CV for anomaly detection in industrial applications

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Abstract

Keywords: deep learning, computer vision, anomaly detection, fault detection, technical systems

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1. INTRODUCTION

Anomaly detection problems have a great importance in industrial applications, because anomalies usually represent faults, failures or the emergence of such. To detect these automatically, we propose deep learning algorithms for anomaly / fault detection and their classification. We develop an algorithm achieving Segmentation Defects classification Its performance will be examined on two different problems: anomaly detection in oil pipelines and fault detection on transmission system components. Both these systems can span over thousands of kilometers, which makes manual inspection very costly. How such computer vision techniques can be applied on an industrial scale is discussed in the following.

Transmission infrastructure, on the other hand, physically connects power sources and consumers extending over thousands of kilometers. Many different components exist, which is why maintaining power grids is a serious cost factor for transmission system operators (TSOs). Automated fault detection could potentially help to decrease costs. To use an automated visual system however, specific infrastructure first needs to be identified and segmented, to then perform any type of fault detection. Therefore, the proposed deep learning-based approach, to segment and identify faulty components (i.e. insulators) in handheld footage, will be tested regarding its viability. If a deep-learning based approach would prove reliable, drones could monitor equipment automatically.

The damage of pipelines that transport petroleum and gas products lead to severe environmental problems. Eliminating breakthroughs and their consequences is expensive. To avoid accidents, it is recommended to improve diagnostics quality and to increase the frequency of in-line-inspection (ILI) tools deployment. ILI tools, also referred to as pipeline inspection gauges (Fig. 1), use Hall effect for measuring localized magnetic flux leakage intensity along the pipe wall. While moving along the pipe gauge inspects the wall and detects the magnetic field leaks. The data collected during the inspection can be further analyzed for main diagnostics problems solving: damage and defects detection, their localization, diagnosis or defects classification. Analysis results are useful for assets managing and repair priorities determination.

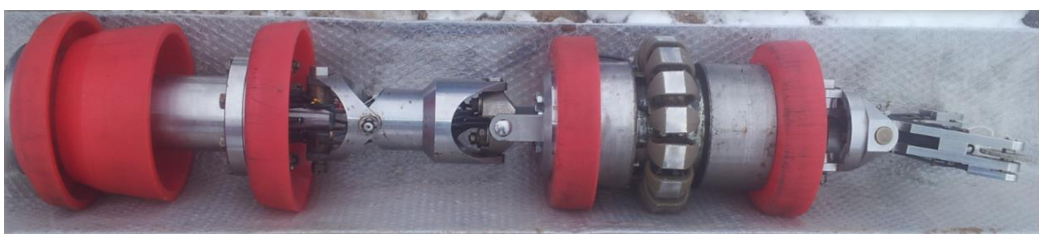

Figure 1: In-line-inspection tool

2. LITERATURE REVIEW

2.1. Pipelines defects diagnostics

Magnetic Flux Leakage (MFL) technique is the most common approach for oil and gas pipelines nondestructive testing. The data obtained during the pipeline inspection process is primarily analyzed by traditional machine learning (ML) methods. A comparison of performance among different ML methods for defects identification problem is presented in [1]. The main challenge for this approach is creating informative and important features that will be used as an input for ML methods. Usually, these diagnostics features are generated using expert knowledge and manually-created heuristics. It imposes the limitation on defects detection problem solving quality. A variety of most successful features is presented and analyzed in details in [2].

Deep Learning showed significant progress and achieved incredible results in numerous applications, just in the past few years. The image classification problem is one of the most successful applications of DL and Convolutional Neural Networks (CNNs) in particular. To automate the process of feature generation in MFL data analysis, CNNs can be used either. As an advantage, they can solve the defects detection and segmentation tasks at the same time. In literature there are examples of applying CNNs for defects detection [3], welds defect detection [4], welds and defects classification [5], defect size estimation [6]. For all mentioned applications, CNNs outperformed existing traditional approaches. Nevertheless, still, there are just a few works dedicated to MFL data analysis using DL. A number of particular problems that can be solved using a novel approach are not covered yet. For instance, we could not find any works on applying CNNs to defects segmentation task, despite the importance of this problem solving according to [3].

In this work, we want to research two different problems:

1. Defects detection (Picture classification task).
2. Defects segmentation (Semantic segmentation task).

For their solving, we propose CNNs of different architectures and compare their results with existing state-of-the-art approaches. Moreover, we research different preprocessing techniques for dealing with typical issues in the MFL data.

