Application of AI to Drill Bit Forensics

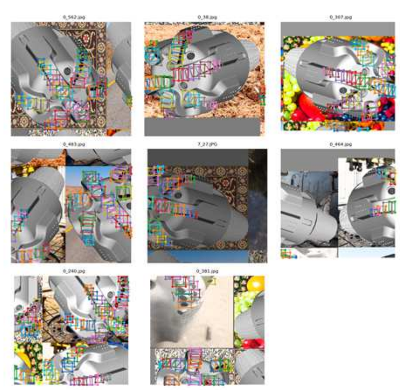
Pradeep Ashok, Senior Research Scientist

RAPID RIG AUTOMATION Performance Improvement in Drilling

TEXAS The University of Texas at Austin

Agenda

- Why Drill Bit Forensics?
- Bit Dull Grading History
- A little About AI
- Automating IADC Dull Grading
- Learning from Bit Images
- Challenges to Address
- Concluding Remarks



Research Collaborators: Prabal Vashist, Hyeok Kong, Jian Chu, Ysabel Witt-Doerring, Zeyu Yan, Dongmei Chen, Eric van Oort, Paul Pastusek, Michael Behounek, Nathan Zenero

2

Why Drill Bit Forensics ?

SPE Online Education

In the absence of downhole sensors, the drill bit is still a good direct indicator of what happened downhole.

Forensics on a used drill bit can help determine changes to drilling parameters and potential BHA and Bit redesign.

Paul Pastusek (ExxonMobil)
https://www.drillingcontractor.org/vpd-registration-04122021

3

The IADC Dull Grading System

SPE Online Education

Cutting Structure				Bearing	Gauge	Remarks	
1. Inner Rows - Average Cutter Wear	2. Outer Rows - Average Cutter Wear	3. Primary Dull Characteristic	4. Location of Primary Dull Characteristic	5. Bearing & Seals	6. Undersize 16th's inch	7. Other Dull Characteristic	8. Reason Pulled

0-5-BT-S/G-X-I-ER-TD

INTRODUCTION

The IADC Fixed Cutter Work Group this year audited the 1987 Fixed Cutter Dull Grading System and determined that some minor refinement was necessary. As was the case with introduction of the fixed cutter dull grading system in 1987, the objective of this revision was to facilitate creation of a "mental picture" of a worn bit's physical condition through a standardized evaluation of certain bit characteristics.[1]

First Revision to the IADC Fixed Cutter Dull Grading System – SPE 23939 (1992)

4

A Major Shortcoming

SPE Online Education

The grading system is subjective

Figure: Example of an 8-1/2” PDC dull grading.

SPE International

And does not capture all the details

5

Good System When Devised (1980’s)

SPE Online Education

http://www.digicamhistory.com/1987.html

https://www.computerhistory.org/timeline/1987/

1987- and before: Digital cameras and computers were not commonplace, and were expensive. Best option they had at that time.

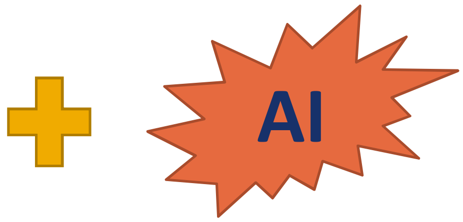
https://www.core77.com/posts/23869/Forum-Frenzy-20-Years-of-Mobile-Phones-in-Japan

SPE International

6

But Times have Changed

https://www.theatlantic.com/photo/2018/11/smartphones-are-everywhere/575878/

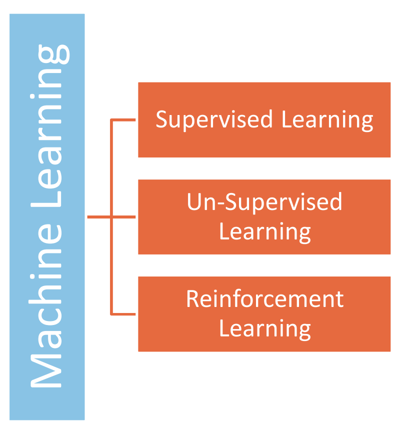


Can we not automate the image capturing of bit damage and use AI to classify bit damage into a standardized output?

7

A Little Something About AI

- AI – It is more than a buzzword
- AI – Non fictional version
  - Able to do some tasks better than humans
- AI – Includes Machine Learning
- AI – Implies algorithms and models
  - Coded by humans
  - Learnt using data



8

Machine Learning Approaches

Input → Feature Selection (Manual) → Features → Shallow Classifier → Output

- Shallow ML
  - Manually select features
  - Time consuming

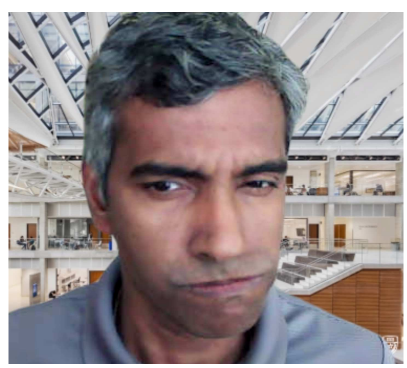
Input → Feature Learning + Classifier → Output

- Deep ML
  - Automatically detects features
  - Black box model

9

AI & Its Adoption Problem

- Can I trust the output? Why is the AI output like this?
  - Can I trust it to help me prevent stuck pipes?
  - Can I trust it to help improve ROP?
- Yes, good. It helped, but can it do even better?
- Is this the best model that can be built?
  - What if new data becomes available?
- Do I need someone monitoring the AI system?

