You Only Look Twice! for Failure Causes Detection of Drill Bits

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16th Feb, 2023

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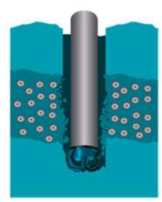
Introduction

Drill bits



Damage to the PDC cutters

Background

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PDC Damage and root causes

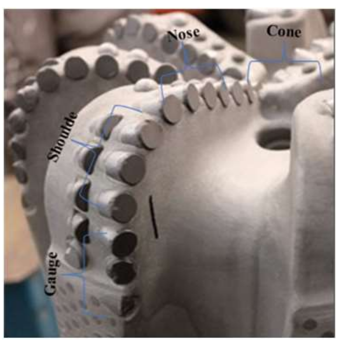

Figure 1: PDC bit structure.

Figure 2: Mechanical root causes.

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Background

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Smooth Wear

Thermal Damage

Normal Fracture

Formation transition

Tangential Fracture

Core-out

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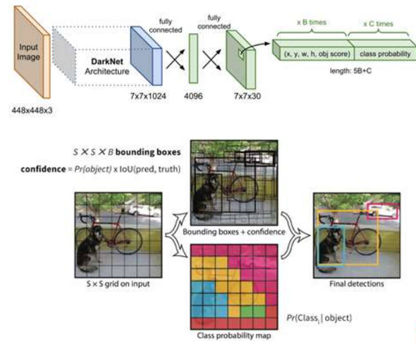
Background

YOLOV5

- The most typical pre-trained models for one-stage object detectors are YOLO (YOU ONLY LOOK ONCE)
- It works by dividing the image into N grids, each having an equal dimensional region of SxS.
- For each N it performs the detection and classification at once



Source: https://lilianweng.github.io/posts/2018-12-27-object-recognition-part-4/

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Literature Review

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Study	Purpose	Method
Dupriest, F. E. et al,2020	Provided a physical knowledge of bit damage and created mitigation strategies.	Manually by experts
A0 Witt-Doerring, Y. et al, 2021	Present a metric methodology to help quantify PDC bit wear and failure using real-time surface sensor data and PDC dull images	Using the proposed PCD bit wear metric, drilling data, and bit images via experts
Ashok, P. et al., 2020	Innovative approach to bit damage classification	Deep learning techniques (YOLO v3)
Ashok, P. et al., 2021	To identify the bit failure cause	Decision trees based on the cutter grades and location

Objective

Automating the process of identifying the location, type, and root cause of drill bit failure using bit images by building several models through a pre-trained YOLOV5.

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Methodology

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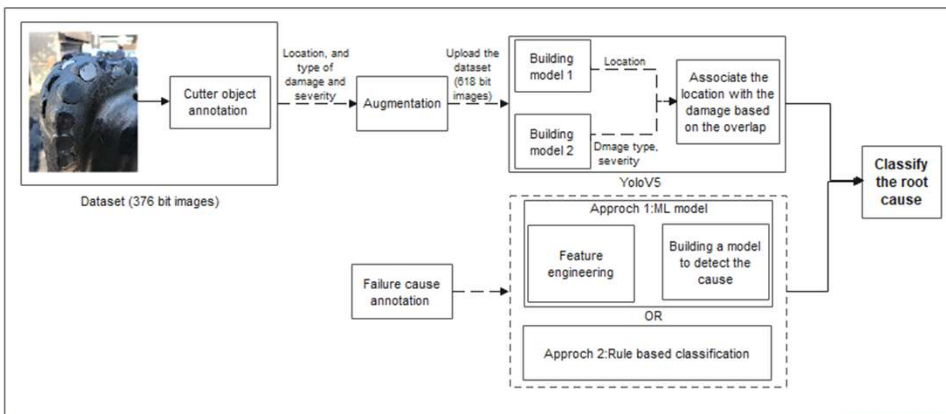

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Dataset

Number of Drilling bit	46 drilling bit with a total of 367 images from different angles
Number of cutters	2360-3200 cutters
Source	[4]
Preprocessing	• Annotation (location, type, and severity). • Dataset splitting (training set (206-bit images), validation set (59-bit images), testing set (30-bit images)). • Augmentation (618-bit images).

