Autonomous oil sheen detection using machine learning and transfer learning approaches

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Chevron
Carnegie Mellon University

- Context & Motivation
- Methodology & Evaluation
- Future work

Context & Motivation

Detecting oil sheen potential is important in many situations

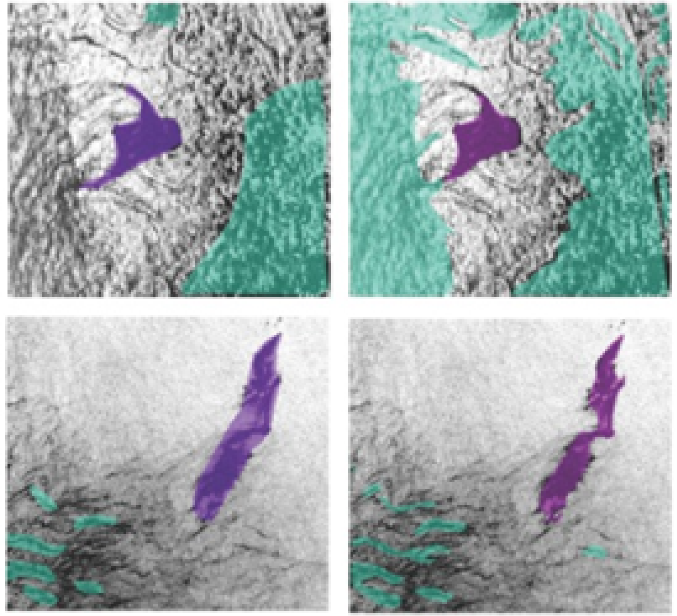
- Oil sheens are common, but unsightly
- May suggest potential for environmental impacts
- May suggest a need for remedial action



Sources of Oil Sheens

- Natural oil seeps or microbial
- Transportation (e.g. boats)
- Runoff
- Oil trapped in subaquatic sediments