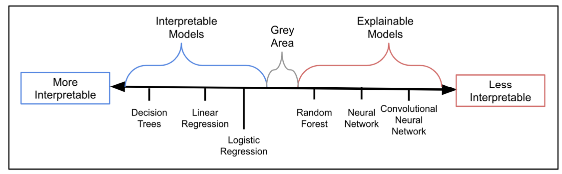


(Me when the AI output does not make sense)

10

Explainable and Interpretable AI

- Not the same
  - Interpretable AI – Model is easily understood by a human
  - Explainable AI – Explaining a black box model after the fact
- Explainability / Interpretability as important as accuracy
- Often ignored in Oil and Gas (and other industries)
  - Is an afterthought



https://towardsdatascience.com/interperable-vs-explainable-machine-learning-1fa525e12f48

- Explainability not always needed
  - Non serious consequences
  - Validated extensively

Are explainable models more accurate than interpretable models?

11

Dull Grading Directly from Digital Photos

Drill Bit Image

Cutter Detection

Grading of Individual Cutters

Cutting Structure				Bearing	Gauge	Remarks	
1. Inner Rows - Average Cutter Wear	2. Outer Rows - Average Cutter Wear	3. Primary Dull Characteristic	4. Location of Primary Dull Characteristic	5. Bearing & Seals	6. Undersize 16th's inch	7. Other Dull Characteristic	8. Reason Pulled

12

Object Detection Algorithms

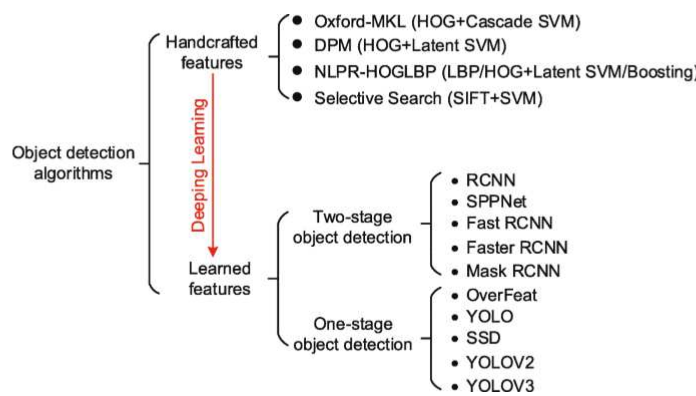
SPE Online Education

Localization

Location of an object in an image

Classification

Assigning a class to that object

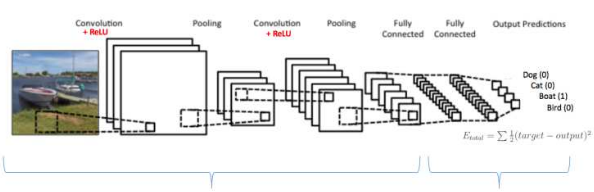


Xiao, Y., Tian, Z., Yu, J. *et al.* A review of object detection based on deep learning. *Multimed Tools Appl* **79,** 23729–23791 (2020). https://doi.org/10.1007/s11042-020-08976-6

Convolutional Neural Network

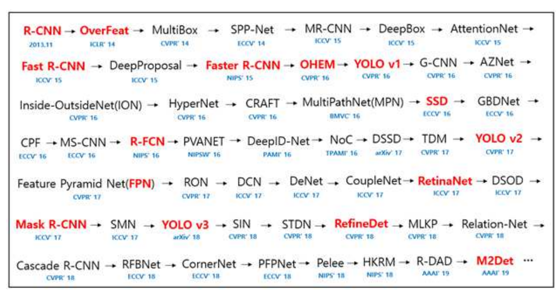
SPE Online Education

CNN – Category of Neural Networks proven to be very effective in object detection



https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/

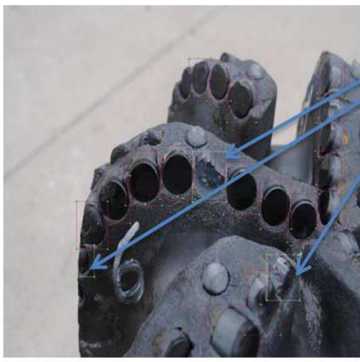
Various CNN architecture over the years



https://github.com/hoya012/deep_learning_object_detection

Convolutional Neural Network for Cutter Detection

SPE Online Education



Derailed cutters
cutter_d class

All other cutters belong to
cutter class

On COCO dataset

Method	mAP	Time (ms)
SSD321	28.0	61
DSSD321	28.0	85
R-FCN	29.9	85
SSD512	31.2	125
DSSD513	33.2	156
FPN FRCN	36.2	172
RetinaNet-50-500	32.5	73
RetinaNet-101-500	34.4	90
RetinaNet-101-800	37.8	198
YOLOv3-320	28.2	22
YOLOv3-416	31.0	29
YOLOv3-608	33.0	51

