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Well Control Space Out: A Deep-Learning Approach for the Optimization of Drilling Safety Operations

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ABSTRACT As drilling of new oil and gas wells increase to meet energy demands, it is essential to optimize processes to ensure the health and safety of the crew as well as the protection of the environment. Drilling operations represent a dynamic and challenging environment with natural and mechanical factors that need to be closely managed. Well control refers to the technique employed while drilling for balancing the hydrostatic and formation pressures to prevent the influx of water, gas, or hydrocarbons that would ultimately result in an uncontrolled flow to the surface. In the event of a well control incident, the crew must take proper and prompt actions to mitigate the risks and shut-in the well. In this study, we introduce the Well Control Space Out technology, an internet-of-things (IoT) environment that couples cameras and an edge server to implement state-of-the-art deep-learning models for the real-time processing of video images recording the drillstring. The computational models automatically perform object detection to keep track of key drilling rig components. The results from the video analysis are displayed on a dashboard describing the state and steps to follow in a well control incident without the need for any time-consuming, manual calculations. The internet-of-things edge foundation laid in drilling can be seamlessly expanded to other upstream sectors, where time-sensitive, critical decisions can be made in real-time, in the field, closer to operations. Finally, this technology can be seamlessly integrated with the current technologies to develop an automated closed-loop control system.

INDEX TERMS Automation, deep-learning, computer vision, edge computing, internet-of-things, oil and gas drilling, well control.

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AP	Average Precision
AR	Average Recall
BOP	Blowout Preventer
CNN	Convolutional Neural Networks
CPU	Central Processing Unit
DL	Deep-learning
FN	False Negatives
FP	False Positives
GPU	Graphic Processing Unit
IoT	Internet of Things
ML	Machine-learning
NPT	Non-productive-time
R-CNN	Regional Convolutional Neural Network
ResNet	Residual Networks
SDD	Single-shot detector
SVM	Support Vector Machine
TN	True Negatives
TP	True Positives

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V-sat Very small-aperture terminal satellite
VGG Visual Geometry Group
YOLO You Only Look Once

I. INTRODUCTION

As world energy consumption continues to increase worldwide, the focus of the oil and gas sector has shifted towards, not only drilling efficiency and cost optimization, but also safety, since recent acquisitions and discoveries require drilling in progressively more extreme and challenging environments. However, the present challenges faced in the industry have come at an appropriate time when new technologies can be employed to evolve and revolutionize the industry.

Recently, the internet-of-things (IoT), along with artificial intelligence (AI) algorithms, have been successfully deployed to address diverse problems across different domains and industries. These applications range from genomics [1]–[5], chemistry [6]–[8], medicine [9]–[14], and manufacturing [15]–[18], to wearable technologies [19]–[22]. Similarly, and inspired by the fourth industrial revolution, IoT and AI have become valuable tools for increasing safety while optimizing drilling efficiency and costs [23]–[28].

Notably, the oil and gas industry has long relied on manual processes and dated technologies to explore, drill, and produce hydrocarbons. The drilling process, for example, has been performed by experienced drillers who have an in-depth knowledge of the local geology and the drilling conditions. However, the reliance on human expertise may lead to performance inconsistencies and increased risks in drilling operations.

Consequently, drilling operations represent an enormous opportunity to deploy new sensors and capitalize on the newly generated data in real-time for the development of AI models, including machine-learning (ML) and deep-learning (DL). These data-driven models are essential for the computation of key performance indicators and surveillance of critical operations, which ultimately would enable the automation of operations [29]–[34]. The IoT has the potential to bring together standardization, automation, sensors and actuators, smart devices, machines, advanced analytics, and people in drilling on a common platform [35]–[43].

The deployment of IoT on drilling rigs complements the legacy sensors already in use and, when combined with new sensors, enables more sophisticated analyses and automation workflows. For instance, while before cameras were simply devices to acquire videos for manual inspection, edge computing makes it possible for these cameras to be 'conscious' and 'intelligent', facilitating automation and remote management of operations. Camera-based IoT platforms can be seamlessly expanded to other areas of drilling operations as well as to other upstream sectors, such as geology, geophysics, production, and reservoir engineering, to increase efficiency and optimize operations.

In this study, we focus on the drilling operations, specifically on well control, which refers to the technique employed for balancing the hydrostatic and formation pressures to prevent the influx of water, gas, or hydrocarbons that may escalate into an uncontrolled flow to the surface. To illustrate the importance of such an operation, consider the Macondo incident in 2010, an oil blowout that resulted in the loss of lives, and environmental damage, at the cost of ~US$ 65 billion [44]. Moreover, the cost to repair the reputation of the company and loss of productivity has been estimated at US$ 150 billion, much more damaging to the organization, not to count the negative consequences to families, societies, the global community, consequences that in many ways cannot be weighed in financial terms [45]. Although the Macondo incident was the result of a series of events and errors, the proper shut-in or kill of the well would have controlled the situation to a large extent. However, shutting-in a well requires a set of manual steps that may be performed incorrectly in the heat of an emergency incident.

Here, we describe the Well Control Space Out technology, an IoT edge-based platform for automatic space out of a drillstring assembly while drilling hydrocarbon wells, a critical step in well control. The platform consists of a waterproof, high-resolution wireless camera, edge computing hardware, and DL models for image/video processing and intelligent analytics. Finally, this technology can be seamlessly integrated with current sensors and lays the foundation for an automated closed-loop process.

II. BACKGROUND KNOWLEDGE

In this section, we provide a brief description of drilling operations with an emphasis on well control, followed by the definition of an IoT edge environment required for isolated environments, such as drilling rigs.

A. DRILLING

Drilling operations include a series of activities to ultimately break rock formations in order to deepen a wellbore. For this purpose, a drill bit and drillstring assembly are used to create a hole vertically or at an angle (directional drilling) targeting a hydrocarbon reservoir [46], [47]. During drilling, a fluid, slurry, or mud (referred to as mud, hereafter) with different properties is circulated into the hole (through the drillstring) and back to the surface (through the annulus) for various functions, including the removal of the rock formation cuttings and for maintaining both downhole temperatures and rock formation pressures [48] (Fig. 1A). Once the hole is at the desired depth, the well requires a cement casing to prevent wellbore collapse and ensure wellbore integrity. Fig. 1B shows a simple example of a casing design.

