PHMSA Quarterly Report – Public Page

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Project Title: *Dual Purpose PIG for Cleaning and Internal Integrity Assessment for Hazardous Liquid Pipelines*

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For quarterly period ending: *December 20th, 2023*

1: Items Completed During this Quarterly Period:

1.1. Team Project Activity 1: Project Discussion with industrial partners to seek additional input

During the first quarterly reporting period, the research team established a technical advisory panel following the requirement of the proposal. The technical advisory panel (TAP) included six members including three from industry, two from academics, and one from PHMSA. The research team is working with the TAP to establish a non-disclosure agreement to ensure secure and smooth information sharing. The research team collected very valuable inputs from the TAP on literature review and development of the tool sets, and will continue working with the TAP during the project to guide the project to success.

1.2. Team Project Activity 2: Review related literatures, summarize the previous research findings, and facilitate kick-off meeting

1.2.1 Kick-off meeting

The kick-off meeting was held on Wednesday, November 29, 2023, from 11:30am - 1:00pm CST. The kick-off meeting included the PHMSA project management team, the TAP, and the research team. The research team presented the project and outlined future plans. In addition, the research team discussed with PHMSA management team for the project objective, expectations, and requirements. The TAP also provided valuable inputs to the research team on the product team and indicated of future supports to the research team for data supports, testing, etc.

1.2.2 Review related literatures and summarize the previous research findings

In the dynamic landscape of the oil and gas industry, the efficient and reliable transportation of hydrocarbons through pipelines is of great importance. Over 200,000 miles of hazardous liquids pipelines in the U.S. Of these, 98% transporting crude oil, refined petroleum products (gasoline or diesel, highly volatile liquids (HVL), and more recently CO_2. The integrity of pipelines is critical for ensuring the safety, environmental sustainability, and cost-effectiveness of energy transport infrastructure. Historical data from PHMSA shows that for liquid pipelines (as oil pipelines), the major causes include equipment failure (41.1%), corrosion (28.1%), incorrect operation (14.8%), natural force damages (4.2%), and weld or material failure (4.1%). To maintain and monitor pipeline health, regular cleaning services using cleaning pigging (PIG) and occasional in-line inspection (ILI) services play a significant role for pipeline integrity. Cleaning PIGs propelled through the pipeline by the flow of the product being transported or by external means such as compressed air or hydraulic pressure. They are used to prevent or mitigate the formation of harmful deposits such as scale, wax, or hydrates. Depending on the products being transported, the volume of debris in a pipeline, and the cleaning methods, cleaning PIGs can be run in various frequencies (up to 2~3 times per week) to reach the desired cleanliness. At the same time, the ILI is to examine the interior of pipelines without disrupting their operational flow. Smart technologies have elevated this process to new heights, enabling comprehensive assessments of structural integrity, identifying potential defects, and enhancing overall asset management strategies. From magnetic flux leakage (MFL) to advanced ultrasonic testing, these inspection technologies play a pivotal role in ensuring the robustness of pipeline infrastructure in the face of evolving industry demands [1].

While facing the challenge of bringing the high techs into the in-line environment, a pipeline inspection gauge (PIG) as the entity of cleaning the pipelines insides is always introduced to carry the device though the pipelines, which makes it possible for technology landing in the pipeline inspection job. In this reporting period, the research team performed a thorough literature review on different PIG types with various ILI tools, the computer vision and digital twin, and the software design. The concepts of how current state-of-art and state-of-practice are involved in the existing smart device assists us with the entity manufacturing, electronics mounting and operational procedures, image analysis, and software design to achieve the project's goal of developing an efficient and cost-effective dual-purpose PIG.

1.2.2.1 PIG types

In the dynamic landscape of the oil and gas industry, the efficient and reliable transportation of hydrocarbons through pipelines is of great importance. Pipelines serve as the lifelines of this industry, and their integrity is critical for ensuring the safety, environmental sustainability, and cost-effectiveness of energy transport infrastructure. To address the challenges of maintaining and monitoring pipeline health, a new era of innovation has emerged, driven by the integration of cutting-edge technologies into the very fabric of these conduits.

