# Avalon Team

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Canada

**Team members**
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# Objectives

| Existing Grading | Proposed Grading |
|---|---|
| Manual process | Machine Learning (ML) automated process |
| Subjective | Objective |
| Paper-based documentation | Digitized documentation (PDF, CSV) |
| | |

- ✓ MVP1 Web-App-based solution (has been built and deployed)
- MVP2 to enable SMEs feedback (in progress)
- MVP3 upgrade to the new IADC code (futuristic)

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# Dataset & Exploratory Analysis

**Photos/Images:**

- ~1200 images from SPE-DUPTS

**Augmentation:**

- Gray scale & brightness

**EDA Observations:**

- Uneven damage distribution (some damage conditions are more prevalent)
- Image quality has large variations in terms of resolution, angle, and lighting

**Very poor-quality images were excluded !**

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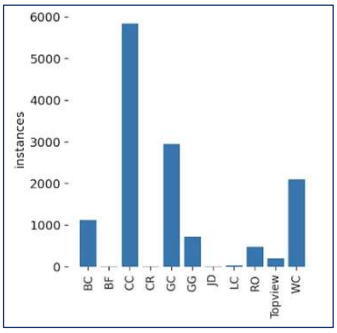
# Image Annotation

**An online annotation tool was used for image annotation**

Labels utilized:

- BC Broken Cutter
- CC Chipped Cutter
- GG Green Gauge
- WC Worn Cutter
- CR Cored-Out
- JD Junk Damage
- BF Bond Failure
- GC Green Cutter
- LC Lost Cutter
- RO Ring-out
- Top view Bit top view

Sample from annotation




Damage type histogram

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# Approach & Workflow

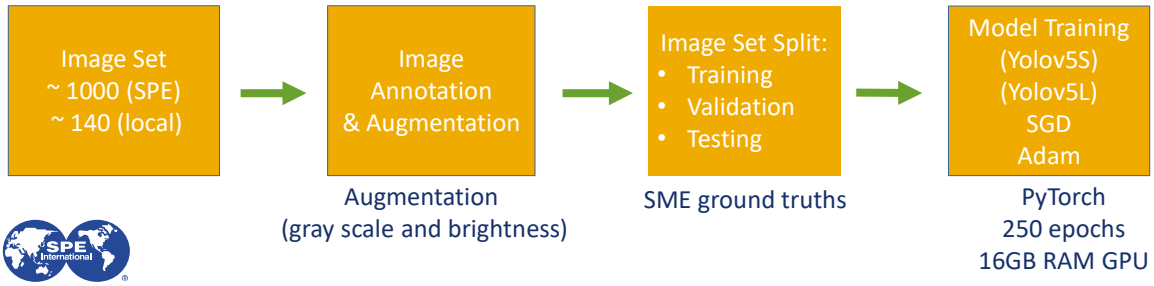
**YOLOv5 Model Training Cycle:**

YOLO You Only Look Once
Open-source single-stage object detection-classification

**Models Investigated:**

S – Small, L - Large

1) YOLOv5S (Adam optimizer)
2) YOLOv5S (SGD optimizer)
3) YOLOv5L (Adam optimizer)
4) YOLOv5L (SGD optimizer)

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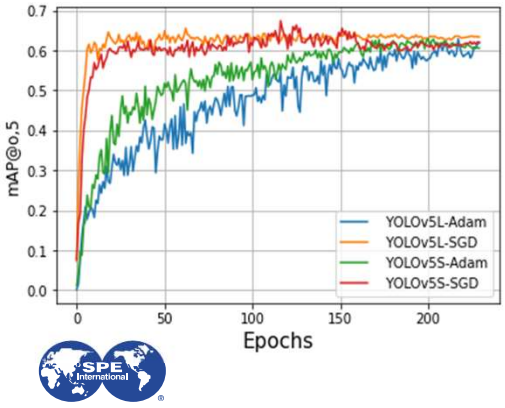
# Model Selection

- Small size models with Adam and SGD optimizers: 2 hours training each (Model size 14MB)
- Large size models with Adam and SGD optimizers: 13 & 8-hours training (Model size 90MB)

✓ Selected model: YOLOv5s with SGD optimizer (small size model preferred for deployment)




**YOLOv5 investigated models results on 65 unseen test set images**

| Model | Labels | Precision | Recall | mAP@.5 |
|---|---|---|---|---|
| YOLOv5-large Adam | 606 | 0.721 | 0.465 | 0.627 |
| YOLOv5-large SGD | 606 | 0.789 | 0.663 | **0.689** |
| YOLOv5-small Adam | 606 | 0.626 | 0.557 | 0.609 |
| YOLOv5-small SGD | 606 | 0.605 | 0.716 | 0.68 |

