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Using AI Cuttings Load Classification to Assess Hole Cleaning and Wellbore Stability

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Abstract

This paper discusses a field test that placed computer vision cameras on rigs' shale shakers to measure drilled cuttings and cavings. The images from the camera were processed using proprietary computer vision software and sent to the drilling team, where it was used to assess drilling performance, hole cleaning, and wellbore stability. This Proof of Concept (PoC) test was conducted over five months on two drilling operations in the Marcellus shale, using three different camera types placed in two shaker locations. Over 200,000ft of video data from 11 wells were collected from the West Virginia / Pennsylvania regions. This paper describes the research and development of this technology's hardware (camera) and software (computer vision).

To the author's knowledge, this is the industry's first use of computer vision to measure drill cuttings autonomously and continuously at the rig site. Computer vision applied at the shaker will increase overall ROP, greatly improve the speed and accuracy of wellbore instability detection, reduce the exposure in a hazardous zone, and improve the detection of pending downhole problems.

Introduction

Problem statement

Oil and gas operations depend on maintaining a clean and stable wellbore while drilling. In 2004, geopressured zones and wellbore stability-related problems were estimated to cost the industry $8 billion annually. These costs are estimated to be, on average, 15% of a well's budget. In the US, 90% of wellbore stability problems occur in shales, and 75% of wells include shale. Wellbore problems are a big cost to the industry.

Operationally this means that drillers are too frequently wasting time working sticky pipe, fighting stuck pipe, drilling too slowly for fear of getting stuck, or circulating a hole that's already clean. This is because, during the drilling and casing phases of wellbore construction, the drilling team lacks reliable and real-time information on the cuttings recovery rate or the detection of cavings.

It is common practice to visually inspect the shale shakers to understand what is happening downhole. But the shaker area is dirty, dynamic, and dangerous. Steam, rain, fog, wet shakers, and hazardous elements make it difficult to inspect the shaker manually. Furthermore, these inspections are typically subjective, relying on ad-hoc descriptions of shaker loading and the morphology of cuttings and cavings. The accuracy of these inspections is questionable because they depend on subjective, qualitative, and non-standard assessments. Suppose these inspections are augmented by technology that could provide objective data and analysis and reveal elements invisible to the human eye. In that case, the drilling team could increase performance, save money and reduce emissions.

Solution

Installing a high-resolution, explosion-proof camera at the shakers, combined with an industrial server, virtual machines, and computer vision software, will provide operators with unprecedented insights into real-time detection of hole cleaning and wellbore instability problems. These data include the drilled cuttings and cavings' volume, shape, and size. The drilling team can then combine this information with the current practice of visual inspection to improve drilling performance.

Such data is obtained by first capturing images of enough quality to allow image classification and object detection. Then a deep learning neural network (DNN) in the drilling domain is applied to analyze shale shaker images. Our team used transfer learning, which employs previously trained DNN models, to shorten the model's development time and address a range of shaker inspection tasks that benefit from computer vision.

Background

Conventional methods for determining the state of hole cleaning and wellbore instability include torque and drag monitoring, drilling hydraulics modeling, circulating pressures, logging while drilling, and cuttings volume meters, among others. These methods have not significantly reduced the industry's multi-billion losses from wellbore instability for several reasons.

Hole Cleaning: The art and science of hole cleaning combine decades of academic research and empirical data. API RP 13 D Rheology and Hydraulics of Oil-well Drilling Fluids is the industry's recommended practice for optimizing the drilling fluid circulating system to improve drilling efficiency, including estimating hole cleaning efficiency. The authors follow the performance limiter methodology developed by ExxonMobil (Fast Drill), where hole cleaning is considered a limiting factor to overall ROP performance. Like Isaac

Asimov's Rule for Robots, the authors present the Rules for Hole Cleaning:

1. If the hole is in-gauge, cleaning is usually trouble-free.
2. When cavings are detected, the hole is no longer in-gauge, and poor hole cleaning is more likely.
3. Do not drill faster than the hole can be cleaned.
4. Drill the dirtiest, fastest hole possible.
5. Do not drill a hole that cannot be easily tripped or cased.

Drillers recognize the need to balance reliance on trends versus deterministic data. The drilling engineer models and calculates using quantitative information, including pressures, weights, flow, and torque, and sets boundaries for the drilling team to follow.

The onsite drilling team uses these limits for guidance and alarm settings yet relies mostly on trends to understand the well's condition and predict its performance.

Many drilling best practices use dimensionless measurements to provide qualitative information. One example is the flow paddle, which uses percentages of its position to indicate a flow rate. The gas detector and funnel viscosity readings are also dimensionless, and their trends are used hourly to understand drilling performance. In hole cleaning, drilling by trend interpretation, as shown in Table 1, is an established recommended practice. (API 13D 2009)

Digitizing Shaker Surveillance: Extracting drilling data at the shale shaker provides an attractive value proposition. Using the camera as a sensor in industrial processes allows cost-effective accuracy, reliability, and safety improvements. While cameras are becoming more commonplace on the rig, they are typically low resolution and used primarily to monitor personnel or equipment status.