SPE International

Yolo V3 was chosen due to its inference speed, coupled with its ability to detect objects accurately

15

Dataset Used in Study

SPE Online Education

Data from 13 different bit runs

- 103 drill bit images, 1944 cutters
- 22 images for testing, 424 cutters
- 800 images synthesized, 10000 cutters

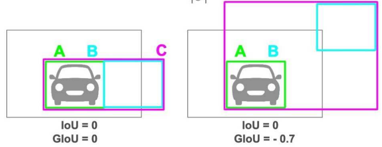
SPE International

16

Results from Training

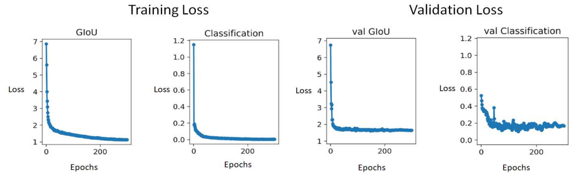
SPE Online Education

$$GIoU = IoU - \frac{|C\backslash(A \cup B)|}{|C|}$$

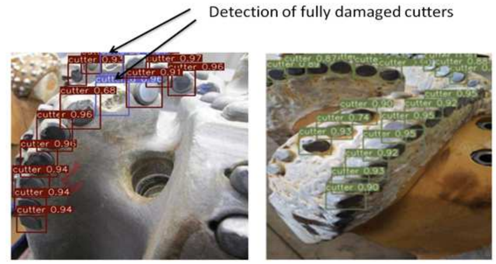


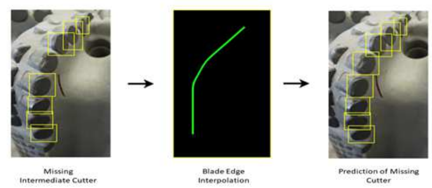
Source: https://www.youtube.com/watch?v=ENZBhDx0kqM

Training Loss Validation Loss



Detection of fully damaged cutters





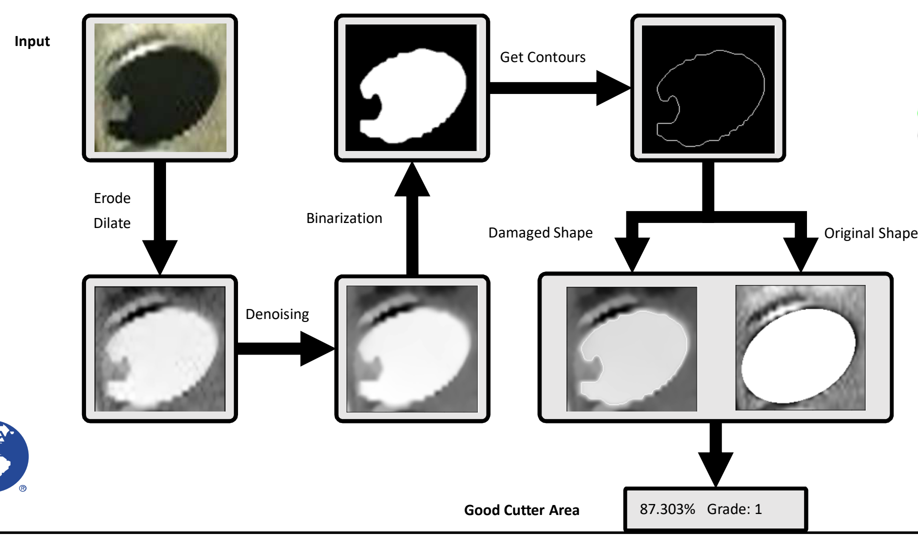
SPE International

Cutter detection accuracy >97%

17

Cutter Damage Quantification

SPE Online Education



OpenCV

SPE International

18

Damage Grading

Original Cutter Image | Damaged Cutter Contour | Estimated Pre-Damage Contour

Good Cutter Area % 99.79, Grade: 0

Original Cutter Image | Damaged Cutter Contour | Estimated Pre-Damage Contour

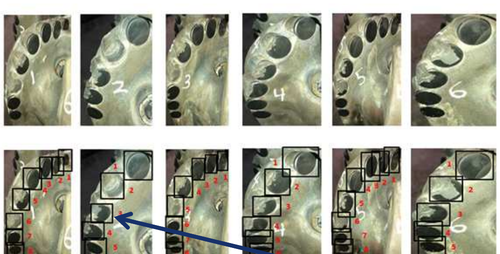
Good Cutter Area % 60.71, Grade: 3

Grading	0	1	2	3	4	5	6	7	8
Good Cutter Area %	100 - 93.75 %	93.74 - 81.25 %	81.24 - 68.75 %	68.75 - 56.25 %	56.24 - 43.75 %	43.74 - 31.25 %	31.24 - 18.75 %	18.74 - 6.25 %	6.24 - 0.00 %