Wells are drilled for different purposes, such as exploration, production, development or production, relief, among others, and start after a thorough, well planning phase. Well planning is complex and requires the integration of engineering principles, casing design, reservoir simulations, geology, experience as well as corporate philosophies to formulate the different variables for drilling a well. Although well planning methods and practices may differ significantly within

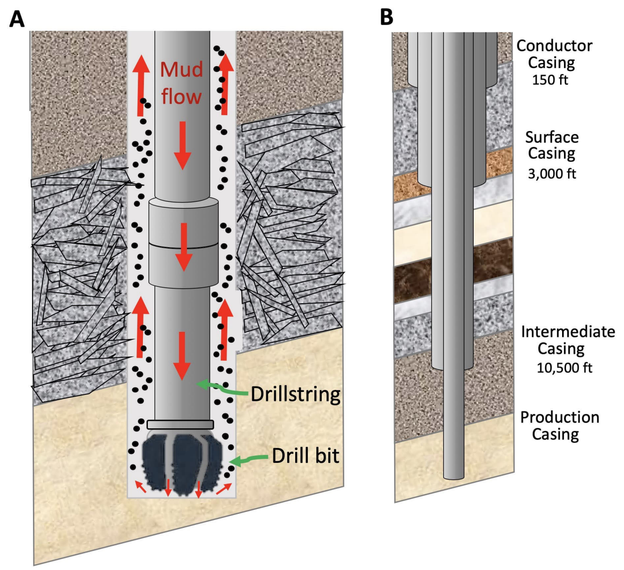

FIGURE 1. **Drilling and casing. A) Drilling representation of a vertical wellbore. The drilling mud is pumped into the drillstring assembly, circulated in to the hole and returns to the surface with the generated rock cuttings. B) example of a casing plan with a production casing.**

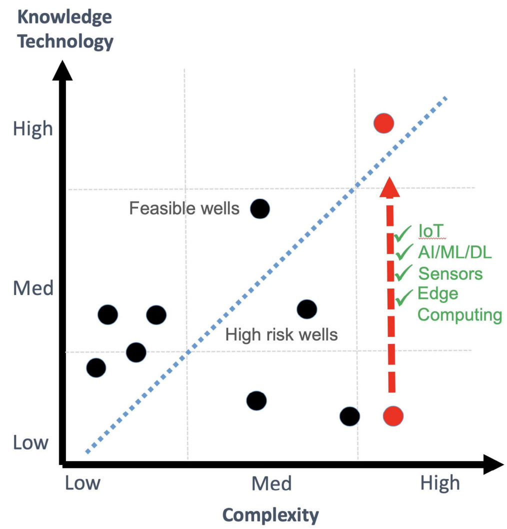

FIGURE 2. **Relationship between the complexity of the drilling operations and available technology.**

the industry, the common objective is to guarantee safety, minimum cost, and usability for oil/gas production.

Thorough preplanning, best drilling practices, and advanced tools are effective in reducing drilling hazards. However, more complex horizontal and extended-reach wells are being planned in order to reach reservoirs under the sea from an onshore drilling rig, limit production of unwanted fluids, maximize production and penetrate vertical fractures [49]. Consequently, some planned wells are unfeasible due to different constraints based on the geology, drilling equipment, downhole temperatures, and casing limitations [50], [51]. Nonetheless, new sensors, IoT, and AI models offer additional insights to enable the drilling of such complex wells while also enhancing the productivity of current operations (Fig. 2).

Drilling operations represent a challenging and dynamic environment due to the combination of human, mechanical, and geological factors. Moreover, despite the experience of the industry, risk management is critical as no two wells are the same. The three main causes of drilling non-productive-time (NPT) are 1) stuck pipe incidents, 2) mud circulation losses, and 3) well influx. Stuck pipe incidents occur when downhole force(s) prevent the movement of the drillstring [23]–[25], [52]. Mud circulation losses occur when the drilling mud flows from the wellbore into the formations (due to natural or induced factors) [26], [27], [53], [54]. Finally, well influx refers to the flow of gas, water, or hydrocarbons from the geology into the wellbore [55], [56]. Notably, these three drilling hazards are interlinked. For instance, failing to maintain the formation pore pressure by having a low mud weight would result in a possible wellbore collapse and influx. Conversely, differential pipe sticking, mud losses, or even fractures may occur if the mud weight is higher than the formation fracture gradient. The focus of this study is on the well control technique to mitigate influxes. An interested reader on other drilling processes may refer to Gooneratne *et al.* [57] for more details.

B. WELL CONTROL

The most significant potential hazard while drilling a well is the risk of an uncontrolled release and flow of hydrocarbons, drilling fluids, formation fluids, or any other combination of the three, from a well to the surface due to complications arising from pressure management. The rheology properties of the drilling mud (plastic viscosity, yield point, density, among others) are critical to ensure proper hole cleaning (removal of rock formation cuttings) and maintaining formation pore pressures. However, since the geological formations are not homogenous, drilling muds with different properties are needed. For instance, the example in Fig. 1B shows a wellbore with four casings as it would be unfeasible to drill from surface to bottom while satisfying all geological conditions with the same mud properties. A well control incident may occur due to the reasons listed in Table 1. A blowout preventer (BOP), a specialized valve/mechanical device located at the surface, is used to seal, control, and monitor the well in case of an influx (Fig. 3). When experiencing a well control event, the decision to either function the shear and seal the BOP with the pipe in the hole or evacuate the rig before shutting in the well is a complex one. A case in point is the Macondo incident. Different human and technical influences come into play in a highly time-dependent, often escalating situation.

However, before sealing or shutting-in a well, a well-established set of manual instructions must be promptly executed by the crew: 1) stop drillstring rotation, 2) pick the drillstring off bottom and space out, 3) stop the mud pumps and check for mud returns, 4) if mud returns continue, shut-in

TABLE 1. Causes of well control incidents.