Since 2009, operators, service companies, and universities have publicized computer vision applications, the most notable being Graves (Halliburton) and Torrione (Covar/H&P). In a 2013 presentation to the Drilling Engineering Association, Covar described computer vision's challenges in drilling operations. Shell (2017), Petrobras (2010), and Halliburton (2019) discuss recording and analyzing offsite shaker video images to describe cutting volumes to optimize circulation times. However, none of these solutions are yet commercially available.

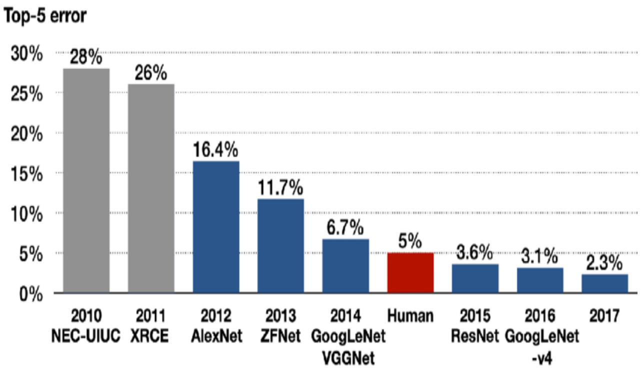


Figure 1 Design Trade-offs Accuracy vs. Hardware Cost for ImageNet Classification (W.Du)

What's Changed: Computer vision technology has significantly progressed since those earlier efforts. For example, from 2010 to 2017, Stanford's ImageNet Challenge gave participating software developers 1.4 million images (none of drilled cuttings or cavings) to correctly classify and detect objects and scenes. As the models began to learn, the accuracy improvements were dramatic, especially starting in 2012 with the introduction of AlexNet, which improved deep learning neural networks (Figure 1). ResNet in 2014 allowed the application of hundreds of layers by adding residual connections that permitted the layers to be skipped by design and thus become truly deep.

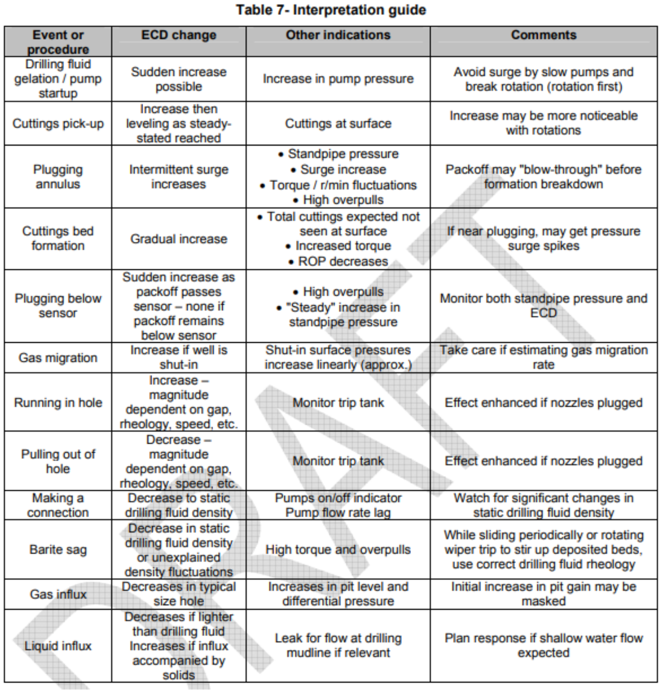
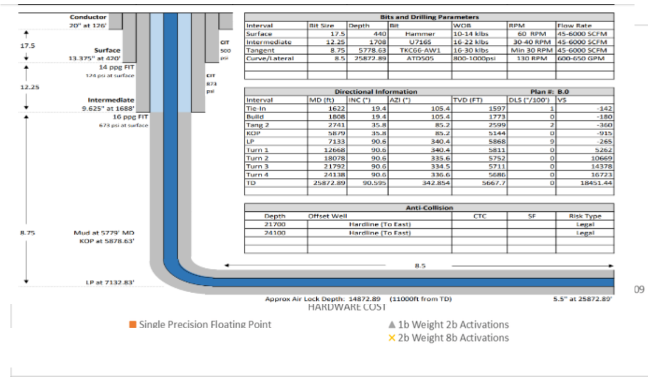