Dataset Annotation

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Cutter Location Annotation

Cutter Damage Annotation

Identifying the main damages

Failure Cause Annotation

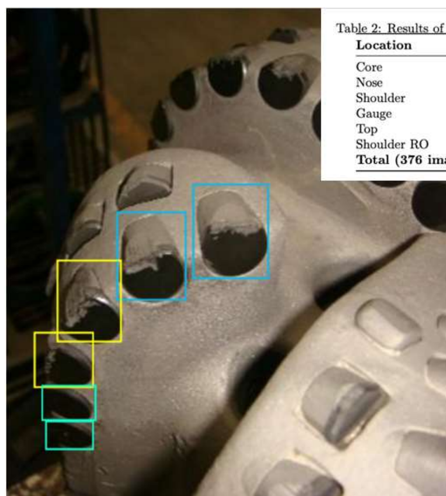

Table 2: Results of Location Detection of Cutter Annotation

Location	Class	Annotations
Core	C	381
Nose	N	626
Shoulder	Sh	647
Gauge	G	647
Top	top	46
Shoulder RO	Shoulder RO	14
Total (376 images)	**6 classes**	**2361**

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Dataset Annotation

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- Cutter Location Annotation
- **Cutter Damage Annotation**
- Identifying the main damages
- Failure Cause Annotation

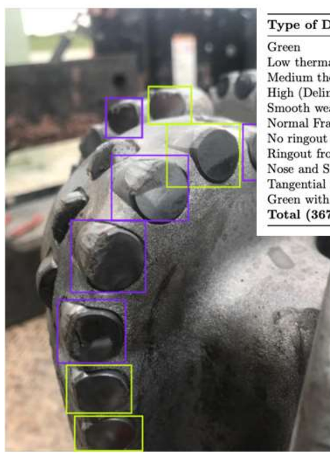

Table 3: Results of Damage Detection of Cutter Annotation.

Type of Damage	Class	Annotations	Comments
Green	G_G	1,465	Over represented
Low thermal wear	L_Th	705	Over represented
Medium thermal wear	M_Th	256	
High (Delimitation, missing cutters)	H	296	
Smooth wear	L_SW	320	
Normal Fracture	NF	89	Under represented
No ringout from top view	no_ro	26	Under represented
Ringout from top view	RO	19	Under represented
Nose and Shoulder missing area	Shoulder_RO	13	Under represented
Tangential Fracture	TF	6	Under represented
Green with TF line present	G_TF	5	Under represented
Total (367 images)	**11 classes**	**3200**	

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Dataset Annotation

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- Cutter Location Annotation
- Cutter Damage Annotation
- **Identifying the main damages**
- Failure Cause Annotation

Hierarchy of damages
Fractures
Missing
Thermal
Smooth wear

Damages for Bit 45

	Damage	Location	Damage	Location	Damage	Location
45_125	no_ringout					
45_127	mm Thermal	nsh				
45_128	NF	Nose				
45_128	Mmm Thermal	Nshsh				
45_129	1 missing	shoulder	ml Thermal	shg		
45_130	NF	Nose	3 missing	shgg	M Therma	Sh
45_131	I bw	Nose	Mm Thermal	Shsh	2 missing	Gg
45_132	mmm Thermal	nshsh				