Cause	Description
Insufficient mud weight (density)	Occurs when the formation pore pressure is greater than the hydrostatic pressure exerted by the mud.
Lost circulation	The hydrostatic pressure to maintain well integrity may suddenly decrease if sufficient amount of mud flows into the formations
Swabbing	A negative pressure (suction) may be created when pulling the drillstring too quickly from the well.
Mud replacement while tripping	When pulling the drillstring out of the wellbore, mud volumes must be pumped to promptly replace the volume previously occupied by the drillstring.
Cut mud	Gas entering the wellbore from the formations effectively reduces the hydrostatic pressure.

the well with the BOP, 5) increase mud weight by adding additives to control the pore pressure (kill mud). Although all steps are critical, spacing out the drillstring ensures both the proper sealing of the well and the integrity of the BOP. Closing a BOP ram on the thickest part of the drillstring, containing the threads/pipe connections (referred to as tool joint, hereafter) does not guarantee proper sealing and damages the ram as well as the drillstring assembly. Fig. 3A shows a simplified side view of a BOP when the tool joint is at the shear ram. Drillstring space out refers to pulling out the drillstring out of the wellbore until a tool joint is observed a few feet above the drill floor to ensure the smallest diameter of the drillstring is inside the BOP (Fig. 3B).

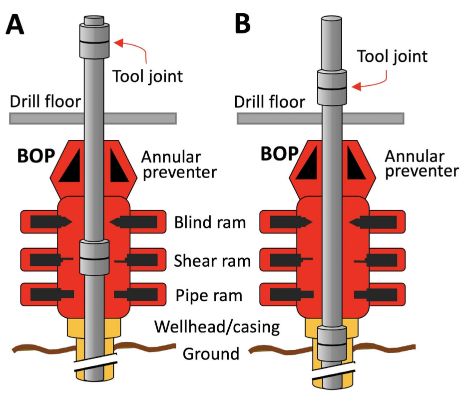

FIGURE 3. Blowout preventer side view. A) Drillstring not spaced out, tool joint at the shear ram. B) Drillstring is spaced out, tool joint just above the drill floor.

As discussed, shutting-in a well is a lengthy process that includes several manual steps and has critical safety implications. Currently, most of the drilling rigs use dated sensors at the surface to control and inspect certain operational aspects and to detect drilling hazards. However, digital transformation technologies, such as IoT and AI, enable the prevention of drilling hazards as well as the optimization of operations. Next, we discuss the impact of IoT and AI in the drilling industry.

C. INTERNET OF THINGS IN THE DRILLING ECOSYSTEM

The IoT refers to a multitude of heterogeneous interconnected sensors that collect and analyze data to accomplish different tasks without manual intervention [58], [59]. To achieve this level of automation, digital technologies have to be embedded in the majority of machines and devices to enable seamless cross-device communication and data analysis to detect events or conditions required to optimize operations and safety [60].

Recently, the IoT has been successfully deployed to address fundamental applications and challenges related to our environment, industries, and society. Similarly, the new sensors, communication protocols, and data analytics have the potential to transform current drilling operations and enable automation. The implementation of IoT has been estimated to increase operational drilling efficiency by at least 5% and reduce upstream operating expenditures by 20-30%, both significant values in a multibillion-dollar industry [61]. A drilling rig represents a dynamic and challenging environment due to all factors involved during operations: 1) isolated places with extreme weather conditions, 2) management of large and heavy mechanical devices, and 3) engineering and best practices required for maintaining safe and efficient operations. Clearly, additional sensors and data analytics models can be used to reduce manual work, increase safety, and standardize operations.

Fig. 4A shows the general structure and communication of the rig location and the remote headquarters. In the legacy drilling rig architecture, the data are initially collected by surface sensors (weight on bit, hook load, standpipe pressure, among others) as well as downhole sensors and are aggregated and displayed at the rig for manual interpretation by highly skilled personnel. These aggregated data are also sent through a very-small-aperture terminal (V-sat) for storage and further analyses at the headquarters.

The oil and gas industry is currently aiming to capitalize on the vast amounts of collected data over the years. Historical data are used to derive novel ML/DL models to recognize drilling hazards or optimization opportunities for real-time operations. However, the deployed models remain at the headquarter servers, with limited applications for real-time operations due to the V-sat restrictions, i.e., high latency and data down-sampling. Moreover, the down-sampling of the data collected at the rigs represents a substantial loss of information available for the models, as the trends may be wholly lost due to the low transmission frequency of $\sim$0.2-1 Hz. For instance, erratic torque is an important sign for detecting stuck drillstring events, however, with a frequency of 0.2Hz, it may be difficult to detect it even by sophisticated non-linear ML models [23], [24], [62].

An alternative communication and processing structure consist of allocating an edge server (located close to the data sources) that processes and consumes the high-frequency data for the generation of actionable items or having results available to the crew in real-time. An edge server not only enables the processing of high-frequency data for real-time