Table 7- Interpretation guide

Event or procedure	ECD change	Other indications	Comments
Drilling fluid gelation / pump startup	Sudden increase possible	Increase in pump pressure	Avoid surge by slow pumps and break rotation (rotation first)
Cuttings pick-up	Increase then leveling as steady-stated reached	Cuttings at surface	Increase may be more noticeable with rotations
Plugging annulus	Intermittent surge increases	• Standpipe pressure • Surge increase • Torque / r/min fluctuations • High overpulls	Packoff may "blow-through" before formation breakdown
Cuttings bed formation	Gradual increase	• Total cuttings expected not seen at surface • Increased torque • ROP decreases	If near plugging, may get pressure surge spikes
Plugging below sensor	Sudden increase as packoff passes sensor – none if packoff remains below sensor	• High overpulls • "Steady" increase in standpipe pressure	Monitor both standpipe pressure and ECD
Gas migration	Increase if well is shut-in	Shut-in surface pressures increase linearly (approx.)	Take care if estimating gas migration rate
Running in hole	Increase – magnitude dependent on gap, rheology, speed, etc.	Monitor trip tank	Effect enhanced if nozzles plugged
Pulling out of hole	Decrease – magnitude dependent on gap, rheology, speed, etc.	Monitor trip tank	Effect enhanced if nozzles plugged
Making a connection	Decrease to static drilling fluid density	Pumps on/off indicator Pump flow rate lag	Watch for significant changes in static drilling fluid density
Barite sag	Decrease in static drilling fluid density or unexplained density fluctuations	High torque and overpulls	While sliding periodically or rotating wiper trip to stir up deposited beds, use correct drilling fluid rheology
Gas influx	Decreases in typical size hole	Increases in pit level and differential pressure	Initial increase in pit gain may be masked
Liquid influx	Decreases if lighter than drilling fluid Increases if influx accompanied by solids	Leak for flow at drilling mudline if relevant	Plan response if shallow water flow expected

Table 1 Hole Cleaning Trend Interpretation Guide API13D

Figure 3 Typical Drilling and Well Profile



Bits and Drilling Parameters						
Interval	Bit Size	Depth	Bit	WOB	RPM	Flow Rate
Surface	17.5	440	Hammer	10-14 klbs	60 RPM	45-6000 SCFM
Intermediate	12.25	1708	U716S	16-22 klbs	30-40 RPM	45-6000 SCFM
Tangent	8.75	5778.63	TKC66-AW1	16-30 klbs	Min 30 RPM	45-6000 SCFM
Curve/Lateral	8.5	25872.89	ATD505	800-1000psi	130 RPM	600-650 GPM

Directional Information					Plan #:	B.0
Interval	MD (ft)	INC (°)	AZI (°)	TVD (FT)	DLS (°/100')	VS
Tie-In	1622	19.4	105.4	1597	1	-142
Build	1808	19.4	105.4	1773	0	-180
Tang 2	2741	35.8	85.2	2599	2	-360
KOP	5879	35.8	85.2	5144	0	-915
LP	7133	90.6	340.4	5868	9	-265
Turn 1	12668	90.6	340.4	5811	0	5262
Turn 2	18078	90.6	335.6	5752	0	10669
Turn 3	21792	90.6	334.5	5711	0	14378
Turn 4	24138	90.6	336.6	5686	0	16723
TD	25872.89	90.595	342.854	5667.7	0	18451.44

Anti-Collision				
Depth	Offset Well	CTC	SF	Risk Type
21700	Hardline (To East)			Legal
24100	Hardline (To East)			Legal

Figure 2 Performance of popular DNN on ImageNet. Mud Engineers achieve an error rate of 5% (W.Du)

The competition ended in 2017 due to diminishing returns and the achievement of superior performance to humans. Current computer vision deep learning neural networks (DNN) has greater than 95% accuracy in image classification, with continued improvement in object detection and image segmentation. When AlexNet was introduced, it took six days for two parallel-running GPUs to be trained. Today it can be done in minutes. Developers must compromise between accuracy and total hardware cost. Because the number of parameters to be processed can range in the tens of millions, a premium is placed on efficiency. To illustrate this, Figure 2 depicts floating points from some of the best DNNs against extrapolated hardware costs.

Field Proof of Concept

The main goal of the fieldwork was to validate the lab Proof of Concept (PoC) work done the previous year, which demonstrated the promise that computer vision could analyze cuttings at the shale shaker. Figure 3 shows the lab and rig camera setups

Figure 4 Lab and Rig Camera installations9

The rig PoC goals were;

1. Install a Class 1 Div. 1 deep learning video imaging system that directly views the shale shaker and provides a continuous image feed.
2. Establish system operational reliability metrics in image quality, processing, and uptime.
3. Build an image classification model that measures the shaker load while drilling.
4. Extract unique cuttings volume estimate data in both qualitative and quantitative forms.
5. Detect unique objects flowing through the shaker.

Drilling program

Our two sponsor operators in the Marcellus had very similar drilling programs. Both drilled approximately 22,000ft of open hole with an 8.5in bit with typical drilling parameters of:

● Pump rate 600-640 GPM ● ROP 300-700 FPH	● Mud weight 12.5- 13.5 PPG ● Rotary 120 RPM

Drilling the Marcellus Shale formation in the Appalachian Mountain range requires drilling pads to be compact and fit-for-purpose. Depths, casings, and well-profile highlights are summarized in Figure 4.

Installation

The original plan was to house the IT hardware in a utility trailer to minimize the interface with the rig. However, the well pad was not large enough to safely park the trailer. The sponsor allowed access to the rig's control panel in the doghouse to store the computer and connect the electronic data recorder (EDR) and driller interface console.

Mount and Frame: Following the minimal interface theme, the camera installation did not require welding or modification of the rig's equipment or third-party shakers. An independent T-slot frame was designed to allow up to three dry shakers to be monitored simultaneously.