	C	N	Sh	G	Stick-Slip	Axial	Whirl-In-Casting	Whirl	Thermal	Core out	Nose-Ringout	Shoulder-Ring	Smooth Wear
19	Green	NF	L Thermal	L Thermal	0	1	0	0	1	0	0	0	0
20	Green	L Thermal	L Thermal	L Thermal	0	0	0	0	1	0	0	0	0
22	Green	H Missing	L Thermal	Green	0	0	0	0	1	0	1	0	0
25	Green	L Thermal	M Thermal	Green	0	0	0	0	1	0	0	0	0
26	Green	L Thermal	M Thermal	Green	0	0	0	0	1	0	0	0	0
29	Green	NF	L Thermal	L SW	0	1	0	0	1	0	0	0	1
30	Green	L Thermal	L Thermal	Green	0	0	0	0	1	0	0	0	0
31	Green	L Thermal	M Thermal	Green	0	0	0	0	1	0	0	0	0
39	Green	NF	L Missing	L Missing	0	1	0	1	0	0	0	0	0
40	Green	NF	M Thermal	Green	0	1	0	0	1	0	0	0	0
41	Green	H Missing	H Missing	H Missing	0	0	0	1	0	0	1	1	0
42	Green	NF	TF	H Missing	0	1	0	1	0	0	0	0	0
45	Green	NF	M Thermal	H Missing	0	1	0	1	0	0	0	0	0
46	Green	NF	M Thermal	H Missing	0	1	0	1	0	0	0	0	0

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Dataset Annotation

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- Cutter Location Annotation
- Cutter Damage Annotation
- Identifying the main damages
- **Failure Cause Annotation**

Table 1: Bit failure cause per main damage and location

	Core	Nose	Shoulder	Gauge
Smooth wear	Smooth wear	Smooth wear	Smooth wear	Smooth wear
Thermal wear (Low/Medium)	Thermal wear	Thermal wear	Thermal wear	Thermal wear
Tangential Fracture	Stick slip	Hard Formation Transition	Whirl (lateral)	Whirl (lateral) if no other damages then inside casing
Normal Fracture	Stick slip	Axial	Whirl (lateral)	Whirl (lateral) if no other damages then inside casing
Nose ringout (High missing)		Hard Formation Transition		
Shoulder ringout (High missing)			Soft formation transition	
Core out (High missing)	Structural overload			
Low Missing	Stick slip	Axial	Whirl (lateral)	Whirl (lateral)

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Preparing Data for training

Step1: Resize to 416x416

Step2: Evaluation Splits

Random: where 90 (around 25%) random image bits across the different image bits were used for testing while the 277 rest images were used for training

Holdout: Split the data to 36 drill bits image sets for training and 10 drill bits image sets for testing (around 21% training and 79% for testing)

Dataset Augmentation

- Flip: Horizontal
- 90° Rotate: Clockwise, Counter-Clockwise
- Brightness: Between -25% and +25%

This will increase the training images from 205 (60% of images) to 615 images.

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Cutter Detection Models

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- 2 YOLO v5 models, one for the location and damage type
- Defult hyperparameters
- Trained for around 250 epochs

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Location and damage association

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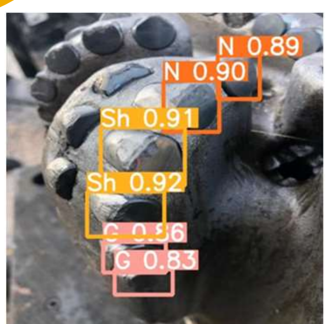
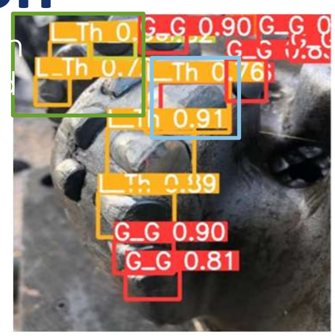


Overlapping bounding box (Green 0.4 and Low Thermal 0.76)



1- Calculate the Euclidean distance between the center of the bounding boxes.
2- Go from the location and determine the overlapping damages with a threshold of 0.3
3- Check the confidence score to pick the overlapping object with the highest test score

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Failure Cause Classification

Approach 1: ML models:
- Decision Tree
- Random Forests

All Using defult hyperparameters

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Failure Cause Classification