SPE International

19

Full Bit Damage Quantification



Average Good Cutter Area %	Average Algorithm Assigned Grade
80.99%	2

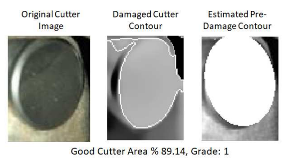
Blade No.	Cutter No.	Good Cutter Area %	Algorithm Assigned Grading	Equivalent IADC Grading	Blade No.	Cutter No.	Good Cutter Area %	Algorithm Assigned Grading	Equivalent IADC Grading
1	1	87.20%	1	1	3	8	96.81%	0	0
1	2	95.77%	0	0	4	1	90.89%	1	1
1	3	98.55%	0	0	4	2	94.47%	0	2
1	4	92.62%	1	1	4	3	66.04%	3	4
1	5	66.22%	3	3-4	4	4	80.02%	2	3
1	6	0.00%	8	8	4	5	100.00%	0	0
1	7	98.52%	0	0	4	6	97.09%	0	0
1	8	97.80%	0	0	5	1	97.53%	0	0
2	1	85.21%	1	1	5	2	98.52%	0	0
2	2	0.00%	8	8	5	3	100.00%	0	0
2	3	70.39%	2	3	5	4	92.85%	1	0
2	4	88.44%	1	2	5	5	64.73%	3	3
2	5	95.49%	0	0	5	6	66.81%	3	7
3	1	100.00%	0	0	5	7	98.15%	0	0
3	2	97.45%	0	0	5	8	95.94%	0	0
3	3	95.54%	0	0	6	1	80.88%	2	2
3	4	74.16%	2	3	6	2	34.82%	5	5
3	5	0.00%	8	8	6	3	60.22%	3	3
3	6	87.50%	1	1	6	4	98.10%	0	0
3	7	98.06%	0	0	6	5	96.85%	1	1

SPE International

Requirements Identified from Study

Multiple images are needed

Shaped cutters are OK
- Need pre-drill photos



Lighting and image resolution are important

21

Revisiting IADC Dull Grading

Bond Failure
Broken Cutter
Chipped Cutter
Erosion
Flat Crested Wear
Heat Checking
Lost Cutter
No Characteristic
Rounded Gauge
Worn Cutters
Etc.

With more data more classes can be included

Cored
Heat Checking
Junk Damage
Ring Out
Wash Out
Etc.

Requires other contextual data

Cutting Structure				Bearing	Gauge	Remarks	
1. Inner Rows - Average Cutter Wear	2. Outer Rows - Average Cutter Wear	3. Primary Dull Characteristic	4. Location of Primary Dull Characteristic	5. Bearing & Seals	6. Undersize 16th's inch	7. Other Dull Characteristic	8. Reason Pulled

We have shown that this is possible

Blade-wise images make this simpler

Difficult from a few 2D images, but scale markers can make this possible

22

Revisiting Drill Bit Forensics

SPE Online Education

Forensics on a used drill bit can help determine changes to Bit /BHA design and (or) drilling parameters.

Run 5 Run 7 Run 8

SPE-205844-MS (ATCE 2021)
Witt-Doerring et al. Quantifying PDC Bit Wear in Real-Time and Establishing an Effective Bit Pull Criterion Using Surface Sensors

SPE International

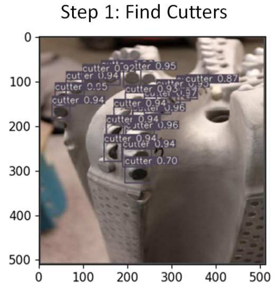
But needs to be done as quickly as possible.