Using the primary waste pit located directly at the dry shaker's exit as the frame foundation, the T-Slot frame, found in robotic industries, enabled the camera to be adjusted to within four feet of the outlet. See Figure 5.

Initially, the camera was roughly centered, relying on the camera's field of view and zoom features to compensate for the off-center field of view. In some instances, the camera viewed the shaker at an offset angle, and although corrected in preprocessing, it was not considered optimum for machine learning. In the future, a camera alignment procedure is required.


Figure 5 T-Slot Frame for Dry Shaker Mount

The frame was removed on the last deployment, and the rig's welder built a clamp mount attached to the blowdown line directly overhead the primary wet shaker. The mount held the camera and light. On later deployments, a custom-designed camera bracket was mounted to the shaker roof of the primary shakers.

Camera: The primary shakers are in a hazardous Class 1 Div. 1 rated zone, so only explosion-proof camera types are allowed. Various box-type camera models from Axis Communications were used at the primary and dry shakers to test their reliability and image quality. See Table 2.

			Resolution			Light Finder		Stabilization	Weight w/ xp housing
Model	Sensor	Lens	Image	Video	FPS		WDR		
P1367	CMOS	2.8	5 MP	3072 x 1728	25/30	x	x	NA	15
P1377	CMOS	3.5	5 MP	2592 x 1944	30/180	x	x	x	15
Q1615	CMOS	3.5	2.1	1920 x 1080	50/120	x	x	x	15
Q1765	CMOS	8	2.1	1921 x 1080	25/30	NA	x	NA	31

Table 2 Axis Camera Model Specifications

The ethernet PoE Class 3 cable provided power for all the cameras.

The Q1615 became the primary test camera for its system-on-chip capability. Embedded with the ARTPEC 7 chipset, it can house a real-time computer vision engine and support analytics based on deep learning on edge.

Lighting: Primary shakers, which the drilling contractor owns, usually had a roof with a fixed light placed over the middle area of each shaker. Drying shakers owned by service suppliers came without a roof or light. Since both shaker outlets were too dark or in the shadows at night, a Class 1 Div. 1 LED rig light rated 4000 lumens was installed.

Weather: From June to early November, temperatures ranged between -1 C to 27 C, with frequent rain and lightning strikes. Due to the rigs' location on hills, the camera was knocked out due to lightning. After a review of the grounding procedure, no more incidents occurred. Subsequently, the camera mount design includes a grounding point. Steam and fog also frequently obscured the shaker, but the model was eventually trained to monitor the cuttings satisfactorily, even under such conditions.

Shaker Setup: In the Marcellus, the most common configuration had three primary shakers operated by the rig and another three downstream, managed by a third-party solids control company. One consequence of the small pad size was high (>10%) low gravity solids in the drilling fluid due to limited storage, less settling time, and thus wetter shakers. The wet cuttings on the dry shakers negatively influenced overall computer vision performance.

Air Drilling: Another unplanned event was the drilling program's air drilling operation performed on each well sequentially, changing from air to fluid in the open-hole section. The solids control system was configured to handle both, which made for a custom installation, dirty environment, and cramped working space. While it was not intended to monitor the shaker during air drilling, it was unavoidable due to the backyard solids control configuration. It made for an extreme environment that tested the reliability of the camera, cable, light, and connection.

Overflow of Shakers: The blowdown frequently dirtied the glass during air connections. Due to the chemicals in the air drilling fluid component, a thin film of scale developed over time. Gradually the lens became covered to the point an image was no longer usable. A household scale remover easily cleaned the glass and restored the image. During mud drilling, cleaning operations were much less frequent. See Figure 6.

Figure 6 Air Drilled Cuttings

System Components: During the five-month field PoC, numerous hardware and software improvements were made that increased the reliability and usability of the images. Its final form factor is shown in Table 3 and Figure 7.

Component	**Initial**	**Final**
Mount	T-Slot, Clamp on wet shaker	Custom roof mount on primary shaker

Camera	1367/1377	1615
Shakers	Dry	Primary
Computer	Dell Laptop	Lanner Server
Display	Laptop then Driller Monitor	Touch Screen Video Display Driller / Co.Man
Model	ImageNet	ImageNet
Uplink	AT&T LTE	Pason
Light	None initially	Dialight 7500 lumens Class 1 Div 1

Table 3 Rig Hardware and Software Improvements

Figure 7 AI Camera on Primary Shaker and Video Touch Screen at Driller Chair

Computer Vision

The main challenge was for the camera hardware to capture good enough images so that the AI software could recognize the amount, size, and shape of drilled cuttings and cavings at the shaker. Convolutional neural network (CNN) is a deep learning (DL) method widely and successfully applied to computer vision tasks, including object localization, detection, and classification. DL for supervised learning tasks is a method that uses the raw data to determine the classification features, unlike other machine learning (ML) techniques that require pre-selection of the input features or attributes. The team used a combination of TensorFlow/Python/Keras software to manage, process, and evaluate data captured by the camera.