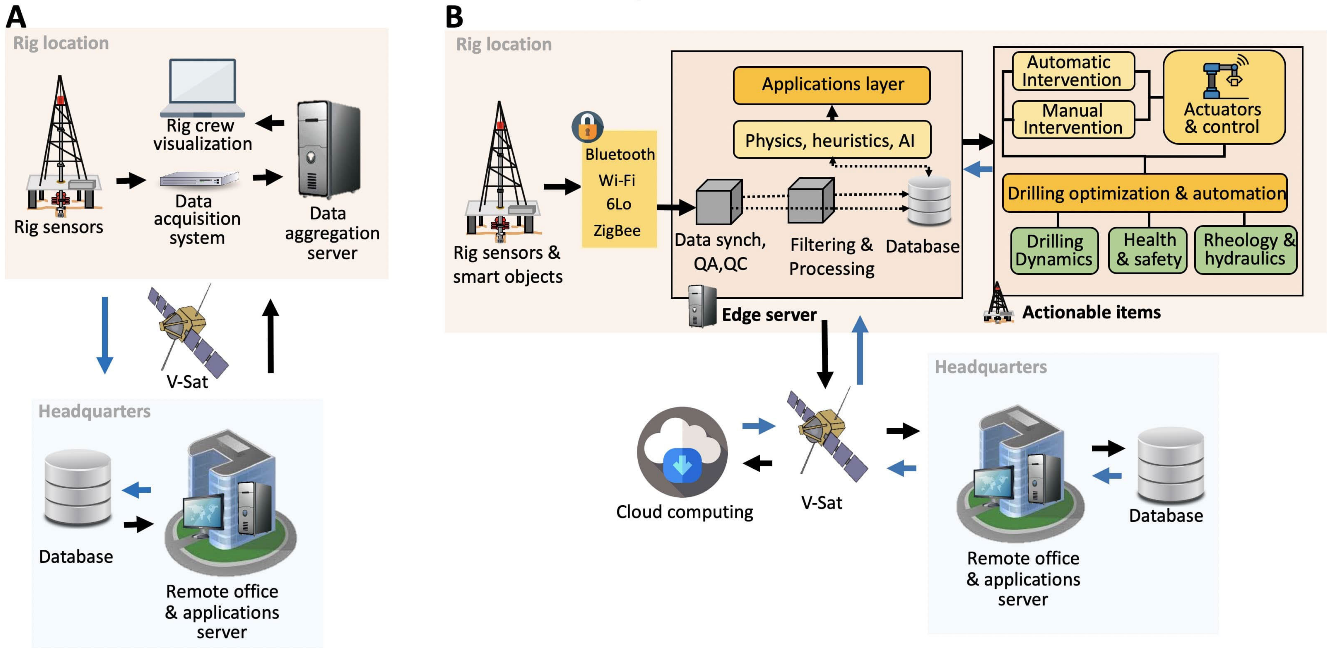

FIGURE 4. **Drilling rig and headquarters communication structure. A) Traditional communication structure where the data storage and data processing are performed at the remote headquarters. B) An IoT structure that enables the synchronization of multiple sensors and processing of the data directly at the rig.**

applications but also reduces both privacy risks and bandwidth required to transfer all data through the V-sat. This is because, instead of sending all the aggregated data to the headquarters, the edge server will only transmit actionable insights or results through the V-sat. Finally, the implemented models at the edge server may directly communicate to the control system and actuators to enable the automation of different processes.

Fig. 4B shows an IoT structure of a drilling rig that enables the processing of heterogeneous data at the rig. Having multiple sensors require the implementation of communication protocols, such as Bluetooth, Wi-Fi, 6Lo, ZigBee, among others, as well as synchronization protocols to time stamp the data before storing them in a database for further analyses. The processed data is then fed into the ML/DL models (data-, physics-based, or hybrid) to identify hidden patterns in the data and predict anomalies associated with drilling before they occur [63].

In this study, we describe an IoT environment that consists of high-resolution cameras, edge servers, and DL models for the automatic recognition of tool joints to enable quick and safe BOP activation in case of well control incidents.

III. CAMERA-BASED IOT AND DEEP LEARNING MODELS FOR AUTOMATIC WELL SPACE OUT

Cameras and recording devices have naturally been used for the surveillance of different industrial processes. While before cameras were simply devices to acquire videos for manual inspection, current computational advances have enabled the development of sophisticated DL models for image processing and recognition with remarkable results [64].

As discussed earlier, the driller is unable to easily determine which BOP ram to close in case of an imminent well control incident. However, cameras and DL models can be used to automatically detect and track the tool joints above the drill floor to accurately estimate the position of tool joints below the drill floor and inside the BOP. The automatic estimation of the tool joint inside the BOP is performed at the rig site in real-time and provides enough details to the crew to ensure immediate reaction and proper shut-in of the well.

Fig. 5 shows a simplified schematic of a drilling rig, camera, edge server, and required operational (static) data to implement the well space out system. The images obtained by the camera recording the drillstring above the drill floor are fed into a DL model for the recognition of the tool joints in real-time. The predicted positions of the tool joints in the images are then mapped to the height of the tool joint in feet relative to the drill floor. With the calculated tool joint height, along with the distance of the BOP to the drill floor and spaces between the annular preventer and rams, the model displays the exact location of the tool joint inside the BOP. Because there are different types of BOP and drilling rig configurations, the distances of both the BOP to the drill floor and the annular and rams in the BOP differ. Consequently, these distances are a critical input for the accurate mapping of the detected tool joints above the drill floor and the tool joints inside the BOP. The dashboard developed and described in this paper allows the crew to immediately identify the ram to close in case of an influx. Moreover, with the information

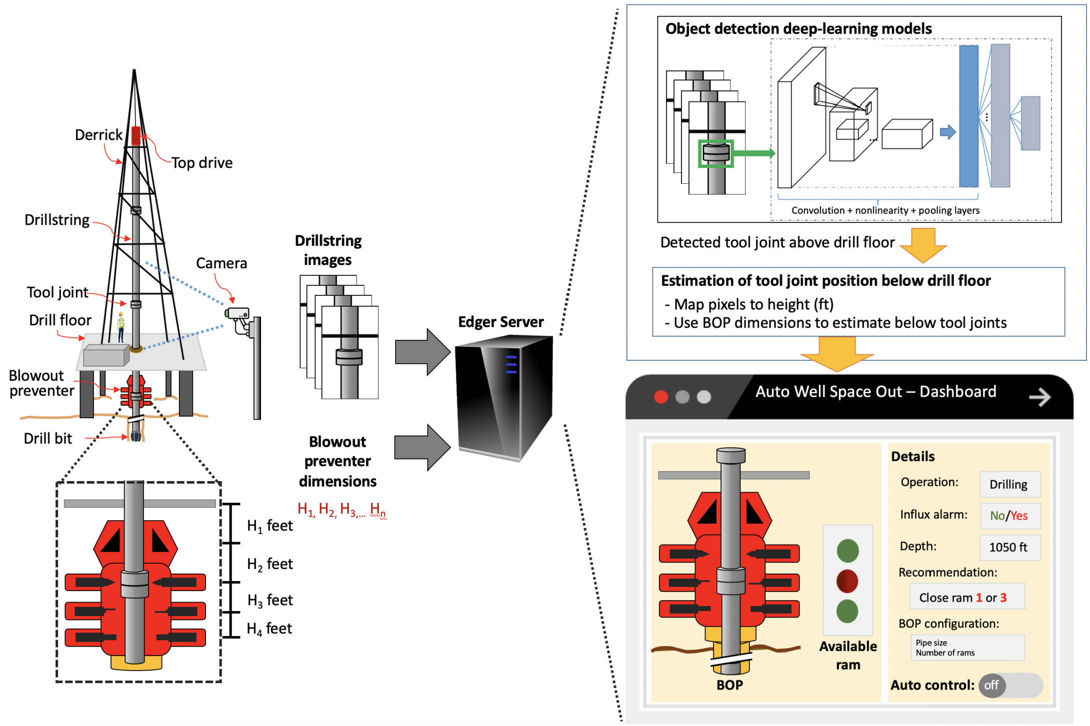

FIGURE 5. **Simplified schematic representation of a drilling rig and the implemented IoT structure for the Well Space Out dashboard.**

from other models (such as influx detection), the edge server can take control and automatically activate the annular preventer or ram, depending on the calculated severity of the influx.