The primary objective of in-line inspection (ILI) is to examine the interior of pipelines without disrupting their operational flow. Smart technologies have elevated this process to new heights, enabling comprehensive assessments of structural integrity, identifying potential defects, and enhancing overall asset management strategies. From magnetic flux leakage (MFL) to advanced ultrasonic testing, these inspection technologies play a pivotal role in ensuring the robustness of pipeline infrastructure in the face of evolving industry demands [1].

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In this report, literature reviews of different PIG types with various ILI tools are conducted to support the dual-purpose design from background knowledge. The concepts of how other ILI technologies are involved in the existed smart device assists us with the entity manufacturing, electronics mounting and operational procedures to achieve the project's goal of developing an efficient and cost-effective dual-purpose PIG.

1.2.2.1.1 Cleaning PIG

The utility PIGs encompass diverse functionalities crucial for the maintenance and optimal operation of pipelines. Among these, cleaning PIGs serve the vital role of eliminating accumulated solids and debris, while sealing PIGs are designed for the removal of liquids, separation of dissimilar fluids, and dewatering processes [2]. According to utility PIG selection guidelines, these PIGs are typically oversized the nominal diameter of the pipe, ensuring effective coverage for their intended tasks. In the realm of cleaning, two predominant materials take the forefront: mandrel PIGs and cast urethane PIGs. The former, equipped with a mandrel structure, and the latter, crafted from cast urethane, both play pivotal roles in restoring pipelines to optimal efficiency. A cleaning PIG, whether mandrel or cast urethane, lies in the meticulous removal of accumulated deposits and contaminants from the internal walls of the pipeline. This process not only enhances operational efficiency but also mitigates the potential for corrosion and blockages.

1.2.2.1.2 In-Line Inspection PIG

An In-line Inspection (ILI) tool serves as a comprehensive solution for evaluating the conditions of pipelines and identifying in-line defects such as cracks, corrosion, and deterioration [3]. The integration of ILI PIGs with advanced sensing technologies, such as

Magnetic Flux Leakage (MFL), and ultrasonic waves significantly enhances their capabilities in detecting the geometry and defects along the pipelines.

MFL tools are typically integrated into smart PIGs for measuring magnetic leakage along pipelines under varying operational requirements [4, 5]. A typical MFL tool-enhanced PIGs consists of a rigid axial main body, sealing cups, and magnetic components as test devices. Due to the need to accommodate magnetic induction devices and data logs along the cylinder's main axial, the main body of the PIG has a larger diameter. The MFL-equipped Pipeline PIGs can be either pulled by a cord or driven by product pressure from the back. The front pull hook provides reliable moving power from traction, while, without a pulling force, the PIG can be pushed by pressured gas or fluid product from the rear end to flow with the transporting product. In extreme scenarios, when the data processing system is located at the rear part, pulling a cord can offer better protection for the MFL devices. Ultrasonic Pipeline Assessment (UPA) technology stands out as a widely adopted nondestructive testing method for inspecting and evaluating the conditions of pipelines. Leveraging ultrasonic waves, this technology is adept at detecting and analyzing anomalies, including corrosion, cracks, and defects within pipeline walls. The application of UPA technology not only provides invaluable insights into pipeline conditions but also plays a pivotal role in facilitating proactive maintenance, ensuring pipeline integrity, and averting potential failures [6, 7].

1.2.2.1.3 Dual-purpose PIG

A dual-purpose PIG stands out as a versatile solution, seamlessly performing two distinct functions simultaneously as it traverses through a pipeline. In contrast to employing separate PIGs for each function, this innovative device integrates two functionalities into a single unit, optimizing operational efficiency and streamlining the number of required runs. The specific functions that a dual-purpose PIG can execute may vary based on its design and intended application. However, common examples include dual cleaning and inspection, inspection, and leakage detection. As advancements in the pipeline industry continue, an increasing number of dual-purpose PIGs are being developed and utilized for the practical tasks of cleaning, inspecting, and maintaining pipelines.

In the realm of dual cleaning and inspection, these PIGs are equipped with cleaning elements such as brushes or scrapers. This allows them to not only conduct inspections but also remove debris, sediment, or deposits from the pipeline walls concurrently. By combining these essential functions, the dual-purpose PIG ensures thorough cleaning during the inspection process, minimizing the need for separate cleaning runs. Noteworthy examples of dual-function PIGs include the Magnetic Flux Leakage (MFL) and Ultrasonic PIGs, typically considered professional types of PIGs. These PIGs are equipped with robust cleaning elements such as hard cups, disks, brushes, and scrapers, enabling effective cleaning activities alongside fundamental pigging processes. The inspection services of these PIGs encompass corrosion detection [8-12], pipeline wall crack detection [4,13,14], and leakage detection.