2.2. Unet

asd [7]

3. CONTRIBUTION

Viacheslav Kozitsin. The main task was to solve problem of semantic segmentation of defects in pipes. Outcomes: A baseline was chosen as a stripped-down version of UNet (Figure **??**). The specifics of applying UNet under conditions of small sizes of the original image (64x64) were investigated. As a result, the problem was solved with IoU=0.2 and good visual results (Figure**??**). Concomitant successes: annotated the data for the defect segmentation of pipe (Table 1); proposed own approach to the preprocessing of raw data from sensors based on expert knowledge (Figure 5); solved the problem of displaced origins between data and report files (Figure7). Active participation in the filling of the report and presentation.

Iurii Katser. The main task was to solve the defects detection problem for the oil pipeline dataset. Exploratory Data Analysis (EDA) was provided. EDA allowed us to define issues in data that impede CV problems solving without data preprocessing. Data preprocessing tools were implemented (abnormal values filling, defects, and welds coordinates searching). The influence of different preprocessing algorithms was analyzed and presented in the results section. The CNN that overperformed the best existing network on the presented pipelines dataset was proposed. Outcomes and future work were marked.

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4. METHODS PIPELINES

Pipeline defect detection is also composed of two problems. First, the defect should be detected, and further, it should be evaluated using segmentation results. We propose here two different CNNs for defect detection and defect segmentation.

For image classification, we used existing architecture that achieves best results in the MFL data classification problem and proposed novel CNN architecture to compare with the existing one. We reimplemented CNN from [3] with one difference: we used squared pictures (64x64 pixels) as an input, so we didn't implement Normalization layer (first layer in the Fig. 2). The

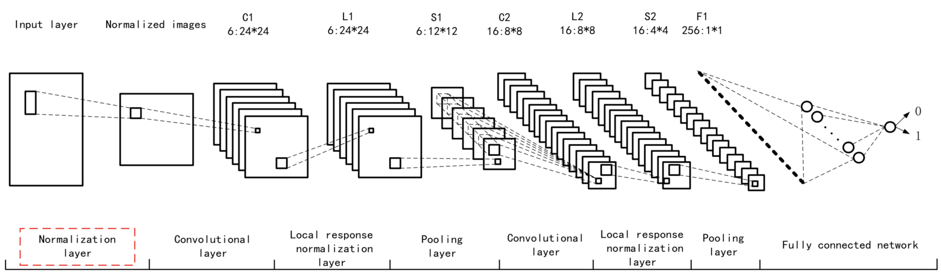

Figure 2: Architecture of CNN from [3]

interested reader can find all details and overall architecture parameters in [3]. From now on this CNN is marked as CNN-2 by the number of Convolutional layers.

Proposed model (Fig. 3) initially contains Dropout layers and Batch Normalization (BN) layers instead of Local Response Normalization (LRN) layers. Our model consists of 5 Convolutional layers overall. Each Convolutional

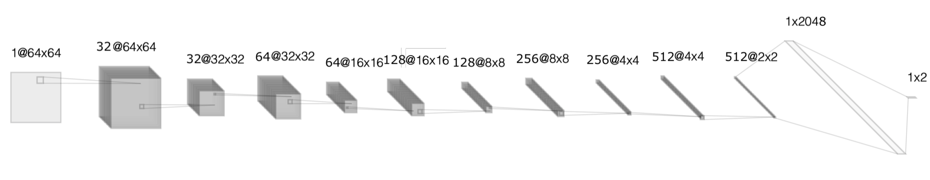

Figure 3: Architecture of the proposed CNN

layer is followed by BN and Dropout sequentially (not shown in Fig. 3). All

Convolutional layers have equal kernel size - 5 x 5. All MaxPooling layers have equal kernel size - 2 x 2, and stride - 2. From now on this CNN is marked as CNN-5.