Approach 2: Rule based approch

```
Algorithm 1 Rule-Based Failure Cause Classification (unfractured cutters)
  Input : bitinfo              ▷ a dictionary containing cutters' locations coupled with the damages
 procedure isGreen
    if The number of green cutters is higher than 80% of the total bits detected then
        return True   ▷ Cutters with smooth wear are counted as half due to probable mixup with green
    else
        return False

 procedure isSmoothWear
    if The number of cutters with smooth wear is higher than the bits with thermal wear then
        return True ▷ Cutters with low thermal wear are counted as (0.75*cutter) due to probable mixup
 with smooth wear
    else
        return False

 procedure isThermalWear
    if The number of cutters with thermal wear on the shoulders are higher than the number of main
 blades (7 in the bits studied) then
        return True   ▷ Cutters with medium thermal wear are counted as (1.25*cutter) due to stronger
 indication
    if The number of cutters with thermal wear on any location are higher than the number of main blades
 * 2 (14 in the bits studied) then
        return True   ▷ Cutters with medium thermal wear are counted as (1.25*cutter) due to stronger
 indication
    else
        return False
```

```
Algorithm 2 Rule-Based Failure Cause Classification (ringouts)
  Input : bitinfo              ▷ a dictionary containing cutters' locations coupled with the damages
 procedure isRingout                                                         ▷ from the top view
    if The top view has a ringout 'RO' then
        return True
    else
        return False

 procedure isCoreout
    if number of missing core cutter is greater than 1 then
        return True
    else
        return False

 procedure isNoseRingout
    if number of missing nose cutter is greater than 5 then
        return True
    if number of detected unmissing cutter is less than 10 then  ▷ To account for errors in the detection
 location model
        return True
    if 'Shoulder_RO' damage is detected for 'Shoulder_RO' location then
        return True
    if isRingout() and number of missing nose cutter is greater than the number of missing shouldere
 cutter and not isCoreout() and number of heavily damaged nose cutter is greater than 2 then      ▷ To
 account for errors in the detection model
        return True
    else
        return False

 procedure isShoulderRingout
    if number of missing shoulder cutter is greater than 5 then
        return True
    if 'Shoulder_RO' damage is detected for 'Shoulder_RO' location then
        return True
    if isRingout() and number of missing shoulder cutter is greater than the number of missing nose cutter
 and not isCoreout() and number of heavily damaged shoulder cutter is greater than 2 then ▷ To account
 for errors in the damage detection model
        return True
    else
        return False
```

```
Algorithm 3 Rule-Based Failure Cause Classification (fractured cutters)
  Input : bitinfo              ▷ a dictionary containing cutters' locations coupled with the damages
 procedure isStickSlip
    if The number of missing core cutters equals 2 and is not isNoseRingout() and is not isCoreout() then
        return True                    ▷ a forgiveness of 1 missing core cutter is due to possible error
    if The number of heavily damage core cutters or medium thermal wear equals 2 and is not is-
 NoseRingout() and is not isCoreout() then
        return True                          ▷ a forgiveness of 1 heavily damage core cutter is
 due to possible error and inclusion of thermal wear is due to misclassification sometimes between normal
 fracture and partial delimitation with medium thermal wear
    else
        return False

 procedure isAxiel
    if Presence of cutters with 'H' annotation and is not isNoseRingout() and is not isCoreout() then
        return True
    if Presence of cutters with normal fracture then
        return True
    if Presence of cutters with medium thermal wear on nose and shoulder is 75% green then
        return True
    if Number of cutters with medium thermal wear on nose is greater than 1.5 * cutters with medium
 thermal wear on shoulder then
        return True     ▷ inclusion of thermal wear is due to misclassification sometimes between normal
 fracture with medium thermal wear, thermal wear based on literature should affects shoulders more than
 any other part, therefore a strong indication of misclassification

    return False

 procedure isWhirlIncasing
    if (presence of heavily damaged cutters on gauge or multiple medium thermal wear) and the shoulder
 cutters are at least 75% green and do not contain heavily damaged cutters then
        return True      ▷ inclusion of thermal wear is due to misclassification sometimes between heavy
 damages with medium thermal wear
    else
        return False

 procedure isWhirl
    if isWhirlIncasing() then
        return False
    if presence of heavily damaged on gauge or (shoulder and not isShoulderRingout()) or the presence of
 tangential fracture on nose then
        return True      ▷ inclusion of thermal wear is due to misclassification sometimes between heavy
 damages with medium thermal wear
    else
        return False
```