While constrained by physical size to accommodate multiple detecting and inspection technologies, the use of dual-function PIGs offers several advantages in pipeline maintenance operations. It significantly reduces the number of separate runs required, leading to time and operational cost savings. Furthermore, the streamlined approach minimizes disruptions to pipeline operations, as fewer intervention points are needed. The ongoing development and adoption of dual-function PIGs underscore their value in enhancing the efficiency, effectiveness, and sustainability of pipeline inspection and maintenance practices. Some example commercially available dual-purpose smart pigging services are detailed below:

(a) **I2I PIPELINES™:** I2ipipelines™ utilizes the mandrel and foam PIGs as the fundamentals of their smart PIGs to perform additional functions attached with external sensing devices. These PIGs include pioneer-mandrel-style PIG, smart foam fig, patrol-integrated style PIG, respectively. i2i™'s Pioneer is a mandrel-style smart PIG that can be run in the same way as a conventional cleaning PIG. The Pioneer PIGs have advanced electromagnetic sensors embedded into the polyurethane. The novel array of electromagnetic sensors which is capable of mapping the XYZ information detects shallow internal corrosion and fatigue cracking (SICC) in dry gas or multiphase pipelines. All the Pioneer PIGs can be launched and recovered from standard pigging facilities. The PU disks that hold the sensors are designed to be disposable items and are easily replaced if damaged. The electronics are housed inside the body of the PIG which acts as a rated pressure vessel. The power pack is rechargeable allowing the tool to be run daily if required.

(b) **Pathfinder Foam Caliper Proving™:** Based on the foam type of PIG, Pipeline Innovations are conducting pipeline inspection projects for subsea and onshore pipelines. Their primary gear is the Pathfinder Smart Foam PIG, and it is capable of communicating with the datalogger for quantitative assessment of the distribution of scale and wax deposits in operational pipelines. The Pathfinder PIG™ comprises a standard polyurethane foam PIG with a bore measurement sensing system integrally molded into the foam matrix. The sensors measure the compression of the foam at points around the circumference of the tool, allowing measurement of bore changes, dents, ovality, scale and wax deposits, and other restrictions. The electronics, battery and logging system are located in a removable cartridge in the center of the PIG. On completion of an inspection run, the data cartridge is removed from the PIG for data download and later re-use. The foam carrier PIG will be discarded.

(c) **ROSEN™:** The ROSEN™ Group is a provider of cutting-edge solutions in pigging, inspection, industrial mitigation, and digital modelling of energy components such as pipelines and storage tanks. The capability of conducting various kinds of PIG traps and analysis technologies incubated numbers of services including pipeline material verification, pipeline diagnostic pigging, crack detection and assessment, pipeline deformation management, pipeline mapping and movement, corrosion management, and storage tank management. The major service of their pipeline pigging is provided as cleaning PIGs as basic service and multi-section smart PIGs as advanced inspection solution of industrial pipelines. The conducted pipeline inspection solutions are integrated by their unique product such as bidirectional sensor carriers and designated data loggers.

1.2.2.1.4 Camera selection

The deployment of Closed-Circuit Television (CCTV) camera systems in the realm of pipeline and sewer inspections has revolutionized the way we perceive and manage underground infrastructure. This sophisticated technology serves as a vital tool for visualizing, assessing, and maintaining pipelines and sewer systems. The CCTV camera system offers a non-intrusive means of gaining crucial insights into the condition of these vital networks, minimizing the need for disruptive and costly excavation. Nowadays, multiple companies have produced various kinds of underwater axial camera to mounted on different motion parts such as robots and ROVs to inspect the components where man cannot reach. However, the video system on PIGs are limited due to the novel concept of visually access the in-line integrity. In this project, axial HD cameras with lights are the main objective in camera review for the further camera adaption task. The detailed information of cameras manufactured in different companies are summarized in Table 2.