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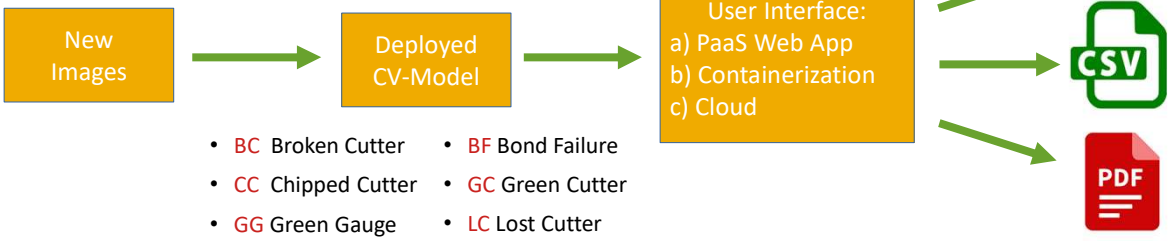
# Minimum Viable Product(MVP)

Webinars

**Model Deployment Cycle:**

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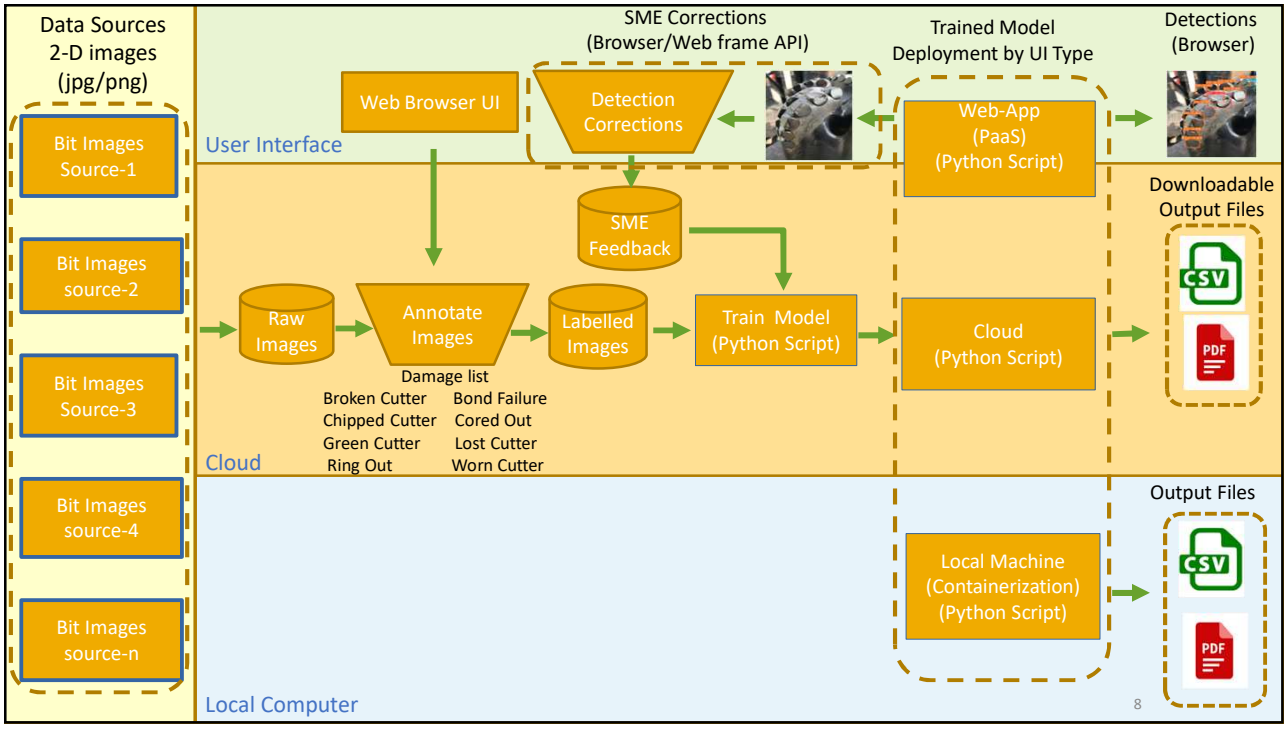
Data Sources
2-D images
(jpg/png)
Bit Images
Source-1
Bit Images
source-2
Bit Images
Source-3
Bit Images
source-4
Bit Images
source-n
SME Corrections
(Browser/Web frame API)
Trained Model
Deployment by UI Type
Detections
(Browser)
Web Browser UI
Detection
Corrections
Web-App
(PaaS)
(Python Script)
User Interface
SME
Feedback
Downloadable
Output Files
CSV
PDF
Raw
Images
Annotate
Images
Labelled
Images
Train Model
(Python Script)
Cloud
(Python Script)
Damage list
Broken Cutter
Bond Failure
Chipped Cutter
Cored Out
Green Cutter
Lost Cutter
Ring Out
Worn Cutter
Cloud
Output Files
Local Machine
(Containerization)
(Python Script)
Local Computer
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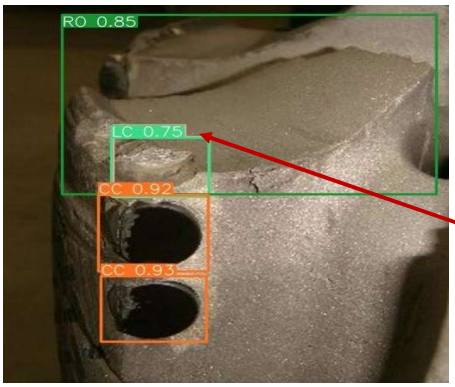
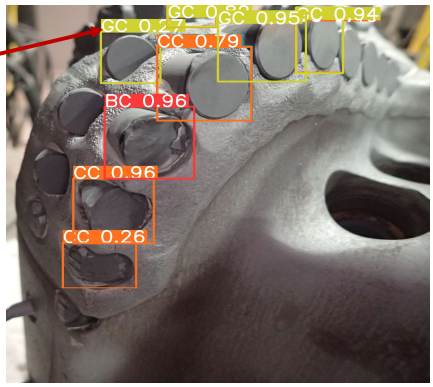
# Sample Results