In the following subsections, we describe in detail the technical aspects for deploying robust and efficient DL models at the edge servers.

A. DEEP-LEARNING MODELS FOR IMAGE PROCESSING

Conventional shallow learning ML models (such as random forest, support vector machines, among others) require a feature generation phase that consists of encoding the samples of a classification problem into a feature set. For instance, a fruit may be defined by a feature vector that describes the color, shape, size, flavor, among others. However, a portion of the manually defined features may not be discriminative and would only require an unnecessarily more complex ML model. Consequently, feature selection is a common phase that follows feature extraction and aims to provide the optimal subset of features to describe the classes [65]–[67].

Although shallow ML models have achieved outstanding results, the extraction and selection of discriminative features from the raw data remain a major challenge for deriving accurate and generalizable ML models. The feature engineering process becomes more challenging when designing features to describe images. For example, consider the different image processing techniques required to design relevant features (edges, curves, etc.) to discriminate between different objects in a picture.

The recent increase in computational power enables the development of DL models that perform more complex operations on larger volumes of data. Although the origins of DL can be traced back to 1943 [68], it was not until the mid-2010s that DL models demonstrated outstanding results in different applications. DL models implement a multi-layered architecture that transforms the data representation at one level to a higher and more abstract level (where features are learned from the data itself without manual feature engineering) [69].

A convolutional neural network (CNN) is a suitable DL model for image classification as it exploits spatial correlation and dependencies in the data. As such, a CNN model is capable of determining the presence of an object in an image but is unable to detect the number of objects occurrence and their position. These limitations are mainly because CNNs are unable to cope with variable outputs layers as the number of objects occurrences in an image is variable. To overcome the CNN limitations for object detection problems, Girshick *et al.* [70] proposed a regional CNN (R-CNN) method that uses a selective search algorithm to extract 2,000 regions from the image, referred to as proposed regions. The proposed regions of interest are later fed into a traditional CNN that produces a 4,096-dimensional feature vector as output. As such, the CNN acts as a feature extractor for each proposed region. The extracted set of features for each proposed region is then fed into a traditional support vector

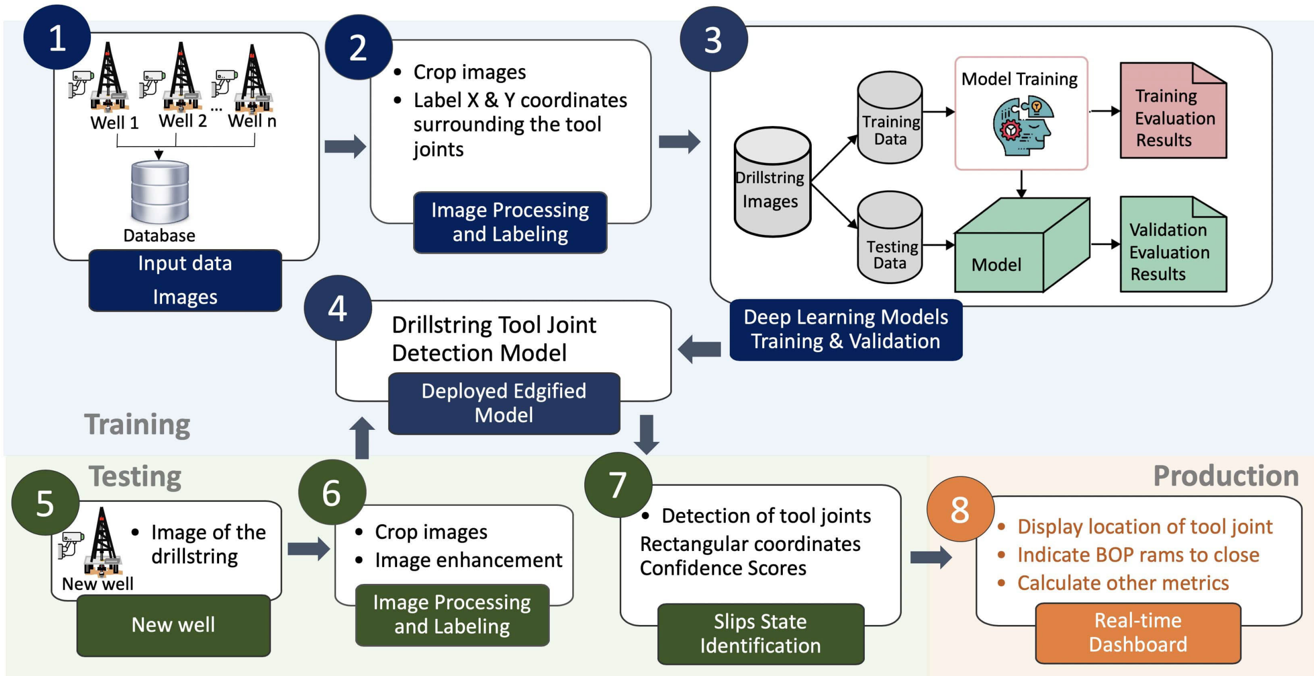

FIGURE 6. **Methodology for the training and testing phases for the identification of drillstring tool joints.**

machine (SVM) model to classify the presence of the object within the proposed regions. Notably, a large number of proposed regions and required SVM models imply enormous computational demands, limiting their applicability for real-time operations. To address the computational requirements, fast R-CNN [71], faster R-CNN [72], You Only Look Once (YOLO) [73], Single-shot Detector (SSD) [74], or other variations, were developed to simplify and enhance the model structure and complexity.

Designing the architecture of a DL model (i.e., number of convolutional layers, number and size of filters, initialization modes, among others) is an extremely challenging problem due to the vast number of variables. However, an already proven DL backbone may be re-trained for a specific image object identification problem (transfer learning). Residual networks (ResNet) [75], Visual Geometry Group (VGG) [76], YOLO darknet [77], and Inception-SSD [78], are among the most popular deep CNN backbones.