1.2.2.2 Software design

Human senses the world with different modalities, such as taste, vision or touch. Similarly, in human computer interaction, a user can exchange information with a computer through various modalities. Multimodal interfaces process two or more combined user input modes (such as speech, pen, gaze, or manual gestures) in a coordinated manner with multimedia system outputs [15]. With a growing consensus multimodal interface improved performance, it has found applications in different domains, such as health monitoring and assessment [16], affective computing [17], cross-device interaction [18] or user study [19].

In the past, several frameworks and models [20-23] have been proposed to support the design and development of multimodal interfaces. For example, Rousseau et al. [23] developed a Multimodal Output Specification Tool, called MOSTe, which specifies multimodal output in terms of interaction components, interaction context, and information units. A behavioral model based on selection rules defined the adaptation upon different situations. Duarte and Carrico [20] proposed a conceptual framework, i.e. FAME, for the development of an adaptive multimodal system. The FAME architecture uses different models to specify the features of a multimodal application from the perspectives of user, platform, and environment. An innovative behavioral matrix is introduced to represent adaptation rules. Kong et. al. [22] proposes a novel approach, which converts the modality adaptation to an optimization problem and considers adaptation from three perspectives: the interaction context in the application layer, the resources allocation in the system layer and the QoS provisioning in the network layer. Recently, Huang and Kong [21] proposed a generic toolkit for prototyping tabletop-centric cross-device applications that involve a large display and multiple smartphones. This toolkit combined different sensing techniques, such as pressure or infrared camera, to detect a user's action. Specifically speaking, a user uses a smartphone as a look-through lens for browsing and selecting objects on a tabletop, and remotely manipulates the selected object with multimodal feedback.

Previous studies on multimodal interaction provide a solid foundation for designing and developing an interface with various interaction modalities, which are especially suitable for interacting with a device in different interaction contexts. Specifically speaking, the usability of a modality can be affected by a factor in an interaction context, including the hardware platform, the physical environment, and the state of a user. For example, the visual effect may be limited by a small screen on a mobile device; a noisy environment can greatly reduce an auditory effect; and blind users are absent of all visual stimuli processing. Therefore, multimodal interface promotes the usability by adapting an appropriate interaction modality based on the interaction context [20,22].

In the domain of pipeline inspection, a user needs to interact with an application in different contexts, such as indoor or outdoor. Therefore, we will implement a multimodal interface to assure usefulness and efficiency of the proposed tool. With the benefits of multimodal interaction discussed above, such a multimodal interface not only promotes the usability of a standard usage in an office environment, but also assures a safe usage in the pipeline field. Previous studies [24, 25] have found that a high cognitive load reduces task performance and limits a person's ability to maintain situational awareness. With a multimodal interface, a user can choose an appropriate interaction modality based on the physical and personal state, which reduces the cognitive load and thus makes a user maintain situational awareness in an outdoor usage.

1.2.2.3 Deep learning-based computer vision review

1.2.2.3.1 Pre-processing algorithms

(a) Noise reduction: Noise reduction involves employing algorithms to eliminate unwanted distortions or irregularities, known as noise, from images. These algorithms aim to enhance the clarity and quality of images by selectively suppressing or smoothing out unwanted elements, which contribute to improved visual analysis, facilitating more accurate interpretation and understanding of the underlying content in images. Common filtering methods include Gaussian filtering [38], median filtering [38], dual filtering [23], and advanced filtering techniques such as wavelet denoising [39] and bilateral filtering [23,40]. Gaussian filtering applies a weighted average to pixels, reducing high-frequency noise, while the median filtering replaces each pixel value with the median of neighboring pixels, effective in removing salt-and-pepper noise [38, 41]. Regarding bilateral filtering, it is a non-linear smoothing method that preserves edges by considering both spatial closeness and intensity similarity [42]. The bilateral filtering reduces noise while maintaining important image details, making it valuable in applications of image pre-processing algorithms [43, 44]. A typical image of a defective polyethylene gas pipe has a single background and is not very complex. After Gaussian filtering and bilateral filtering, processed image pipe edges were not clear; the mean filtering method kept some noise after processing; and the dual filtering retained the edge details and eliminated the noise [23]. There are some advanced denoising techniques, such as wavelet denoising [45,46], non-local means [47], block-matching 3D (BM3D) [48], and Canny edge detector [49]. The wavelet denoising decomposes the image into frequency components using wavelets, allowing selective noise reduction in different frequency bands [50,51]. The non-local means method averages similar patches in images [52], leveraging redundancy for effective denoising, while the BM3D method groups similar blocks of pixels and applies collaborative filtering to reduce noise [53]. The effect of the wavelet denoising method on image noise reduction was investigated in detail in the study of identifying and localizing structural damages [54]. In a study of anomaly detection inside a pipeline, a Canny edge detector was applied to remove noise and improve image quality before extracting image features [49]. The above noise reduction algorithms are widely used in image preprocessing for underwater and in-pipe structural damage detection [46,49]. In addition, some other deep convolutional image-denoiser networks were also developed to reduce noises in original collected data [55].

