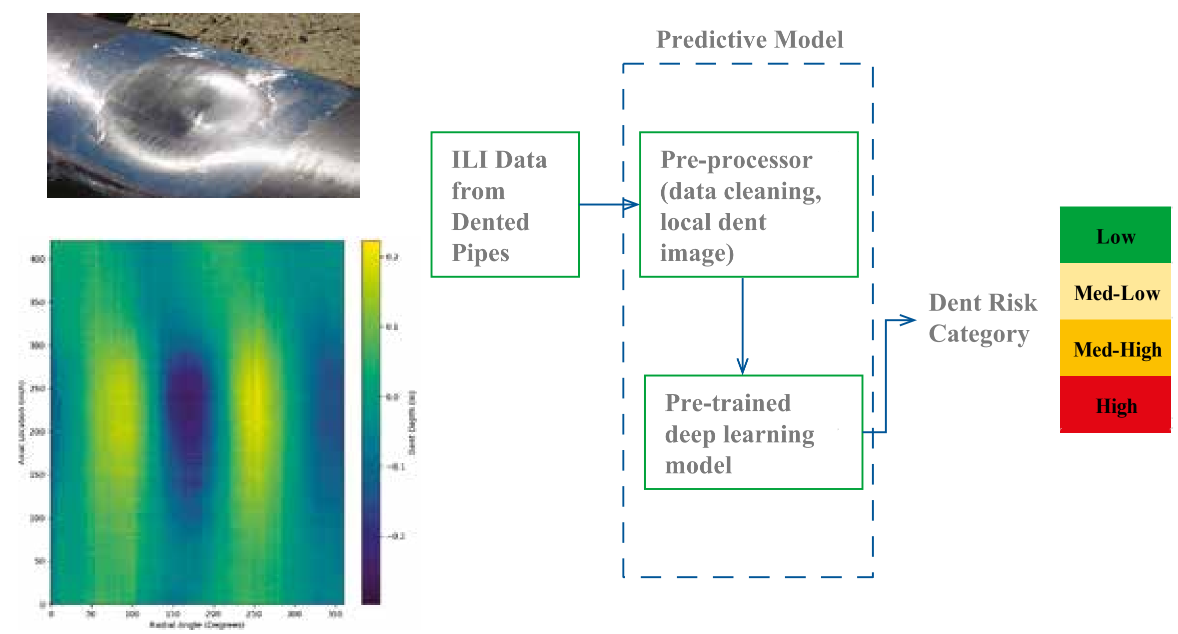

Figure 9. *Predictive model capable of operating in real time for dent classification (top left image from Google Images).*

Model evaluation

The full data set is randomly divided in 75% training set and 25% test set. A multi-layer deep learning model with optimum hyperparameters is trained on the training set. The performance of the model is tested on both the training and test set (blind data unseen to the model). In order to evaluate the performance of a multi-class predictive model, a 'confusion matrix' is used. A confusion matrix shows the number of true predictions and false predictions of a classifier in the form of a matrix. The horizontal axis is the predicted label and the vertical axis is the true label in the confusion matrix. The confusion matrix for the training set for the dent classifier is shown in Fig. 7. The confusion matrix here is shown as a heatmap, with the lightest color representing a value of 100%. The classifier fits the training data perfectly with all zero off-diagonal terms in the confusion matrix. So, all the risk categories are perfectly predicted by the model in the training data.

The confusion matrix for the test set for the dent classifier is shown in Fig. 8. The overall accuracy of the deep learning model for the unseen test set is 94%. The percentage of data that the classifier does not classify correctly is shown in the off-diagonal terms. Of the dents of Med-Low Risk category, 10% has been predicted as Low, and 17% dents of the High-risk category has been predicted as Med-High by the deep learning model.

The cases where the classifier makes a wrong prediction, the predicted class is always adjacent to the actual class. This shows that although the classifier does not predict the dent class with 100% accuracy, the predicted class is close to the actual class.

The performance of the predictive model is likely to increase as the model is trained on more and more data. As observed in the performance of the model in the training set and the test set, there exists some opportunity to reduce overfitting and achieve a closer overall accuracy in the training and the test set.

Findings

A deep neural network model is trained on a series of data from ILI inspection of dented pipelines. The dents are classified in four risk categories: low, medium-low, medium-high, and high. The risk categories are based on estimated SCF at the dent location, which has a direct effect on the remaining fatigue life of the dented pipe. The SCFs are determined from past finite element simulations conducted on models built from the ILI data.

Concepts from computer vision are used in building the deep learning model and it predicts the dent class with 94% accuracy for a previously unseen ILI data. The model can be potentially employed in real time at the time of collection of the ILI data. It can identify a dent from a relatively large scan data and predict the severity of the dent. This program can run on an edge device or in the cloud. A schematic of the operational method of this tool is shown in Fig. 9.

This tool can be accessible to both ILI vendors and pipeline operators as a method of preliminary check and to identify dents with a higher risk for further assessment. This tool is easy to use and can predict the risk category of a dent in real time, even during the collection of data.

This has the potential to reduce engineering analysis time and can be used as a 'first pass' dent assessment tool. The risk categories can be re-defined based on the operational requirements and the deep learning model can be continuously updated and upgraded as more and more data are available.

In addition to classifying the severity of dents, this tool can also be used to predict the range of fatigue life if pressure cycle data is available to the pipeline operator. The predicted SCF can be combined with the cyclic pressure history data to predict a range for expected fatigue life of the pipeline. This calculation can also be done in conjunction with the dent classification and it can be made a part of the same tool.

This is an example where deep learning has been used to classify dents according to their risk categories. In future, this approach can be further used to analyse raw data from ILI tools and classify potential anomalies, thus developing a standard frame work for all pipeline operators and ILI vendors.

Competing interests

The authors declare that there is no competing interest regarding the publication of this paper.

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Image courtesy of Nord Stream 2 and Axel Schmidt.