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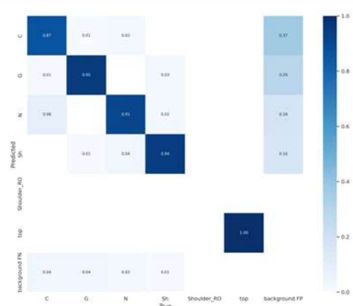
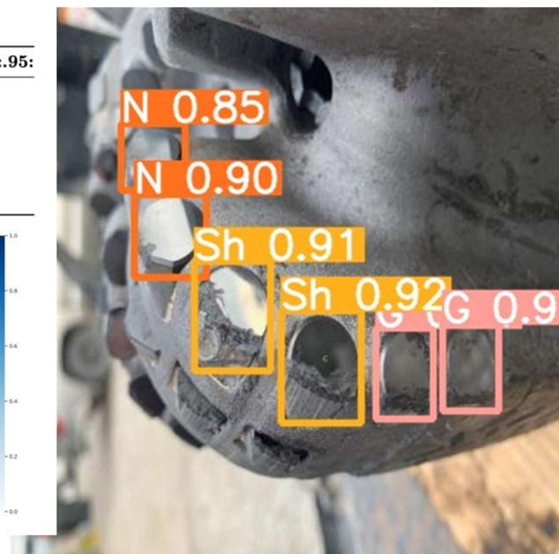
Cutter's location detection

Table 4: Cutter location model results (10 Drill bits test set)

Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95:
All	80	515	0.957	0.95	0.973	0.699
C	80	84	0.949	0.917	0.955	0.641
G	80	140	0.973	0.943	0.971	0.658
N	80	139	0.954	0.914	0.961	0.647
Sh	80	142	0.943	0.979	0.984	0.725
Top	80	10	0.966	1	0.995	0.826





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Damage type and severity identification

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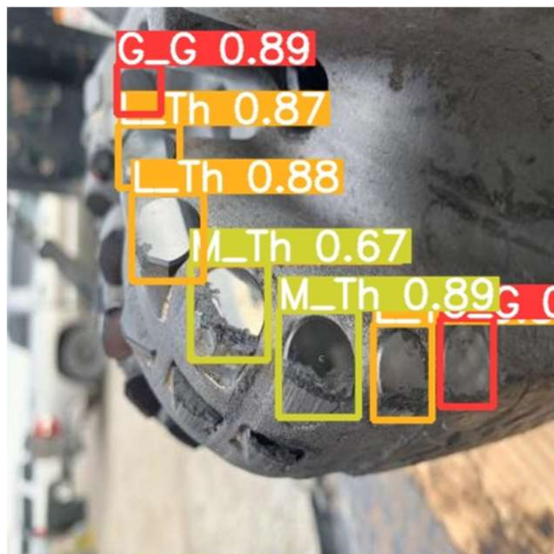
Table 5: Cutter Damage model results (10 Drill bits test set)

Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95:
all	80	731	0.646	0.532	0.49	0.35
Green (G_G)	80	349	0.77	0.777	0.851	0.534
Green with TF line (G_TF)	80	1	1	0	0.00318	0.00254
Missing (H)	80	70	0.628	0.443	0.505	0.282
Smooth Wear (L_SW)	80	58	0.218	0.481	0.29	0.225
Low Thermal Wear(L_Th)	80	178	0.516	0.753	0.619	0.444
Medium Thermal Wear (M_Th)	80	51	0.404	0.412	0.4	0.278
Normal Fracture (NF)	80	11	0.202	0.455	0.215	0.134
Ring out (RO)	80	4	0.73	1	0.995	0.696
Tangential Fracture (TF)	80	3	1	0	0.0243	0.0206
No Ring out (no_ro)	80	6	0.99	1	0.995	0.885