(b) Contrast enhancement: Contrast enhancement involves employing algorithms to improve the visual distinction between different elements in an image [56]. The contrast enhancement algorithms adjust pixel intensity values to amplify the differences in brightness, resulting in a more vivid and perceptually clear image. Common contrast enhancement methods include histogram equalization [23,57], contrast stretching [58], adaptive histogram equalization (AHE) [59,60], and Retinex image enhancement algorithms [61,62]. The histogram equalization algorithm is an image enhancement technique that redistributes pixel intensities across the entire dynamic range, effectively stretching the histogram to cover the full spectrum [63]. As a comparison, the contrast stretching algorithm aims to enhance image contrast by linearly expanding the range of pixel intensities between the minimum and maximum values in the original image [64]. Therefore, the contrast stretching algorithm stretches the histogram, making subtle differences more discernible and enhancing overall image clarity [56]. The AHE algorithm is an extension of histogram equalization that operates on localized regions of an image.

By adapting the contrast enhancement to specific image regions, the AHE mitigates over-amplification of noise, making it suitable for enhancing details in both dark and bright areas of an image independently. These contrast enhancement algorithms can solve the problems of uneven illumination and inaccurate extraction of anomaly edges in the image acquisition during the pipeline detection process [49]. The AHE algorithm improved the quality of the image by making a clear separation between the strong and weak parts of the light, forming a light mutation boundary. The Retinex-based adaptive image enhancement algorithm can simultaneously attenuate the image light too bright part, enhance the image too dark part, realize the image brightness equalization, effectively improve the image due to uneven illumination caused by the phenomenon of loss of details, and better maintain the image texture details.

(c) Other types of pre-processing algorithms: In addition to noise reduction and contrast enhancement, there are some other types of pre-processing algorithms to enhance image quality, including normalization, color space conversion, and image augmentation. Normalization involves algorithms that scale pixel values in images to a predefined range, typically between 0 and 1 [65]. This type of pre-processing algorithm is crucial for standardizing the input data, mitigating the impact of varying pixel value scales, and ensuring uniformity in image features during machine learning tasks. Common normalization algorithms include min-max normalization [66] and standard score (or Z-score) normalization [67]. These normalization methods contribute to enhancing the comparability and convergence of algorithms in image processing and machine learning tasks, contributing to more effective and stable anomaly analysis, classification, and detection applications. In a study of structural health monitoring for a submarine pipeline system, a process of signal normalization was introduced for signal pre-processing [68]. The min-max normalization algorithm was also applied to pre-process original collected data in a distance measurement research [69]. Color space conversion is the process of transforming the representation of color information in an image [70]. Common color space conversion algorithms include RGB (red, green, and blue) to grayscale [23,49], RGB to HSV (hue, saturation, and value) [71,72], and RGB to YCbCr (a specific color space widely utilized in processing digital video) [73]. In the RGB to grayscale conversion, the intensity of each pixel is computed as a weighted sum of its red, green, and blue components. The resulting grayscale image retains luminance information but discards color, making it suitable for reducing computational complexity [74]. Identifying corrosion in images in the RGB color space becomes both expensive and cumbersome because the chromaticity component of an image can only be obtained using information from the red, green, and blue channels. Therefore, the conversion of RGB to HSV can transform a given colorful image into HSV color space, where the chromatic and achromatic components of the image can be readily distinguished [73,75]. RGB to YCbCr conversion converts RGB values into luminance and chrominance components. This transformation separates brightness information from color information, making it useful for compression algorithms and video processing, where changes in color may be more perceptually significant than changes in brightness [73]. Grayscale images cannot be used to identify corrosion in the RGB color space, while the saturation component of the HSV color space made it easy to distinguish between chromatic and achromatic components of in-pipe inspection images, which can be used to detect pipe corrosion [75].