Fig. 6 shows the methodology for training (shaded in blue) and testing (shaded in green) phases of the DL model for the detection of the drillstring tool joints. The first step of the training phase consists of storing sufficient video recordings capturing the drillstring above the drill floor (as shown in Fig. 5). The recordings must provide a complete set of images capturing the different drilling conditions (i.e., weather, lighting, different drillstring diameters, movement speeds/directions, and color due to coating by different fluids, among others). The second step consists of simple image processing to crop and enhance the captured frames, followed by assigning labels (drillstring tool joints coordinates in the image). The third step refers to the training and testing of the pre-trained DL architecture. Finally, the trained and validated model is deployed for the identification of the tool joints (step 4).

Steps 5-7 relate to the testing phase once the model is trained, validated, and deployed. In more detail, steps 5-6 are the video recording of the drillstring tool joints at the rig floor and the image processing of the captured data. As opposed to step 2, step 6 does not require the identification of the coordinates surrounding the tool joints, as this is the objective of the model. The processed images containing the drill floor photo for a new drilling operation are then the input for the deployed model, which outputs the coordinates of the slips (step 7). Finally, step 8 implements a post prediction process to increase the accuracy of detection and the final dashboard for the crew. In the next subsections, we describe in more detail the critical methods for deriving robust DL models, such as data collection and labeling, data augmentation, and model training.

B. DATA COLLECTION AND LABELING

Approximately four hours of video data with a resolution of 1920×1080 were carefully selected to account for the different lighting, weather, and operational conditions. We reduced the dimensions of the images to only focus on the 200 pixels containing the drillstring, resulting in images with a resolution of 1920×200 Although we tried reducing the image size further 1920×30, focusing only on the drillstring, the best results were achieved when using a width of 200. The underlying reason for this may be that the pre-trained DL architectures used for transfer learning had images with similar resolution [79]. We used OpenCV-python library [80] to randomly extract 1,100 individual frames from the complete dataset. The data was labeled using VGG-Annotator [81]. Bounding boxes surrounding the tool joint were drawn, and the corresponding coordinates were later used for training the model. For each of the bounding box coordinates, a map of all pixels was derived and used for training the models.

Although we tried to include the bounding boxes containing the full drillstring (as a separation region of interest), the accuracy of the DL models remained the same. Therefore, we only provided the bounding boxes surrounding the tool joints.

C. DATA AUGMENTATION

As discussed previously, the selection of the images used for training is critical to ensure the DL model will perform as expected during different scenarios. To achieve this, data augmentation, a technique that performs a series of transformations on the images to increase the diversity of data available for training the models, was utilized [82]. Therefore, the additional data generated by using the data augmentation techniques increased the generalization of the models by decreasing the overfitting in the models [83].

Table 2 describes the data augmentation techniques used in our model. Although we tested other augmentation techniques, such as blurring and deblurring, experimental results showed that the performance of the DL models reduced. A possible reason for these findings is that the appearance of the background and the drill string was similar and, hence, blurring/deblurring made it more difficult for the model to detect the tool joint.

TABLE 2. Considered data augmentation techniques.

Technique	Description
Scale pixels of the image	This technique effectively scales every pixel independently of the rest. For every pixel in the input image a random number between 0.6 and 1.1 is chosen and the pixel value is multiplied with it. Note that standard values for range for minimum and maximum values to draw a random number are 0.9 and 1.1, but sensitivity analysis revealed that a minimum value of 0.6 achieved better results. This technique improved the ability to discriminate the concentric design near the tool joint.
Scale the image size	This technique scales the image to some random value between 0.5 and 2.0. This process enhanced the capability of the model to cope with the scenario of the drill string being partially visible that was originally represented by limited number of images.
Flip image horizontally	A horizontally flipped image is produced with a probability of 60% and added to the training data. This technique considerably reduced model overfitting, resulting in a more generalizable model.
Convert image RGB to grayscale	Images in the training set are chosen randomly and converted to greyscale. This kind of augmentation technique improved the accuracy of tool joints prediction under different light conditions.
Adjust contrast hue and brightness	All these three (different) augmentation techniques help to increase the variation of the lighting condition of the labeled data. Using these augmentation techniques, it becomes possible for the model to generalize to different visibility conditions even if the model has not seen training data for that exact scenario.

TABLE 3. DL backbones parameters.

Parameters	Search space
Optimizer	**Adam**
Learning rate	3e-5
Learning batch size	**16**
Max detections per image	2 (maximum two tool joints per image)
Stride (width, height)	[10, 11, **12**, 13, 14]
Stride scales	Default (0.25, 0.5, 1.0, and 2.0)
Localization loss weight	1.5
Classification loss weight	2
Dropout expectation	[0, **0.1**, 0.2, 0.3]

Parameters in bold indicate the optimized values by using random search algorithm.

D. PRE-TRAINED DEEP-LEARNING ARCHITECTURES FOR TRANSFER LEARNING

As mentioned above, designing the DL architecture is a challenging task due to the vast number of parameters and possible configurations. Nevertheless, it is possible to use a pre-trained DL backbone and re-train it for a similar object identification problem. As such, transfer learning refers to the re-training of a model to optimize the connection weights while the DL structure (number of convolutional layers, activation functions, among others) remains the same [84]. ResNet, Inception, and DarkNet are DL architectures that have achieved outstanding results while focusing on the processing speed, which is essential for real-time applications.

We used the DL backbones in TensorFlow [85] for Python with a data split scheme for training, validation, and testing of the models. As such, 80% of the images were used for training and 20% for testing and validation of the final model. The training phase continued until a maximum limit of model parameter updates was reached, or the validation loss did not change for x consecutive parameter updates, where x is a hyperparameter. With these training constraints, it took approximately 14 hours to train the ResNet and DarkNet backbones using a Faster-R-CNN.

We used a random search algorithm for selecting the optimized hyperparameters. Table 3 shows the hyperparameters search space and the selected optimal values in bold. Note that the maximum detections per class are set to two as the maximum number of tool joints observable in an image is two (each tool joint is usually 31 feet apart). The fact that we can only observe two tool joints inspired a post prediction processing to further increase the performance of the models.

E. TOOL JOINT POST-PREDICTION PROCESSING

Usually, post-processing logic can further improve the accuracy of an object detection model. The post-processing algorithm exploits the fact that there can be a maximum of two tool joints at a given time and that they are 31 feet apart (standard drill pipe dimensions).