23

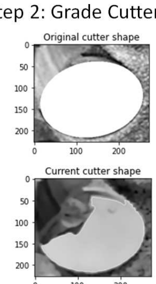
Towards Automating Root Cause of Failure

SPE Online Education

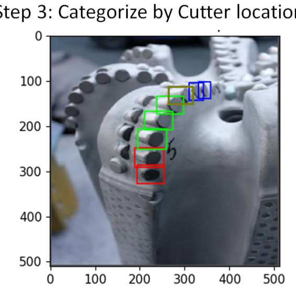
Step 1: Find Cutters



Step 2: Grade Cutters



Step 3: Categorize by Cutter locations



Step 4: Classifier to Infer Root Cause

A > 0.3

AA

B <0.5

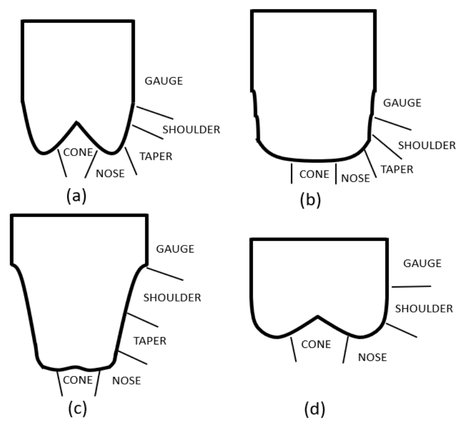
BB

CC

SPE International

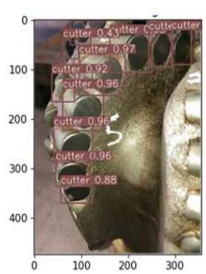
24

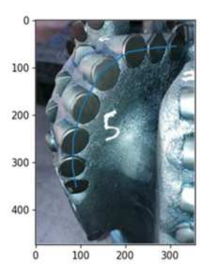
Locating the Cutters

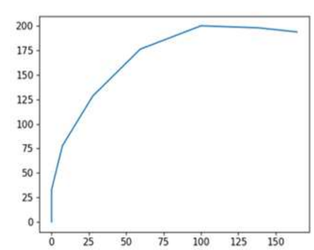


- Identify the main blade in the image
- Scale the blade profile for comparison to a reference profile
- Categorize cutters as belonging to the cone, nose, shoulder or gauge

Locating the Cutters





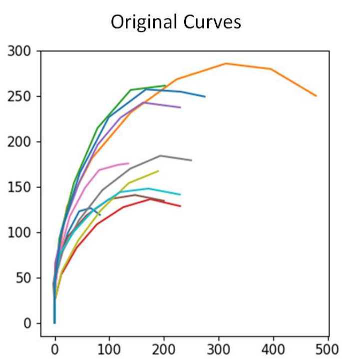


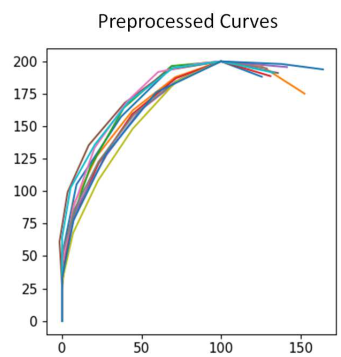
Identifying the main blade in the image

- Algorithm used inspired by the gift wrapping algorithm (Jarvis, R. A., 1973)
  - Generally used to find the convex hull given a set of points
- The main adaptation done was to start with the bottom-most cutter in the image, and move only clockwise.

Locating the Cutters

SPE Online Education





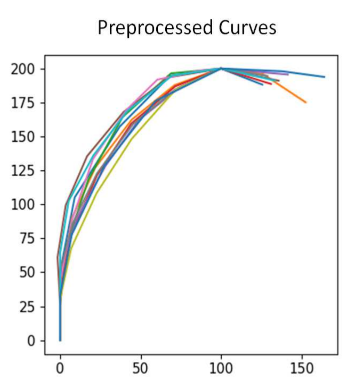
The curve is rescaled to a predetermined scale, using the top most cutter in the image as the basis.

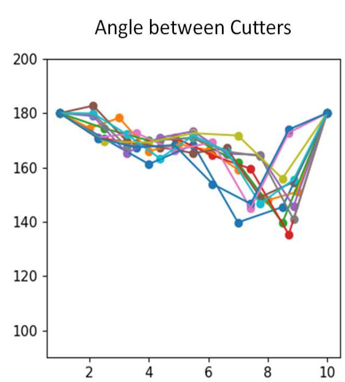
SPE International

Curves shown for a multiple blade profiles

Locating the Cutters

SPE Online Education



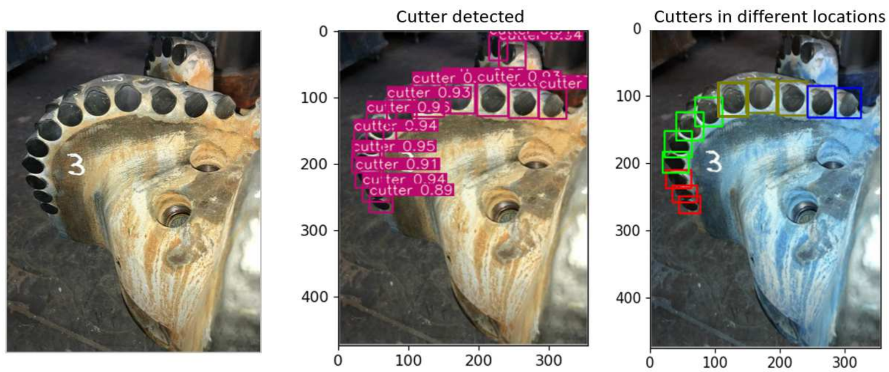


- Ideally, it is expected that the angles between adjacent cutters would start from 180 degrees (at the gauge)
- then reduce to around 150 degrees (at the shoulder and the nose)
- finally go back to 180 degrees (at the cone).