Class imbalance and data scarcity are challenging issues when training deep learning models, augmentation involves algorithms that generate new images by applying various transformations to existing ones to diversify training datasets, enhance model generalization, and mitigate overfitting by introducing variations in the input data [76]. Common transformations include horizontal flipping, vertical flipping, translation, scaling, hue, saturation, and lightness [76]. Notably, a generative adversarial network (GAN) can also be used to augment the dataset used to train deep learning models for pipeline anomaly inspection [3]. For example, an artificial neural network model significantly improved the detection accuracy of the depth of corrosion pits in oil and gas pipelines when trained with a dataset augmented by a GAN [3]. A hybrid generative adversarial network (GAN) integrates two GAN modules, namely a deep convolutional generative adversarial network (DCGAN) [77] and conditional generative adversarial network (CGAN) [78], which are used to automatically generate labels for artificial images.

1.2.2.5 Deep learning models

Depending on the various purposes of pipeline anomaly inspection, existing deep learning models can be categorized into classification [80], detection [81], and segmentation models [82].

(a) Classification: Classification is the task of assigning predefined anomalies to collected in-pipe inspection images. Neural networks, especially CNN, are widely used in classification tasks, demonstrating high effectiveness in various in-pipe inspection applications [83, 84]. Moreover, as the number of neural network layers increases, the neural network structure becomes more and more complex [85], and in this case the deep convolutional neural network (DCNN) can handle more anomaly classification cases. For example, during in-pipe inspections, a multilayer classification method based on deep convolutional neural networks was developed for classifying different anomalies, including broken, deformation, and so on [86]. However, the training of such DCNN often requires a larger dataset of in-pipe anomaly images [87]. In addition, the well-known You Only Look Once (YOLO) deep learning model was also used to classify pipeline anomalies, which was validated with an average F1 score of 87.6% through training on 4,056 inspection images [88]. Table 1 summarizes representative applications of deep learning methods using images for pipe anomaly classification. The accuracy of the deep learning models was up to 100%, indicating that it is promising to use deep learning models for classifying various pipe anomalies.

Table 1. Applications of deep learning models for automatically classifying pipeline anomalies

#	Ref.	Year	Dataset size	Anomaly types	Deep learning model	Accuracy
1	[88]	2020	4,056	Broken, hole, crack, etc.	You Only Look Once (YOLO)	87.6%
2	[86]	2019	18,333	Broken, deformation, etc.	DCNN	83.2%
3	[89]	2019	2.5 million	Crack, surface damage, etc.	CNN	91.6%
4	[90]	2019	736	Leakage	Multi-layer perceptron	100%
5	[91]	2017	480	Leakage	Support vector machine	98%
6	[92]	2015	239	Crack, collapse, etc.	Random forest	89.96%
7	[93]	2009	/	Cracks, corrosion, etc.	Change detection approach	84%
8	[94]	2009	291	Broken, crack, etc.	Radial basis network	95%
9	[95]	2008	291	Crack, broken pipe, etc.	Radial basis network	60%
10	[96]	2006	500	Cracks, holes, etc.	Neuro-fuzzy classifier	90%
11	[97]	2005	868	Infiltration	Back-propagation neural network	84%
12	[98]	2002	/	Crack and hole	Neuro-fuzzy algorithm	92%
13	[84]	2000	1,096	Cracks, deformation, etc.	Back-propagation neural network	98.2%

(b) Detection: Pipeline anomaly detection requires an efficient, accurate and automated method for pipeline defect localization and fine grading. Anomaly detection involves locating and classifying anomalies within an in-pipe inspection image or video. Common deep learning models for object detection include fast R-CNN [99], faster R-CNN [100], You Only Look Once (YOLO) [88], and single shot multi-box detector (SSD) [99]. These models employ CNN to efficiently process in-pipe inspection images, enabling accurate identification and localization of anomalies in diverse scenarios, ranging from real-time video analysis to image-based anomaly recognition tasks [99]. The fusion of local defect features with global context features helps to improve pipeline anomaly detection. In addition, some neural networks with novel structures such as the strengthened region proposal network (SRPN) were proposed to enhance feature representation of the fine-grained anomaly detection [99]. This deep learning model generated representative region suggestions for pipeline anomaly detection and localization by fusing multi-scale feature maps from the backbone network. In addition, the YOLO deep learning model has been proven to accurately and quickly detect pipe cracks, breaks, and other anomalies with a mean average precision (mAP) of 85.37% [88]. Table 2 summarizes representative applications of deep learning methods for detecting pipeline anomalies. Cracks and broken are the main types of anomalies to be detected and located. The accuracy of the deep learning models was up to 96%, indicating that it is promising to use deep learning models for detecting pipeline anomalies. Table 2 highlights the diversity of deep learning models such as YOLO, faster R-CNN, SSD, and DCNN, showcasing the successful applications in pipeline anomaly detection across different studies.