## Sample of Single Image Results (File mode)




Damage Type

Confidence Score




BC → Broken Cutter CC → Chipped Cutter

GC → Green Cutter RO → Ring-Out

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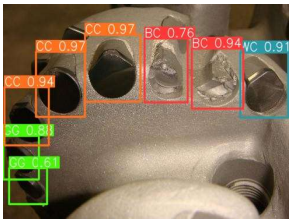
# Auto-generated Results/Docs

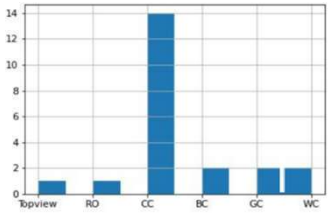
**Sample of Multi Image Results (Folder mode)**

Export detections as CSV& PDF files to run further data analysis and visualization

Filter results
For example: min conf. level

| | xmin | ymin | xmax | ymax | confidence | name | FileName |
|---|---|---|---|---|---|---|---|
| 0 | 0.00 | 7.97 | 379.00 | 361.78 | 0.90 | Topview | bit46-6.jpeg |
| 1 | 353.95 | 146.00 | 378.99 | 250.70 | 0.28 | RO | bit46-6.jpeg |
| 2 | 117.69 | 246.31 | 230.97 | 370.78 | 0.96 | CC | bit46-7.jpeg |
| 3 | 2.47 | 122.72 | 84.90 | 235.51 | 0.95 | CC | bit46-7.jpeg |
| 4 | 31.61 | 186.56 | 127.91 | 316.32 | 0.95 | CC | bit46-7.jpeg |
| 5 | 367.65 | 263.01 | 454.78 | 367.46 | 0.95 | CC | bit46-7.jpeg |

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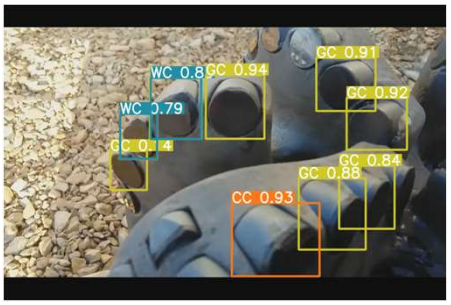
# Recent Work

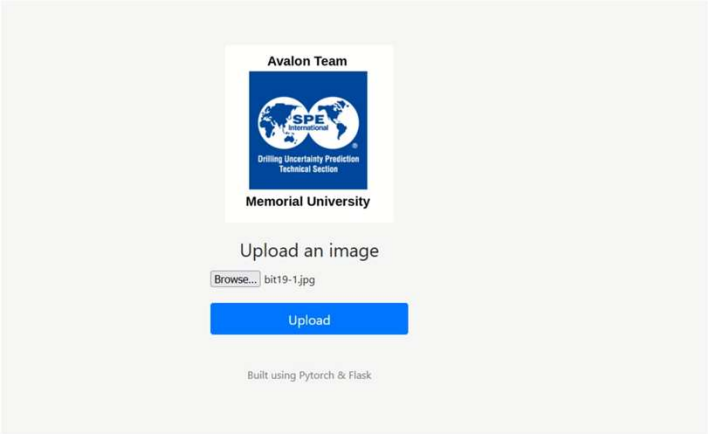
**Processing video flies**




File source : https://www.youtube.com/watch?v=sP0eJ8hR9h4

# Deployment & Demonstration

- PaaS Web App (Online)
  https://drill-bit.herokuapp.com/
- Local Environment Containerization
- Cloud

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# Solution Differentiators

- Fast & efficient single-stage multi-type damage classification of PDC cutters
- Detect ring-out and core-out categories from top view image
- User-friendly interface auto-generates results in .pdf or .csv files:
  - ✓ Enable cutter damage analysis
  - ✓ Visualization
  - ✓ Documentation

# Next Steps/Future Directions

- Update used computer vision algorithm (Ex: YOLOv7/8)
- Upgrade ML model with the new IADC code/ damage types
- Enable SMEs feedback for continues learning
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- We welcome integrating  our work with other teams' work

# Acknowledgements


- Government of Newfoundland
- SPE-DUPTS Computer Vision Competition Committee
- Roboflow online annotation platform
- NOV Inc. local office in St. John's,NL




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# References

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# Thank You

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