Table 6: Cutter Damage model results (random 25% images test set)

Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95:
all	90	913	0.564	0.69	0.664	0.464
G_G	90	452	0.812	0.878	0.877	0.553
G_TF	90	1	0.479	1	0.995	0.995
H	90	84	0.752	0.759	0.772	0.407
L_SW	90	85	0.451	0.474	0.417	0.298
L_Th	90	183	0.535	0.601	0.571	0.406
M_Th	90	81	0.518	0.407	0.438	0.325
NF	90	21	0.428	0.476	0.404	0.293
RO	90	1	0.778	1	0.995	0.497
Shoulder_RO	90	3	0.7	1	0.83	0.432
TF	90	1	0	0	0.00562	0.00506
no_ro	90	1	0.752	1	0.995	0.895



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Damage type and severity identification

Figure 18: Confusion matrix of the cutter location detection model (10 Drill bits test set).

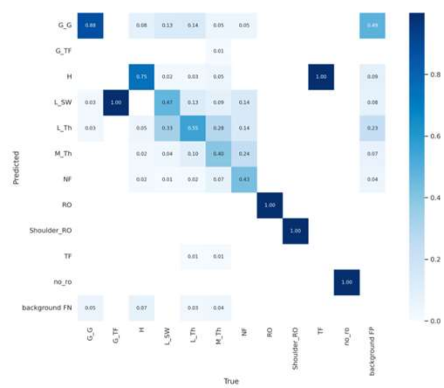

Figure 20: Confusion matrix of the cutter location detection model (random 25% images test set).

Failure Cause Model Accuracy

ML-Based approach

Table 7: Results of the ML based approach (Decision Tree model) for Bit Failure Cause identification

	Smooth Wear	Thermal Wear	Core out	Hard Formation transition	Soft Formation transition	Axiel	Whirl	macro-Average
Accuracy	82.61%	86.96%	89.13%	97.83%	89.13%	97.83%	58.70%	86.02%
Precision	0.83	0.95	0.80	1.00	0.00	0.93	0.67	86.33%
Recall	0.42	0.91	0.50	0.92	0.00	1.00	0.69	73.94%
F1 score	0.56	0.93	0.62	0.96	-	0.96	0.68	78.34%

Table 8: Results of the ML based approach (Random Forest model) for Bit Failure Cause identification

	Smooth Wear	Thermal Wear	Core out	Hard Formation transition	Soft Formation transition	Axiel	Whirl	macro-Average
Accuracy	80.43%	91.30%	93.48%	97.83%	91.30%	93.48%	71.74%	88.51%
Precision	0.75	0.95	1.00	1.00	0.00	0.92	0.81	90.58%
Recall	0.27	0.95	0.63	0.92	0.00	0.85	0.73	72.56%
F1 score	0.40	0.95	0.77	0.96	-	0.88	0.77	78.91%

Rule-Based approach

Table 9: Results of the rule-based approach for Bit Failure Cause identification

	Smooth Wear	Thermal Wear	Core out	Hard Formation transition	Soft Formation transition	Axiel	Whirl	macro-Average
Accuracy	93.48%	93.48%	97.83%	100.00%	100.00%	93.48%	93.48%	95.96%
Precision	0.89	0.97	1.00	1.00	1.00	0.81	0.91	0.94
Recall	0.80	0.95	0.89	1.00	1.00	1.00	1.00	0.95
F1 score	0.84	0.96	0.94	1.00	1.00	0.90	0.96	0.94