Axis Camera Station allows video and shaker load data to be displayed in individual windows. Multiple cameras, a firewall, the main Linux server, a recorder, storage, and a camera station are hosted on one physical server as virtual machines (VM). For example, one VM can run the inference processes with a Ubuntu server, with TensorFlow and Keras libraries installed. The python code calls the model, putting it in Tensorflow to execute it. The goal of subsequent deployments is to have the camera's CPU run this process. What is beneficial is that the VM platform allows various networks to be built.

Various workflows are triggered when pre-defined conditions are detected. Output alerts, signal feedback to sister data systems, and data storage routines for manual analysis and further model training are integrated within one configuration. All collected data and generated indicators are archived in a time series data historian, an event log database, and an image storage system. One iteration of the network architecture is shown in Figure 8.

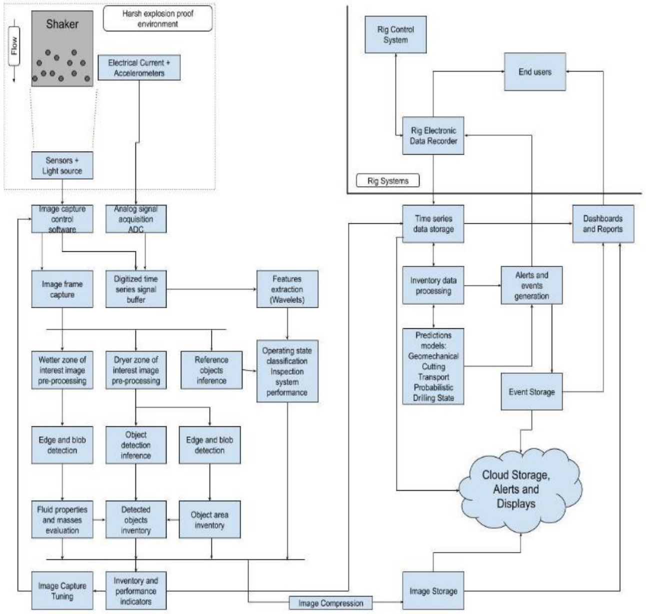


Figure 8 Computer Vision Network Architecture

The team's AI methodology uses supervised machine learning with pre-trained convolutional neural network (CNN) models to predict the object(s) present in the images and video. The methodology is divided into the following workflow stages.

- Image capture and preprocessing
- Build an input pipeline to the model
- Select the model
- Train the model
- Test the model
- Improve the model and repeat the process

Image capture and preprocessing: Image processing is the first step to making the data suitable for analysis and is called preprocessing. The camera manages its sensor, lens, light compensation, stability, and focus. It is the foundation, and we strove for the highest quality possible, following the logic of "garbage in, garbage out." The pixel count in the usable image is limited and must be optimized so that all the layers in the CNN run efficiently as possible.

Broadly, the steps required to prepare an image for analysis.

1- Receive the full-resolution image
2- Rotate the image if required to have a horizontal image of the ROI
3- Crop around the ROI
4- Extract a sub-portion of the cropped image (zone)
5- Perform bit depth, grayscale conversion, and brightness histogram equalization on the sub-image.

6- Resize the image to match the DNN input structure (ex: 224x224)
7- Call the DNN passing the preprocessed sub-image.
8- Save results and repeat for the next zone

The image resolution and the lens adjustment must be tuned so that the pixel size corresponds to the field of view. Pixel count is directly related to the camera's sensor and lens configuration resolution, with 224x224x3 being the most common. Because the CNN reduces the image to very low pixel counts, 7x7x256, this application does not need the highest resolution camera. To reduce computational power even further, the color features were often discarded in favor of only black and white, reducing the depth to 1. The dynamic movement of the shaker load on the screen determines the camera location. The camera's electronic image stabilizer was required based on camera mounting, process vibration, and exposure time. See Figure 9.

The camera sensor gain is adjusted to the exposure time to ensure the resulting image brightness allows clear distinction of the particle's edges. The focus is on the image portion corresponding to the drop zone's beginning. The compression was adjusted to reduce decompression processing time as low as possible.

Select the Model: The second form of processing is the computational work done by the CNN models to predict the image captured by the video camera.

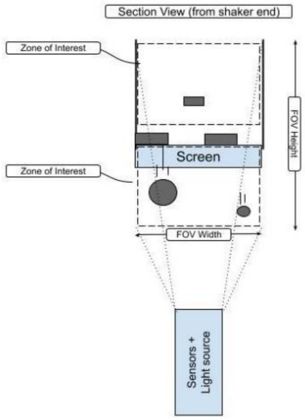


Figure 9 Field of View for Image Capture

One of the project's first tasks was to decide how to approach model selection. Ten years ago, the best choice may have been building, but today, open source, pre-trained CNN models can capture a high-level representation of the input data. Note that none of the models are pre-trained on cuttings or cavings. The team initially reviewed Shell's work built on VGG architecture but rejected it for more modern and less computationally intensive options. Today, image classification (e.g., ResNet50, Inceptionv3, EfficientNet, ResNet, MobileNet) and object detection (e.g., Fast R-CNN, Mask R-CNN, YOLO, SSD) are some of the most popular models. In this paper, the results from image classification work are described.