4.1. Data and preprocessing description

Although MFL data looks quite similar for different pipes and ILI tool types, it can differ significantly. The data mainly depends on pipe size, wall width, sensors geometry, and other geometric characteristics. Moreover, ILI tools differ a lot for different pipe sizes. Therefore, the repeatability of the results for different datasets should be investigated additionally. Following, we provide dataset characteristics. We have data collected from the 219 mm in diameter pipe. MFL dataset provides information about a single inspection tool run. Dataset has 64 features collected as an array with a constant step along with the ILI tool movement inside the pipe. Dataset has 4470704 samples that represent 15162.85 meters long pipeline part. Sample values vary from 0 to 4095 units. It has 745 defects of different types and 1462 welds, 34 of which are defected. Fig. 4 shows examples of normal data, data with a weld, and with a defect. Attached to the dataset technical report contains information about welds and defects location, defects types, sizes, and other related characteristics.

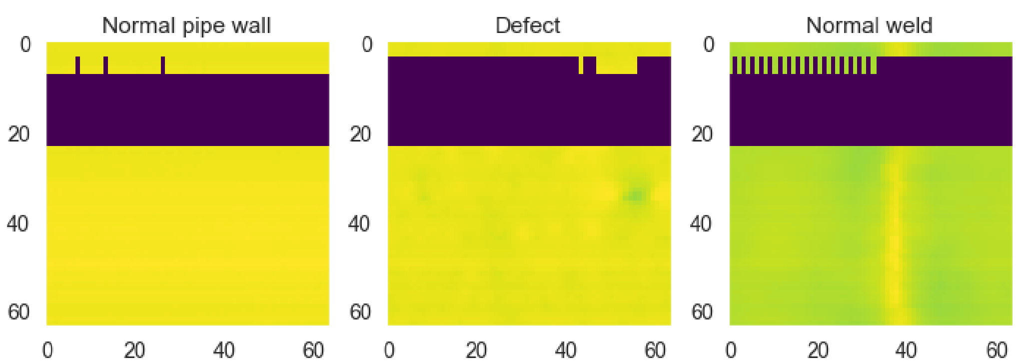

Figure 4: Example of the MFL data

Raw data has several issues that don't allow us to solve CV problems without proper preprocessing. They are:

1. Sensors malfunctions (zeroed values cause bold horizontal line in Fig. 4);
2. Displaced origins between data and reports coordinates;

3. Inaccurate annotations, e.g., missed defects, wrong defect location, etc.
4. No annotated data for the segmentation task.

4.1.1. Sensors malfunctions problem

To deal with sensors malfunctions we suppose to fill the gaps (zeroed values) with values calculated by different methods. Additionaly, we will consider values less than 2000 abnormal and replace them with zeroes during the preprocessing.

1. Abnormal values are equal to 0. Then Min-Max scaling to [0.5 : 1] range.
2. Abnormal values are equal to the mean of normal values from one picture. Then Min-Max scaling.
3. Abnormal values are equal to the mean of normal values over the column. Then Min-Max scaling.
4. Abnormal values are equal to the mean of neighboring sensors over the column. Then Min-Max scaling.
5. Abnormal values are equal to the interpolation results over the column. Then Min-Max scaling.
6. Rerange initial set of values to 0...255 uint8 range.
7. Rerange initial set of values to 0...1 float range (Fig. 5). Such a specific function due to the range of normal operation of the sensor from 2500 to 3500 units.

pictures/preproc_fun.png

Figure 5: The function for converting the initial values of signal to the input of network

The results of all applied methods are presented in Fig. 6.

Min-Max scaling can be applied using whole dataset or just one image. Both approaches will be compared during the experiment conducting.

Since the ILI tool location data did not match the defect location data from the report, it was necessary to merge the data. The key factor here turned out to be that signal values from magnetic flux sensors grow at the weld site (Figure 7).

The solution was to find the locations of the maxima of sensors data values and then to combine it with the weld coordinates.

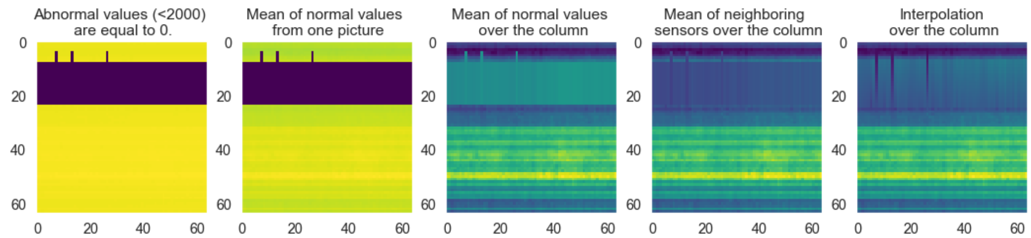

Figure 6: Comparison of missing values filling methods

pipes/prepr.png

Figure 7: Location of a weld. The black vertical line is a weld, according to the report. Other lines are values from sensors.