We derived two different heuristics for reducing false positive and false negative predictions. For the reduction of false positive predictions, if more than two joints were detected, then the pair of joints having a predetermined distance of 31 feet among them were considered to be ideal and used as final detected joints. Moreover, if two tool joints were detected by the model and had a distance of 31 feet between them, then the two tool joints were considered as final detected joints, otherwise, the tool joint with higher confidence was considered as the predicted tool joint. In rare scenarios (not encountered in our tests), when both tool joints had the same confidence, then the joint having Euclidean distance closer to the previously detected joints was considered as the final detected joint.

To reduce false negative predictions, we created a queue (last_detected) of the last ten detections. If no tool joint was detected and last_detected had elements, then the next tool joint was approximated based on the distance between the first two joints present in the last_detected. Whenever a tool joint was not detected, an element was removed from last_detected, and whenever a tool joint was detected, it was inserted in last_detected, keeping the maximum length of last_detected to 10. Fig. 7 shows the diagrammatic representation of the implemented logic.

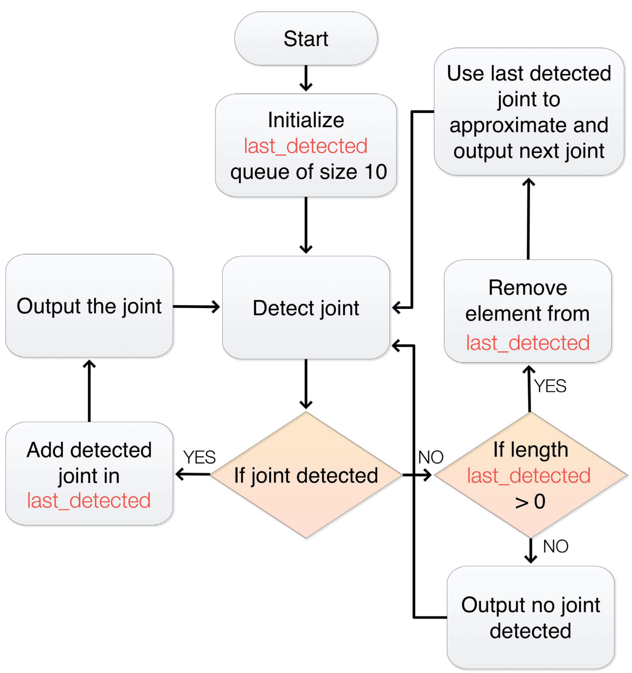

FIGURE 7. Post prediction processing to reduce false positive and false negative predictions.

F. SPEED OPTIMIZATION FOR REAL-TIME OPERATIONS

DL models perform different convolutions and data transformations that require considerable computational demands for both training and testing phases. Lately, graphic processing units (GPUs) have been used to considerably reduce the time required during training and testing [86].

Because the DL model for the detection of tool joints is used for a critical operation (deciding which ram of the BOP to close), the deployed model is required to process the image and predict the location of the tool joint as fast and efficient as possible. However, because the video frames cannot be sent to the headquarters (Fig. 4A), the processing and prediction need to be performed at the drilling site, a remote location with limited hardware capabilities (no GPUs available).

The minimum requirement for a successful deployed DL model for the tool joint detection must process at least two frames per second (fps) on a computer with an Intel i7 central processing unit (CPU). However, Vanilla Faster R-CNN and Mask RCNN algorithms are usually slower to infer on the CPU. To optimize the execution time for the deployed models, we used FogHorn's edgification process to compile the trained model coupled with OpenVino toolkit [87] for fast scoring on Intel hardware edge computer. The implemented optimization technologies enabled the model to process two fps using Faster R-CNN ResNet 50 and up to 10 fps using SSD Inception backbone on a four-core Intel CPU with 6 GB of RAM.

G. DEEP-LEARNING MODELS PERFORMANCE AND VALIDATION

As mentioned in the sections above, we tested the performance of different DL models and backbones for the detection of tool joints. In object detection problems, different criteria are defined for determining true positives (TP), true negatives (TN), false negatives (FN), and false positives (FP), which are required to compute the statistical measures to assess model performance. A detected object is considered a TP if 1) prediction score is greater than a threshold (0.6 in this study), 2) the predicted class matches the real class (tool joint class), and if intersection over the union of the predicted box coordinates is greater than a threshold (0.5 in this study). An FP is determined when the predicted score is higher than the threshold, but the intersection over the union is less than a threshold (0.5) and/or the predicted class does not match the real class. An FN occurs when the prediction score that is supposed to capture the real object (tool joint) is less than the threshold. Finally, TN refers to the cases where the confidence score for other irrelevant objects is less than the threshold. Notably, statistical metrics that rely on TN are irrelevant for most object detection problems. Therefore, we considered average precision (AP) and average recall (AR) to measure the performance of the implemented models. AP and AR are defined as the area under the interpolated precision-recall curve, and the recall averaged over all intersection over union, respectively [88], [89].