Pipeline Evaluation Results

Table 10: Results of complete pipeline

Bit	Existing Failure Causes	Detected Failure Causes by DT	Detected Failure Causes by RF	Detected Failure Causes by rule-based approach
15	**Thermal Wear, Soft to Hard Formation Transition**	Thermal Wear, Soft to Hard Formation Transition, Whirl	Thermal Wear, Soft to Hard Formation Transition, Whirl	**Thermal Wear, Soft to Hard Formation Transition**
20	**Thermal Wear**	Smooth Wear	Smooth Wear	**Thermal Wear**
32	**Thermal Wear, Soft to Hard Formation Transition**	Thermal Wear, Soft to Hard Formation Transition, Whirl	Thermal Wear, Soft to Hard Formation Transition, Whirl	Thermal Wear, Soft to Hard Formation Transition, Whirl
39	**Thermal Wear, Axial, Whirl**	Smooth Wear, Whirl	Thermal Wear, Axial	**Thermal Wear, Axial, Whirl**
47	**Thermal Wear, Whirl**	Thermal Wear	Thermal Wear	Thermal Wear, Axial, Whirl
49	**Thermal Wear, Soft to Hard Formation Transition, Whirl**	Thermal Wear, Soft to Hard Formation Transition	Thermal Wear, Soft to Hard Formation Transition	**Thermal Wear, Soft to Hard Formation Transition, Whirl**
50	**Smooth Wear, Whirl**	Thermal Wear, Whirl	Thermal Wear, Whirl	**Smooth Wear, Whirl**
52	**Thermal Wear, Whirl**	Thermal Wear, Smooth Wear, Whirl	Thermal Wear, Smooth Wear, Whirl	**Thermal Wear, Whirl**
57	**Thermal Wear, Soft to Hard Formation Transition, Axial, Whirl**	Thermal Wear, Smooth Wear, Axial	**Thermal Wear, Soft to Hard Formation Transition, Axial, Whirl**	**Thermal Wear, Soft to Hard Formation Transition, Axial, Whirl**
58	**Thermal Wear, Axial, Whirl**	Thermal Wear, Smooth Wear, Whirl	Thermal Wear, Smooth Wear, Whirl	**Thermal Wear, Axial, Whirl**
Total	**24 failure causes**	15 correctly detected Failure Causes and 8 False detected	18 correctly detected Failure Causes and 6 False detected	**24 correctly detected Failure Causes and 2 False detected**

Discussion

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ML-Based models and Rule-based Failure cause approaches

The hierarchy proposed to identify the main cause of damage per location may over-simplify the problem.

This could be mitigated in the future by using the full damage profile

As the ML models were fit based on the ground truth annotation of the cutter damages, it cannot deal with errors propagating from the damage detection model.

This could be mitigated by data augmentation through adding some perturbation or noise to the features.

When we have a problem that follows some scientific rules, the use of ML models becomes unjustifiable especially with the lack of balanced representative data that allows the ML model to induce those rules.

Start with straightforward solutions and move to ML models just when needed (such as in the object detection approach)

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Discussion

Challenges faced

1. Subjectivity of the domain and limited resources
2. Dimensionality of the problem
3. Annotation

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Conclusion

- Two modules were built, the first model to determine the location and damages of the cutter and the second module is rule-based to identify the associated type and root cause of drill bit failure.
- The results provide good evidence that our models were highly accurate by examining the mAP of the first and second models, which are 0.97 and 0.66-0.49 mAP, respectively.
- The rule-based approach to classifying the failure cause achieved an accuracy of 95% and a macro-average F1-score of 0.94.
- The complete pipeline was able to identify all the 24 failure causes present in 10 bits that were used as a holdout test set.

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Future work
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As future work, we would like to consider
01
Larger dataset containing bit images and drilling data
02
Expert validation to enhance the model accuracy
03
Building a more field friendly interface
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Acknowledgment

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We would like to thank SPE DUPTS Competition team. Also, special thanks to our advisor **Dr. Imane boudellioua** and **Meshal Al-Otaibi**, **Jawhara Al-Mulhim**

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