4.1.2. Manual annotations for the segmentation task

Since there was no annotated data for the segmentation problem, it was necessary to annotate it manually (Figure 8). The characteristics of the obtained dataset can be seen in table 1.

pictures/annot.png

Figure 8: The methodology for obtaining the mask

4.1.3. Inaccurate annotations problem

This problem is a common one for oil and gas pipeline nondestructive testing [1]. It appears to be a lot of missing defects that affect the quality of the problem. Besides, there are wrong defect types and locations. To eliminate wrong location issue, we additionaly searched extremums around the provided location and chose the defects or welds taking into account new coordinates.

4.1.4. Augmentation

Although we have a lot of data, we don't have a lot of defects and welds in comparison with normal pipe wall instances. We use the augmentation procedure to balance classes of pictures and increase the model's quality by increasing the number of instances in small classes (defects, welds). As an augmentation tool we use Albumentations library [8]. For welds pictures we apply following augmentations:

1. Rotate (limit=180, p=1),
2. VerticalFlip (p=1),
3. HorizontalFlip (p=1),
4. ElasticTransform (p=1, alpha=20, sigma=120 * 0.05, alpha affine=120 * 0.03),
5. GridDistortion (p=1),
6. OpticalDistortion (p=1, distort limit=2, shift limit=0.5).

And for defects we apply following ones:

1. Transpose (p=1),
2. Rotate (limit=90, p=1),
3. Rotate (limit=180, p=1),
4. Rotate (limit=270, p=1,),
5. VerticalFlip (p=1),

6. HorizontalFlip (p=1),
7. ElasticTransform (p=1, alpha=20, sigma=120 * 0.05, alpha affine=120 * 0.03),
8. RandomRotate90 (p=1),
9. GridDistortion (p=1),
10. OpticalDistortion (p=1, distort limit=1, shift limit=0.3).

Examples of augmentations are shown in Fig. 9.

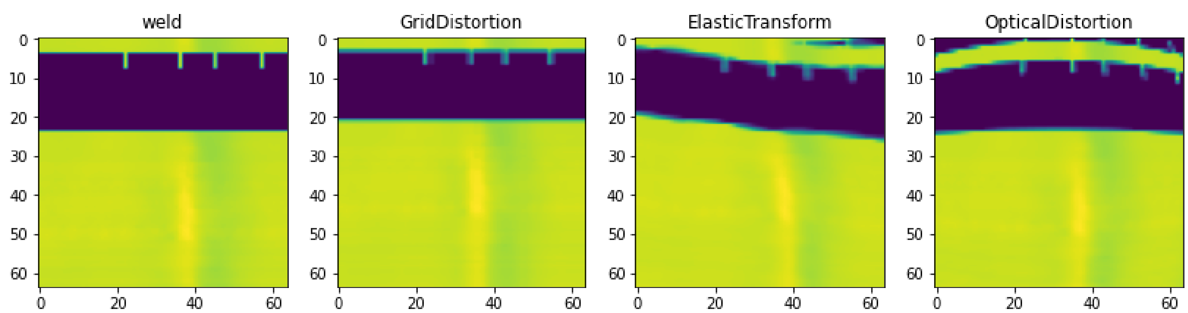

Figure 9: Examples of the augmentation results

The characteristics of the pipeline defects dataset are described in Table 1, where * symbol indicates a random call function 5 and 6 from the defects augmentation list, so the exact number is unknown.

Table 1: Dataset size for pipeline defects detection and segmentation problems

	Classification			Segmentation	
Data	Normal	Defect	Weld	Normal	Defect
Before augmentation					
Train	11106	569	1130	181	450
Validation	584	142	282	33	111
After augmentation					
Train	11106	8535	11300	*	*
Validation	584	142	282	*	*

4.2. Performance metrics

For the classification problem we use Accuracy. Accuracy is defined by the formula:

$$Acc = \frac{\sum_{i=0}^{N} 1_{\{\hat{y}_i = y_i\}}}{N},$$

where N - number of samples, $\hat{y}$ - predicted label, y - true label.