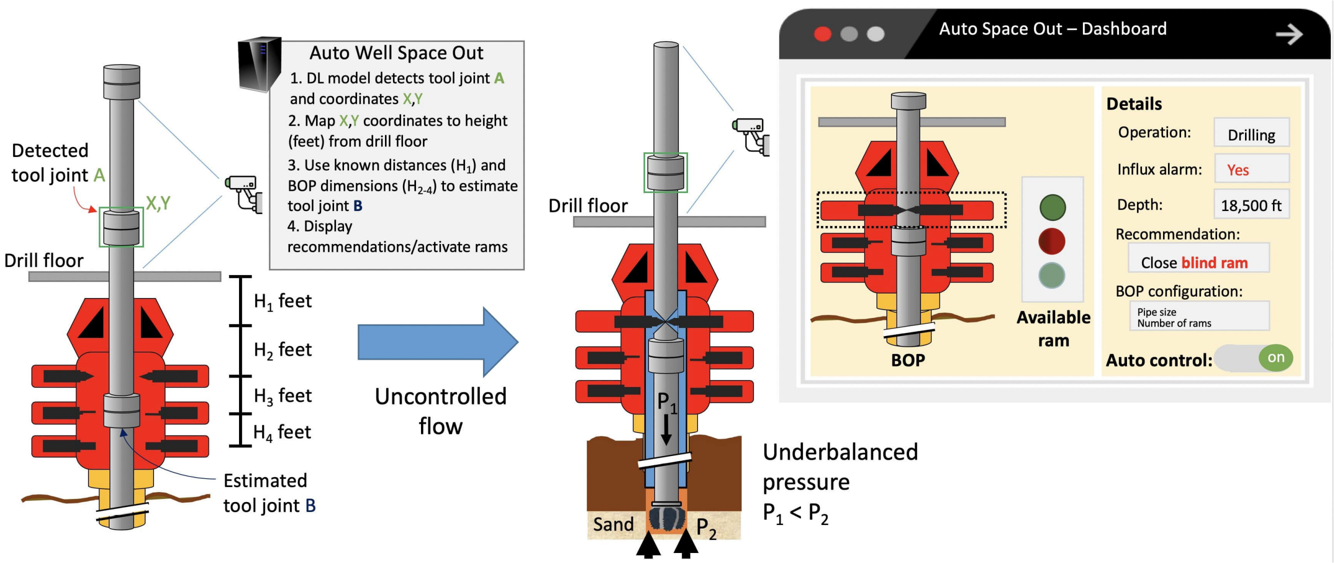

FIGURE 8. **Well Control Space Out schematic. The implemented DL model for tool joint detection along with the BOP dimensions are used compute the location of the tool joint below the drill floor. In the case of an uncontrolled flow, the Well Control Space Out determines the appropriate measures to take (close blind ram in the example on the right).**

TABLE 4. **Comparison of the results obtained by different.**

Model	Backbone	Average Precision (mAP)	Average Recall (AR)
Faster R-CNN	ResNet 100	0.79	0.75
Faster R-CNN	ResNet 50	0.75	0.73
SSD	Inception	0.64	0.60
SSD (RetinaNet)	ResNet 50	0.67	0.63
YOLOv3	DarkNet	0.71	0.68
Faster R-CNN	Inception	0.70	0.69
Faster R-CNN -LRP	ResNet50	0.69	0.63

Table 4 shows the results obtained by using the considered models and backbones. Notably, Faster R-CNN with ResNet 100 backbone achieved the best AP and AR. ResNet 50 backbone achieved the second-best results. Because of the lower latency, we considered ResNet 50 as the final model for the production environment. Using the described augmentation techniques and the post prediction processing (described in Fig. 7), we were able to further increase the AP by 4.52%.

IV. RESULTS

The key contributions of our study are the integration of multiple technologies (from sensors to computational models) to form a fully functional IoT technology to ensure safe drilling operations. The technology has fully installed on a drilling rig and is currently in the testing phase.

Current practices in the event of an influx involve the driller using a remote control system to provide hydraulic power to the rams to sever the drillstring. A critical responsibility of the driller during this process is to ensure the drillstring assembly connections are spaced out for the BOP to successfully seal or shear the drillstring.

In this study, we focus on the application of an IoT platform to ensure well control since such an incident has a significant impact on the health and safety, profitability, and reputation of an organization, which is self-evident from many historical examples like the Macondo incident. The Well Control Space Out technology records the drillstring above the drill floor and implements a DL model to automatically detect the tool joints. With the detected tool joints and known BOP dimensions, the system calculates the position of the tool joint inside the BOP (below the drill floor), as shown in Fig. 8. Moreover, the system implements a dashboard that displays the correct ram to close in a well control incident without the need for any other manual steps. Fig. 8 shows an underbalanced example, where the formation pressure P_2 is greater than P_1 from the drilling mud. The benefits of this technology have been measured by 1) elimination of well control space out errors by improving well shut-in probability and 2) elimination of extra time to space out and equipment damage through incorrect BOP closure. Moreover, the edge server combines different physics-based and data-driven models to display actionable insights, recommendations, alarms, among others, that may be directly connected to the actuators at the drilling rig to close the automation loop.

Although in this study we focused on the well control, the system can be seamlessly expanded to other upstream sectors such as production, reservoir, and geophysics, where sensor data can be collected, validated, and enriched at the edge to identify patterns and create models to predict and mitigate problems associated with operations. The Well Space Out technology creates an ideal framework for an IoT platform with cameras, additional sensors, machine learning, data analytics, and edge computing.

V. FUTURE WORK

This same knowledge and know-how can then also be extended to other upstream sectors, such as geology, geophysics, production, and reservoir engineering, to increase efficiency and optimize operations. In future work, we plan to expand the applications to cover the following oil and gas sectors:

1. Production. Sensory enhanced intelligent systems that have the capability to interact with their environment, i.e., sensors and other ESPs, in order to autonomously accomplish specific missions that allow reliable and optimal oil production in a given field.

2. Reservoir. Better prediction to obtain more accurate reservoir models based on real-time updates from production as well as an automatic calculation of injection pressures for water/CO2 enhanced oil recovery. Integration of surface and downhole data obtained by technologies such as smart mapping materials in reservoirs.

3. Drilling. Real-time updates on wells with predictive data analytics (stuck-pipe, early kick detection, lost circulation prediction). Engineers can use virtual modules on tablets and augmented reality data on smart glasses to perform remote assistance, control, monitoring, and supervision.

4. Geophysics/Geology. Faster processing of seismic data and surface modeling. Autonomous vehicles with IoT integration in harsh environments. Integration of real-time seismic data with real-time drilling data for predictive analytics.

5. Upstream Asset Management. Intelligent transportation and logistics, effective management, and timely maintenance of equipment and machinery, workflow automation, asset tracking.

VI. CONCLUSION

Drilling operations represent a challenging environment where the expertise of the crew is essential to maintain optimal and safe operations. Although existing sensors are currently deployed at the drilling rigs, most of the analysis of the captured data remains manual. In this study, we describe the deployed IoT technology that processes data from cameras and provides an advisory system for a particular operation in drilling. However, a similar technology using cameras, additional sensors, and ML/DL models may be deployed at a broader scale across different industries.

The process of understanding how the vast amounts of sensor data can be enriched and converted to useful information to increase operational efficiency and link to clear business objectives requires transformation. Implementation of the IoT for business and industrial applications has the potential to increase business opportunities, enhance asset utilization, improve safety and security, increase productivity, enhance the efficiency of processes, and reduce costs, among others.

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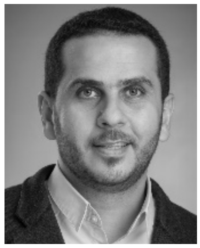

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