SPE International

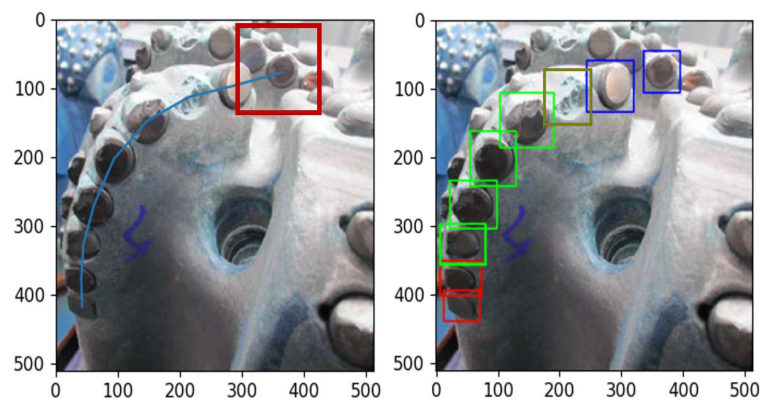
Through proper tuning of these angle change thresholds, the cutters can be successfully separated as belonging to one of the 4 different locations.

Locating the Cutters



29

Locating the Cutters: Potential for Errors

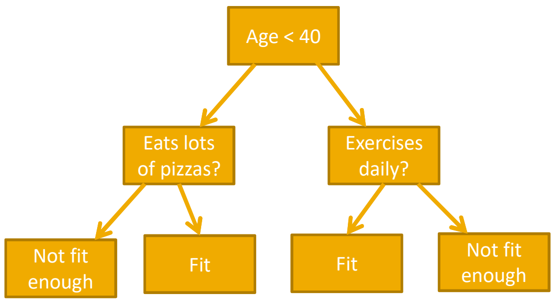


30

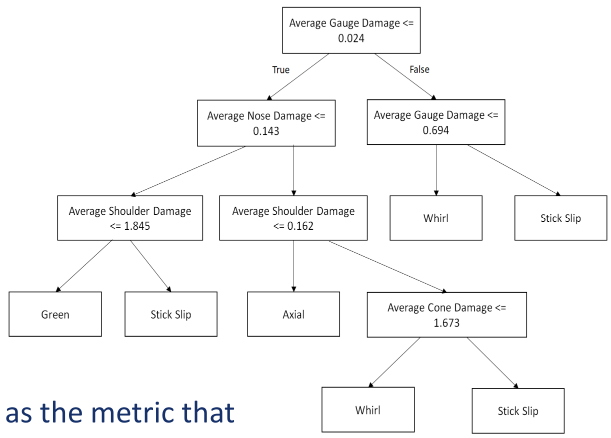
Build a Classifier

SPE Online Education

Choice: Decision Tree



Dataset Size: 24 Drill Bits



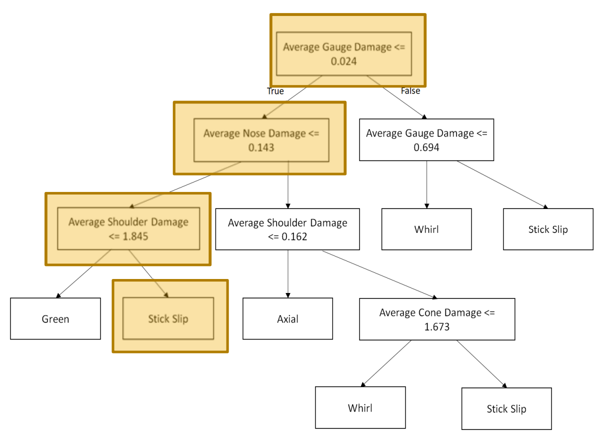
SPE International

Gini impurity was chosen as the metric that measures the quality of the data split in the model

31

Case 1

SPE Online Education



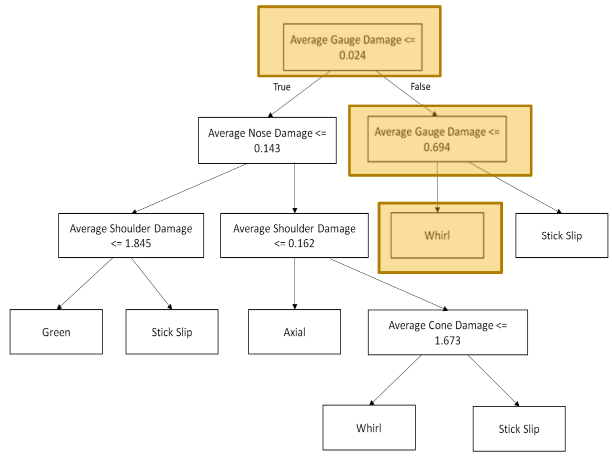
Location	Cone	Nose	Shoulder	Gauge
Average damage	0	0	3.41	0