Table 2. Applications of deep learning models for automatically detecting pipeline anomalies

#	Ref.	Year	Dataset size	Anomaly types	Deep learning model	Accuracy
1	[81]	2021	3,600	Crack, etc.	Faster R-CNN	77%
2	[49]	2021	3,000	Crack, etc.	Faster R-CNN	83%
3	[101]	2021	3,000	Crack, etc.	YOLO and Faster R-CNN	86.3%
4	[99]	2021	20,000	Crack, deformation, etc.	SRPN	82.4%
5	[99]	2021	20,000	Crack, deformation, etc.	SSD	66.6%
6	[99]	2021	20,000	Crack, deformation, etc.	YOLO	73.2%
7	[99]	2021	20,000	Crack, deformation, etc.	Fast R-CNN	72.1%
8	[99]	2021	20,000	Crack, deformation, etc.	Faster R-CNN	75.2%
9	[88]	2020	4,056	Broken, crack, etc.	YOLO	85.37%
10	[102]	2018	12,000	Cracks, etc.	DCNN	86.2%
11	[100]	2018	3,000	Crack, etc.	Faster R-CNN	83%
12	[103]	2018	350	Crack, perforation, etc.	Neural network	96%

(c) Segmentation: Segmentation is the process of dividing pipeline inspection images into meaningful segments or regions [57]. After segmentation, the pipeline inspection images can be clearly labeled with the shape and size of the anomalies present in the pipeline [104], thus providing a more accurate basis for quantitative assessment of the anomalies than the detection results [23]. Deep learning models like DCNN [105], U-shaped encoder-decoder network (U-Net) [82], mask R-CNN [106,107], and fully convolutional network (FCN) [105,108] excel in image segmentation tasks. These models contribute to accurate and detailed segmentation across various applications. A novel semantic segmentation network based on U-Net was investigated for image segmentation of pipeline anomalies, such as cracks [82]. The mean intersection over union (mIoU) [109] reached 76.37% and the segmentation speed reached 32 images per second, proving the efficiency of the segmentation network [82]. The novel semantic segmentation network can segment the shape of in-pipe cracks accurately despite these complicated backgrounds. In addition, a DCNN-based neural network, namely DilaSeg-CRF, was proposed to segment pipeline anomalies [105]. The DCNN model was trained using 1,880 images with a resolution of 512×256 and the corresponding mean intersection over union (mIoU) was improved from 52.23% in FCN to 84.85% [105].

Table 3 summarizes applications of deep learning models for automatically segmenting pipeline anomalies across various studies. Notable examples include [110] using the improved PointNet++ for dent segmentation with an accuracy of 94.15%, [111] employing Mask R-CNN for leakage segmentation with 96.35% accuracy, and [112] utilizing U-Net for corrosion segmentation achieving an accuracy of 96.10%. Other studies, such as [105], focus on applications like crack segmentation. Table 3 highlights the diverse applications of deep learning in pipeline anomaly segmentation, emphasizing the potential for achieving high accuracy across different anomaly types and dataset sizes.