Although the models are pre-trained, none have been trained on images from the shale shaker. The selection process was a trial-and-error of three different prototypes that eventually produced sufficiently accurate results. Due to the dynamic nature of the outdoor shale shaker environment, the weights, bias, camera settings, and other tuning parameters were also learned through successive field deployments. For proprietary reasons, the actual models and parameter settings are not discussed.

Train the model: With over 200,000ft of shaker video data captured, the next step is to train the model. Labeled image data is fed into the CNN model, and output from each layer is obtained. The training process includes a data augmentation mechanism based on spatial augmentation, color space augmentation, and image blur. Supervised learning is how the team trained the model using images tagged with the correct answer (i.e., no flow, low flow, high flow). The model is provided with a new set of previously unseen images so that the supervised learning algorithm trained on training data produces a correct prediction.

Supervised learning was performed for two sets of outputs:

- Classification: The shaker load estimate (SLE) is a collection of categories, such as "No Flow" or "Low Flow," "High Flow," or "Overflow." In this project, 11 shaker load estimates were labeled.
- Regression: The shaker load actual (SLA) is measured as a quantitative value such as "bbls" or "tons." The images can be calibrated or "fingerprinted" to known ROPs in the vertical hole section.

With both types of learning, the team calculated the error using an error function, and some common error functions are cross-entropy, square loss error, etc. This step, called backpropagation, minimizes losses within the 224x224 pixelated image.

Data augmentation, including adding noise, was used to increase the overall size of the data set. A fraction of the data set was used for validating the inference. The dropout layer is critical for model training to strengthen its predictive algorithms to prevent it from trying to memorize the input data, much like humans who memorize words but cannot read.

An example of the classification process is shown in Figure 10. The model analyzes an image of the shaker that should fit one of the 11 shaker load rankings. The DNN outputs the probability assigned to each possible class, where their sum equals zero. In this example, the model did just as well as the rig crew identifying the shaker load and was more consistent. It is important to note that implementing the DNN will classify any image as one of the eleven learned classes, even if the image is not cuttings. This highlights the importance of domain expert oversight and other models to look for anomalies like cavings, motor rubber, or shoetrack objects.

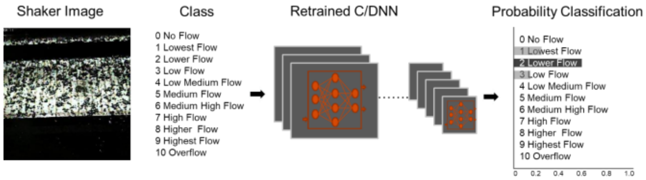


Figure 10 Shaker Load Classification using DNN

Testing and improving the model: Overfitting occurs when the difference in accuracy between training and validation accuracy is noticeable. The team encountered several episodes of overfitting and eventually prevented it by identifying a small number of learnable parameters determined by the number of layers and units per layer. While a model with more parameters would have more "memorization capacity" and, therefore, can easily learn between training images and actual cuttings and cavings, a mapping without generalization power, i.e., overfitting, would be useless. The team is striving to build a deep learning model with correct architecture, in terms of the number of layers and their size, that can excel in the real challenge of generalization, not fitting.

Results

Hardware: The camera and network system performed well enough to complete the PoC without major changes or interruptions. It successfully captured over 200,000ft of shaker video. On the last well, it captured 22,000ft of 8.5in with no interventions required for cleaning or adjustments. The most significant problem was data storage, as one well would have over one terabyte of data. Because model training requires large amounts of image data and streaming data back to cloud storage is expensive, some image data was lost.

The driller and company man enthusiastically welcomed the high-resolution video touchscreen introduction. Managing rig network bandwidth to stream the video was difficult as the high data loads sometimes interfered.

No issues were encountered streaming the SLE via WITS to the rig's EDR.

Predictive Models: Intuitively, we know that when we see drill fluid and cuttings increasing or decreasing on the shaker, this should be reflected in the computer vision model. Three qualitative measurement examples demonstrate the system accurately predicts the SLE during different drilling operations.

Pumps On/ Off: During connections, the first validation test detected the shaker load estimate (SLE). Like the gas trace, the SLE should follow the pump's flow output when it ramps down or up. The lab PoC's GEN 1 model worked well in detecting the presence and absence of shaker load objects. The SLE is the black trace on a scale of 0-9 and ranges from 0.4 to 6, following the pump flow rate. A distinct and consistent lag (~ 30 seconds) in SLE and Gas is observed during these connection intervals and is most likely due to the storage capacity of the upstream piping. See Figure 11.