32

Case 2

SPE Online Education

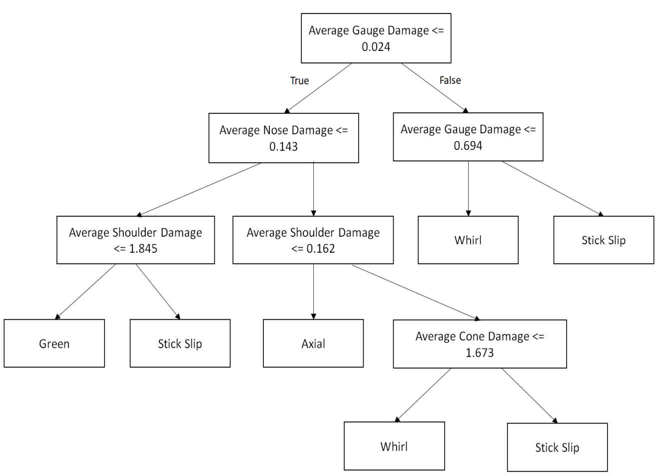
Location	Cone	Nose	Shoulder	Gauge
Average damage	0	0.33	1.58	0.05



33

Note & Reminder

SPE Online Education

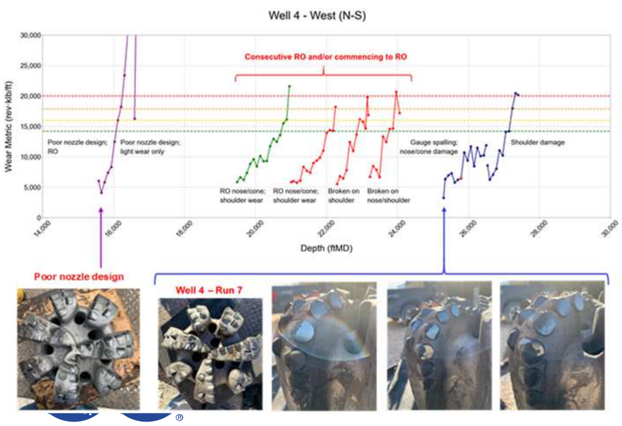


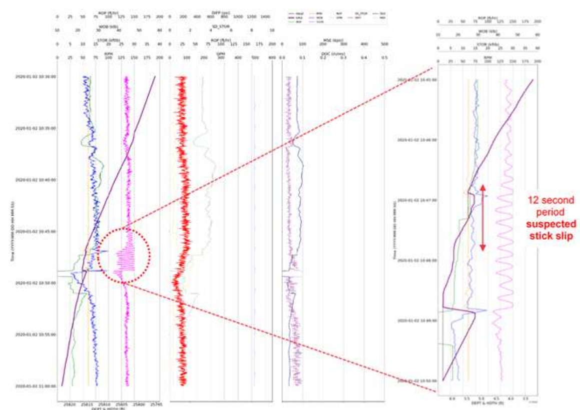
- This is an expert system with interpretability embedded in it
- This decision tree will change, based on a variety of factors
  - Including Profile

34

Combining with Time Series Data

SPE-205844-MS (ATCE 2021)
Witt-Doerring et al. Quantifying PDC Bit Wear in Real-Time and Establishing an Effective Bit Pull Criterion Using Surface Sensors



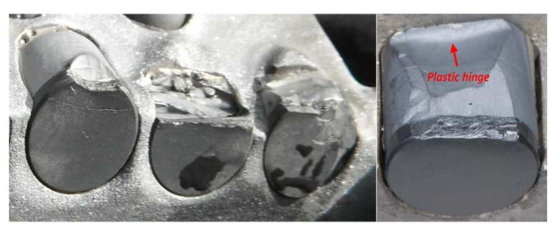


35

Capture More Specific Cutter / Bit Damage

Smooth Wear

Interfacial Delamination



Tangential Fractures

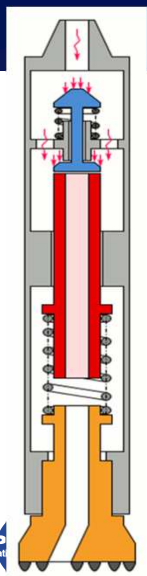
Micro Spalls

Ring-Out

Poor Nozzle Design

36

Percussion / Hammer Bit



The cutters are mainly on the bottom surface

https://hartrusion.com/en/hydrdthhammer/drivemechanisms/

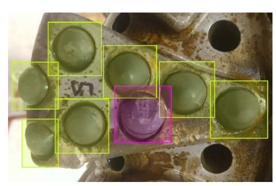
Percussion/Hammer Bit – Results on Dataset