Table 3. Applications of deep learning models for automatically segmenting pipeline anomalies

#	Ref.	Year	Dataset size	Anomaly types	Deep learning model	Accuracy
1	[110]	2024	8,100	Dent	Improved PointNet++	94.15%
2	[111]	2023	11,000	Leakage	Mask R-CNN	96.35%
3	[112]	2023	2,378	Corrosion	U-Net	96.10%
4	[105]	2020	1,880	Crack, etc.	DCNN	85%
5	[82]	2020	3,654	Crack, etc.	U-Net	76%
6	[113]	2019	1,510	Crack, etc.	Deep dilated CNN	95%

1.2.2.6 Emerging technologies (digital twin and advanced sensors)

Emerging technologies in pipeline inspection and anomaly detection are revolutionizing the field, offering more efficient, accurate, and safer methods for anomaly detection and maintenance in complex and critical infrastructure. Augmented reality and digital twin technologies are applied for immersive training, simulation, and visualization during pipeline inspection [24]. These technologies offer enhanced training experiences and facilitate real-time decision-making by providing a virtual overlay of data onto the physical pipeline environment [123]. Siemens has proposed the Pipeline 4.0 concept, which utilizes digital twin technology to reduce the operating costs of pipeline systems without risk or cost [124]. At this stage, Pipeline 4.0 mainly focuses on the development of digital twins for pumping stations rather than pipelines. Petro China used digital restoration techniques, such as digital 3D modeling, to construct the digital twin of the China-Myanmar oil and gas pipeline [125]. A digital twin framework for underground pipeline safety assessment was proposed based on augmented reality [24].

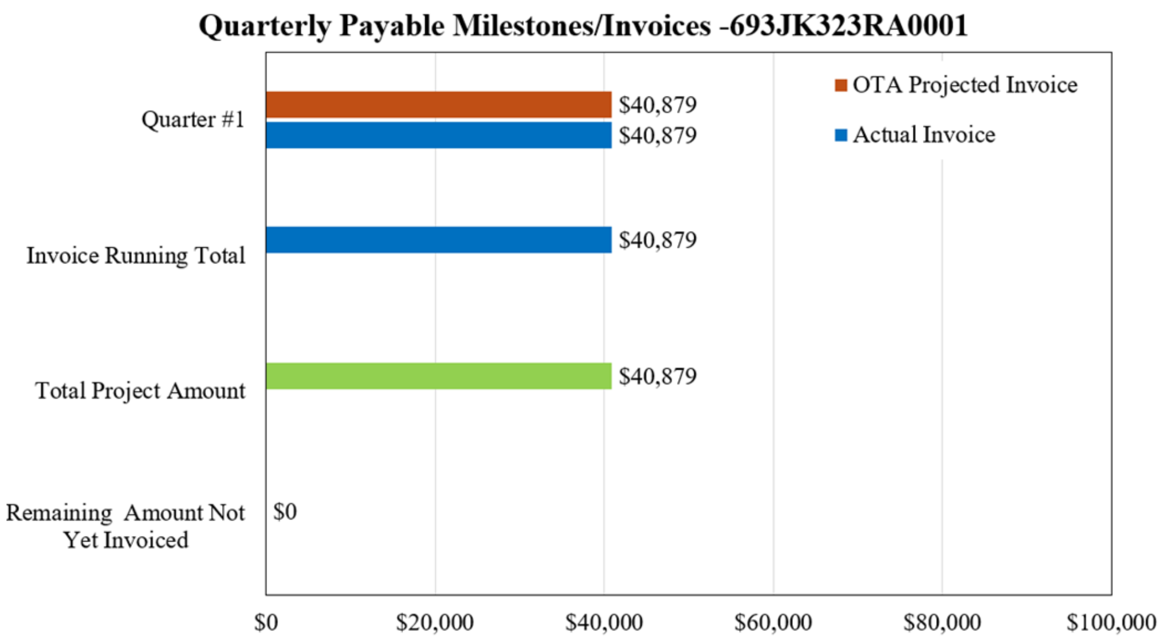
Utilizing advanced sensor technologies, such as distributed fiber optic sensors [126,127] and hyperspectral imaging [128], allows for more comprehensive data collection. These advanced sensors enhance the ability to detect anomalies by capturing detailed information about pipeline conditions, including structural integrity [24,127] and material composition [128]. A distributed fiber optic system for monitoring pipelines was developed to address the problem of real-time monitoring of various anomalies over long distances [127]. The experimental results show that the detection rate of the method is higher than 96% [127]. In addition, by analyzing the strain profile of the distributed fiber optic sensors, a comprehensive view of the pipe deformation can be obtained [129].

2: Items Not-Completed During this Quarterly Period:

All tasks and subtasks planned for this quarter season have been fulfilled and completed.

3: Project Financial Tracking During this Quarterly Period:

The following figure including the project financial tracking during this quarterly period:



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