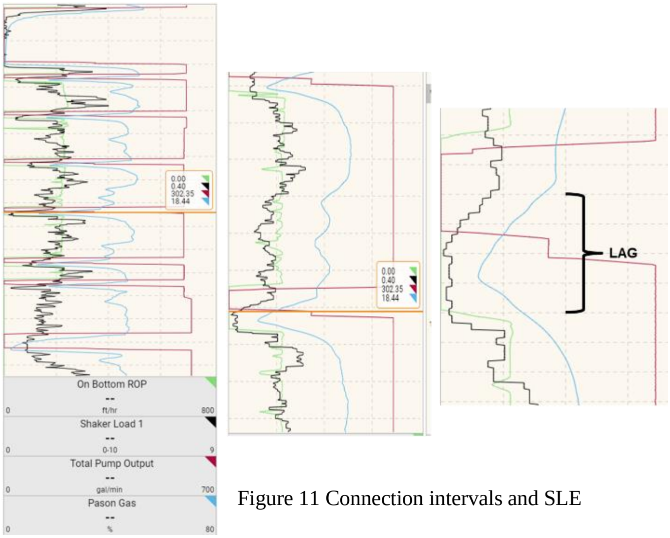


Figure 11 Connection intervals and SLE

Another observation at the shaker is that it is rarely empty. Consequently, the SLE does not reach zero, even though there are no significant amounts to practically measure. Because the SLE is a trend trace, this is not a significant issue. This short period can be removed from the SLA calculation to avoid overestimating the cuttings recovery.

Rate of Penetration: The rate of penetration is another important parameter to validate the SLE. The volume of drilled rock for a specific hole size is determined by the interval drilled for a given period. The SLE aligned logically with ROP in the 15,000ft long hole section. In Figure 12, the SLE trace gradually reduces as the drilling rate slows.

Figure 12 SLE vs. ROP

A significant anomaly is observed with two SLE waves within 24 hours, occurring at the same time of the day, from 3am till noon. Since ROP was decreasing and the flow rate was constant, the team believed an error was occurring in the SLE. Figure 13 shows that the empty shaker screen image changes from shadows to non-shadow within eight seconds. This was determined to be the camera adjusting its wide dynamic rangefinder (WDR). The WDR automatically seeks to improve image quality under high-contrast lighting conditions where dimly and brightly lit areas are in the field of view. Because the GEN 1 model had not been trained for this condition, it did not predict the SLE appropriately.

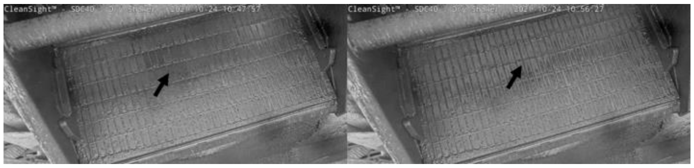


Figure 13 Image quality affected by WDR

Hole Caliper: To support the drilling operation and increase the SLE's credibility, the drilling engineer agreed to pump a pill before the fourth bottomed up before tripping. The goals were to estimate hole volume before cementing and see if the system could detect a sudden shaker load (influx) during connections. A 15 bbl. Poly-E-Flake® pill typically used to mitigate lost circulation was pumped and detected on the shaker precisely 100 minutes later.

The shaker load influx lasted over eight minutes before returning to the baseline load trend seen during the three bottom-up circulations. Note that both the gas and flow-paddle traces did not see the increased load at the shaker. The SLE is the black trace on a scale of 0-9, reaching 8 at the peak of the influx. See Figure 14.

The drilling engineer determined with the SLE that the hole had enlarged by 7.7% for an effective hole diameter of 9.2in. He believed the calculation was accurate and superior to their previous method of using the gas trace during the first casing circulation before cementing. Detecting sudden or high shaker loads can indicate wellbore instability due to excess cavings entering the wellbore.

Quantitative Measurements: Drilling by trends is an industry best practice. However, determining the volume of the actual cutting is necessary for modeling, well planning, and benchmarking.

The cuttings volume meter (CVM) or a five-gallon bucket are the two most common methods to quantify the cuttings recovery rate, as they both weigh the cuttings at timed intervals. Yet neither has gained wide acceptance due to their high cost or limited accuracy and effectiveness.

For computer vision to perform well, it must have images of sufficient quality that a human would use to perform the same task. While image classification is more forgiving on image quality, object detection requires drier shakers to identify cuttings or cavings. As described earlier, the drying shakers were run wetter than normal due to the small pad size. Since cutting dryness is a significant factor in computer vision model accuracy, the object detection model did not perform well. As a result, although cavings were observed sporadically by visual inspection of the shakers during the project, the model did not detect them while drilling due to the extremely wet conditions. During connections, with pumps off, the cavings were easily recognized. Early in the project, splintery cavings were seen at the shaker during an 8.5in lateral section at approximately 15,500ft. Drilling experienced abnormally high torque, even though higher than normal mud weight was in use due to a nearby frac job. The event lasted approximately 45 minutes.

Encouragingly, larger objects are seen from the shoe track and BHA components and were easily identified in the video. These images are being used to train the model.

To effectively use computer vision technology at the shakers, the drilling engineer must balance the need for accurate cutting volume measurements and caving detection with the solid control system design and fluid rheology metrics.

Next Steps

At the time of this paper, the team continues to train and tune the SLE and SLA to deploy with minimal calibration and provide reliable qualitative and quantitative measurements. It is preparing to deploy in the Permian Basin for real-time drilling operation trials.