5. RESULTS PIPELINES

We present the results of comparison for different preprocessing techniques and different CNN architectures for binary classification (normal pipe wall or defect/weld) in Tab. 2 and multiclass classification problem (normal pipe wall, defect or weld) in Tab. 3.

Batch size is equal to 64, so the input to the network has shape (64, 1, 64, 64). For all experiments, we use Adam optimizer with initial learning rate 0.001 and learning rate scheduler with parameters: threshold = 0.0001, factor = 0.5, min lr = 0.0001, patience = 484. Also, for all experiments, the number of epochs is equal to 12. Dropout rate for all experiments is equal to 0.33. All mentioned parameters were selected by using grid search procedure.

Table 2: Comparison of performance among different classification methods for binary classification problem

Method	$\hat{y} = y = 0$ (normal)	$\hat{y} = y = 1$ (defect/weld)	Average
CNN-2	95.55	82.08	89.88
CNN-5	97.95	**91.51**	**95.24**
CNN-5+LRN	**98.29**	89.86	94.74
Filling techniques comparison			
CNN-5 (filling 1)	97.95	**91.51**	**95.24**
CNN-5 (filling 2)	97.95	84.20	92.16
CNN-5 (filling 3)	97.26	83.02	91.27
CNN-5 (filling 4)	**98.63**	81.13	91.27
CNN-5 (filling 5)	98.12	81.84	91.27
Centering influence for the first filling method			
CNN-5 (centered)	97.95	**91.51**	95.24
CNN-5 (not centered)	**98.46**	91.27	**95.44**
CNN-2 (centered)	95.55	82.08	89.88
CNN-2 (not centered)	96.92	80.42	89.81
Image min-max normalization vs Whole dataset min-max normalization			
CNN-5 (centered)			
CNN-5 (not centered)			
CNN-2 (centered)			
CNN-2 (not centered)			

Filling methods were researched for binary classification problem. Centering means using peaks (extremums) searching procedure for welds or defects correct coordinates defining. The centering procedure was research both for binary and multiclass classification problems. Moreover, Min-Max normalization using either a single image or whole dataset was investigated. Finally, CNN-2 and CNN-5 were compared for centered images with the first filling method using single image Min-Max normalization.

Table 3: Comparison of performance among different classification methods for multiclass classification problem

Method	$\hat{y} = y = 0$ (normal)	$\hat{y} = y = 1$ (defect)	$\hat{y} = y = 2$ (weld)	Average
CNN-2	97.60	59.86	92.91	90.97
CNN-5	**98.12**	**76.76**	**98.23**	**95.14**
Centering influence for the first filling method				
CNN-5 (centered)	**98.12**	**85.21**	75.18	89.88
CNN-5 (not centered)	**98.12**	76.76	**98.23**	**95.14**
CNN-2 (centered)	96.75	71.13	52.13	80.65
CNN-2 (not centered)	97.60	59.86	92.91	90.97
Single image min-max normalization vs Whole dataset min-max normalization				
CNN-5 (1) (whole)	97.95	64.08	**99.65**	93.65
CNN-5 (1) (image)	98.12	**76.76**	98.23	**95.14**
CNN-2 (1) (whole)	**99.32**	13.38	96.45	86.41
CNN-2 (1) (image)	97.60	59.86	92.91	90.97
CNN-5 (3) (whole)	99.66	81.69	99.65	97.12
CNN-2 (3) (whole)	95.72	13.38	97.52	89.58

6. RESULTS PIPELINES

7. CONCLUSION

Today, manual analysis of a magnetographic image is a bottleneck for the diagnosis of pipeline transport, since it costs a lot of money and is limited by human resources. This study allows us to hope that this process can be fully automated, which is likely to make the analysis more reliable, faster and cheaper.

Also, the network (CNN-5) that outperformed currently used CNNs for defect detection of pipelines was proposed. Moreover, we proposed a modified UNet for defects of pipelines segmentation. The results of segmentation show the applicability of the proposed UNet for the size of defects evaluation. The results of the experiments prove that all parts of the oil pipeline diagnostics process can be fully automated with high quality.

Finally, there can be defined several project development options:

1. better preprocessing, including manual pictures selection;
2. multiclass defects classification;
3. defected welds detection;
4. applying some common archictures like VGG or ResNet;
5. adding layers to the last Convolutional layer for defect depth evaluation;
6. investigate the repeatability of the results for different datasets;
7. using separate dataset for results evaluation.

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