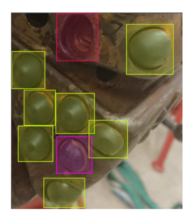
Class 0: Green

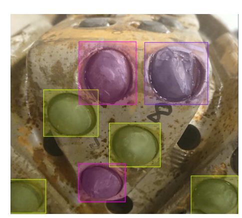
Class 1: Worn

Class 2: Chipped

Class 3: Pop-out







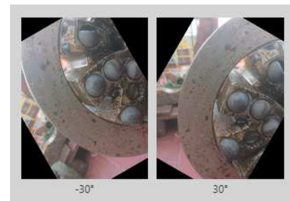
- 548 cutters labelled from 57 different bit images
- Class balance: class 0-3 have 365, 80, 24, 79 samples, respectively

Percussion/Hammer Bit – Data Augmentation

Original

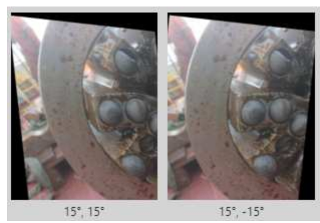
Flip
(Vertical and horizontal)

Brightness
(Between 30% and +30%)



Rotation
(Randomly from -90% and +90%)

Grayscale



Shear

...

Percussion/Hammer Bit - Localization

- Generated the outer ellipse by fitting all the detected cutters' locations
- Split Outer / Inner rows cutters (2/3 diameter)
- Cutters in both outer and inner area – determined by the area overlapped

Revisiting IADC Dull Grading

- Do we need a new IADC dull grading scheme?
- What problem is it solving?
  - Subjectivity is not removed
- Why create a mental picture when we can have an actual picture
- What is a desired standardized output?
  - Why do we want a standardized output?

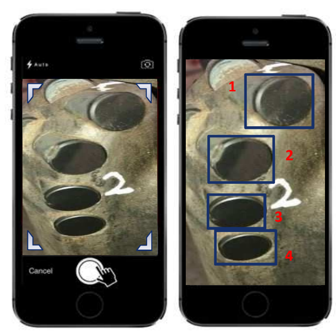
Get involved in industry discussions

Lots of industry participants

Paul Pastusek

41

Build Mobile Phone Apps



- **Mobile apps** that assist in taking quality blade-wise and other guided photos as appropriate

Yes, Yolo can be run on Android phones

https://github.com/nightsnack/YOLObile

42

Closing Comments

- Drill bits are fundamental to reduce the cost of any drilling operation
  - Oil and Gas Wells
  - Geothermal Anywhere Wells
- Drill bit forensics are key – and not should not be subjective
- AI can and should be applied to improving and accelerating drill bit forensics
  - Great opportunity for drill bit vendors and entrepreneurs
- When building AI models think long-term
  - Plan for interpretability / explainability and model extensibility in addition to accuracy

43

Acknowledgement

- Thanks to SPE and especially the SPE DUPTS Technical Section for supporting this presentation, and the dissemination of ideas and research
- Thanks to RAPID consortium and our research sponsors

44

References

- Ashok, P., Chu, J., Witt-Doerring, Y., Yan, Z., Chen, D., & van Oort, E. (2021, March). Drill Bit Failure Forensics using 2D Bit Images Captured at the Rig Site. In SPE/IADC International Drilling Conference and Exhibition. OnePetro. SPE 204124-MS https://doi.org/10.2118/204124-MS
- Ashok, P., Vashisht, P., Kong, H., Witt-Doerring, Y., Chu, J., Yan, Z., Chen, D., van Oort, E. & Behounek, M. (2020, October). Drill Bit Damage Assessment Using Image Analysis and Deep Learning as an Alternative to Traditional IADC Dull Grading. In SPE Annual Technical Conference and Exhibition. Society of Petroleum Engineers. SPE 201664-MS https://doi.org/10.2118/201664-MS
- Witt-Doerring, Y., Pastusek, P., Ashok, P., & van Oort, E., (2021 Sept). Quantifying PDC Bit Wear in Real-Time and Establishing an Effective Bit Pull Criterion Using Surface Sensors. In SPE Annual Technical Conference and Exhibition. Society of Petroleum Engineers. SPE-205844-MS
- Paul Pastusek – Drill Bit Forensics (https://www.drillingcontractor.org/vpd-registration-04122021)
- Cynthia Rudin – Please stop doing explainable AI !!! (https://www.youtube.com/watch?v=I0yrJz8uc5Q)
- Yolo on Android – (https://github.com/nightsnack/YOLObile)
- Ujwal Karn CNN blog – (https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/)
- SPE DUPTS student competition – (https://connect.spe.org/dupts/events/spe-dupts-competition)

45

Questions

Thank You for Your Time

46