Calibration: On future deployments, the SLE will be converted to the SLA by calibrating the shaker load during the well's vertical section. After ROP and hole size, the next assumption is that all the cuttings are being removed, and the cutting's bed height is zero. For example, when the SLE measures a 5, the SLA calculation will determine that a certain quantity of drilled cuttings measured in barrels are being removed for the current ROP (e.g., 1.1 bbls/min). The video images, corrected for lag, will train the model in real-time for the current ROP and hole size. Like fingerprinting during connections or characterizing the pressure profile of a closed loop circulation system like MPD, the SLA would quantify the cuttings removal rate for planned ROPs in the vertical or near vertical sections.

The team tested several DNN models to determine the best one to use as the basic feature extraction network. The training data and the camera GPU will be used to accelerate the training of the shaker event identification model. Finally, the precise identification of the shaker load estimates and sweep images was realized.

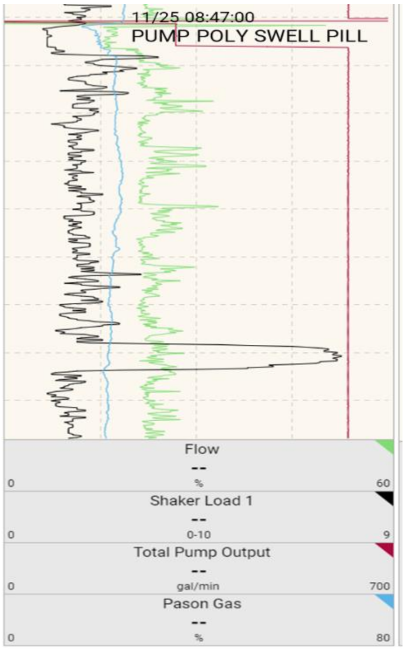


Figure 14 Sweep detected by SLE

Connections on Air: SLE performance during air drilling operation was excellent when the camera window was clean because the top-hole air drilled cuttings were cleaner, drier, and larger. It demonstrated the need for the cuttings to be as dry as possible.

It was observed in the 8.75in section that there was no consistent approach to circulation periods before a connection was made. Time varied between 3 to 5 minutes with no correlation to depth. Using the SLE or SLA to establish baseline performance during connections, the drilling engineer could standardize the cleanup period and increase overall ROP.

Cutting Size Transition: A well-known phenomenon affecting cuttings recovery is their pulverization as they flow from bit to surface. Hole cleaning practices have well established that fluid rheology, flow rate, and drill pipe rotation positively impact cuttings recovery. Conversely, increased cuttings size and eccentricity in annular clearance significantly affect cuttings transport performance. Cutting size is a key parameter in cuttings transport models, and according to one study (Huque 2020), cuttings sizes between 1mm to 2mm are difficult to clean compared to larger cuttings.

Although the GEN 1 model was not trained to detect the cutting size, the authors believe that a sequential size degradation could be detected in the early stages of the lateral using image classification. During the field PoC, it was frequently observed that the horizontal section lengthened. Identifying when this occurs could help draw the mud engineer's attention to low gravity monitoring and solids control.

Shaker Performance: During the project, it was observed that the shaker's performance was dynamic. Issues and events related to balance, worn screens, overflow, and maintenance were recorded. Shaker status information could be detected and signaled.

Hardware: The most obvious need was a wiper for the enclosure's window. The explosion-proof models chosen for the project were not fitted with wipers due to their design, and the team was aware of the risk. One model with a wiper was available, but its weight (31 lbs.) and other connectivity issues made it unsuitable. Next deployments will have cameras with wipers.

Conclusion

Although gaining popularity and becoming established as robust technologies in other industrial applications, computer vision models are still novel in the drilling community. The field PoC described in this paper established that computer vision applied to the shaker could provide useful information on hole cleaning and wellbore stability. After installing several explosion-proof cameras and streaming a continuous image feed over several months and many wells, the team established operational reliability metrics in image quality, processing, and uptime. The field PoC's objectives were broadly accomplished and demonstrated that image classification and shaker load measurements in qualitative and quantitative forms are useful to drilling teams making decisions about hole cleaning and wellbore instability.

For all the examples, we achieved adequate accuracy by repurposing two different CNN models originally assembled for generic computer vision tasks. During the model training and classification process, the training and test data were randomly selected, and there were no artificial interventions on the images' pixels, imaging distance, and illumination intensity. Moreover, the convolutional network automatically extracted the shaker image features of various flows, which made using this model to identify the shaker events more consistent and accurate than the alternatives.

While the system performs machine learning tasks, the drilling and geoscience teams must continue to analyze events independently to provide context to the data quality control of the generated results. In the end, the expert validates the correctness of the results and looks for anomalies poorly represented by the desired classes. Computer vision can help maintain interpretation consistency and provide insight into anomalous observations and data variations. We predict that versatile computer vision and camera technologies will play a role in the industry's need for drilling efficiency and decreasing emissions. Computer vision applied at the shaker will increase overall ROP, the speed and accuracy of wellbore instability detection and pending downhole problems, and reduce operator exposure to hazardous zones.

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