Methods are available for oil sheen detection and monitoring

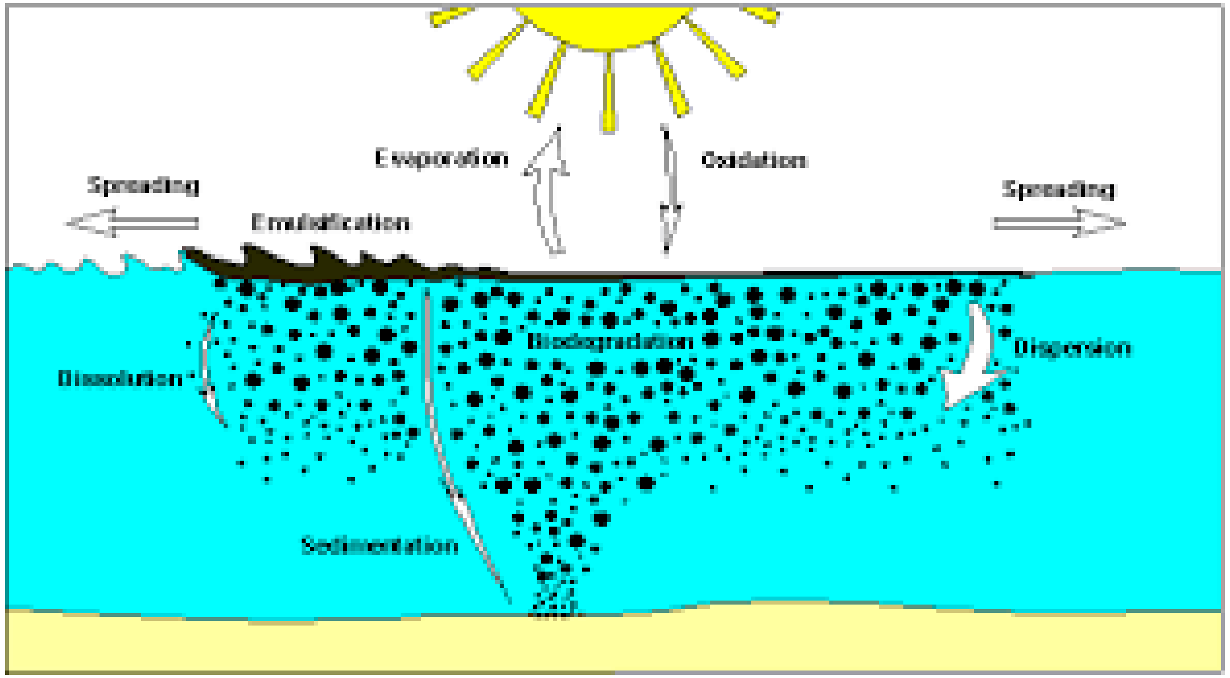


1. Large scale: Satellite Images

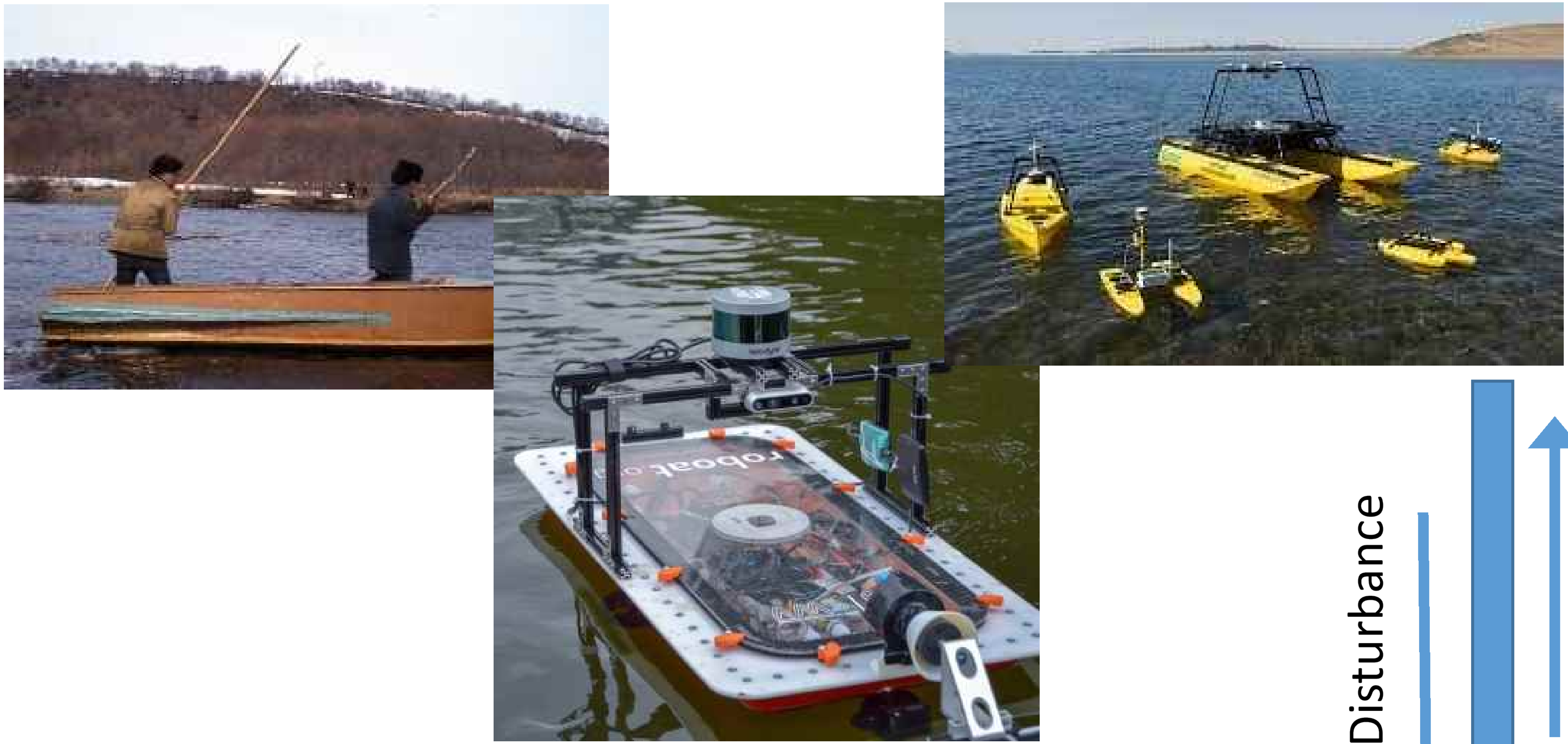
2. Small-scale:
    - Human inspection --> high cost, low sample density
    - Cameras and various sensors (UV, visible, IR, thermal)
    - Drones

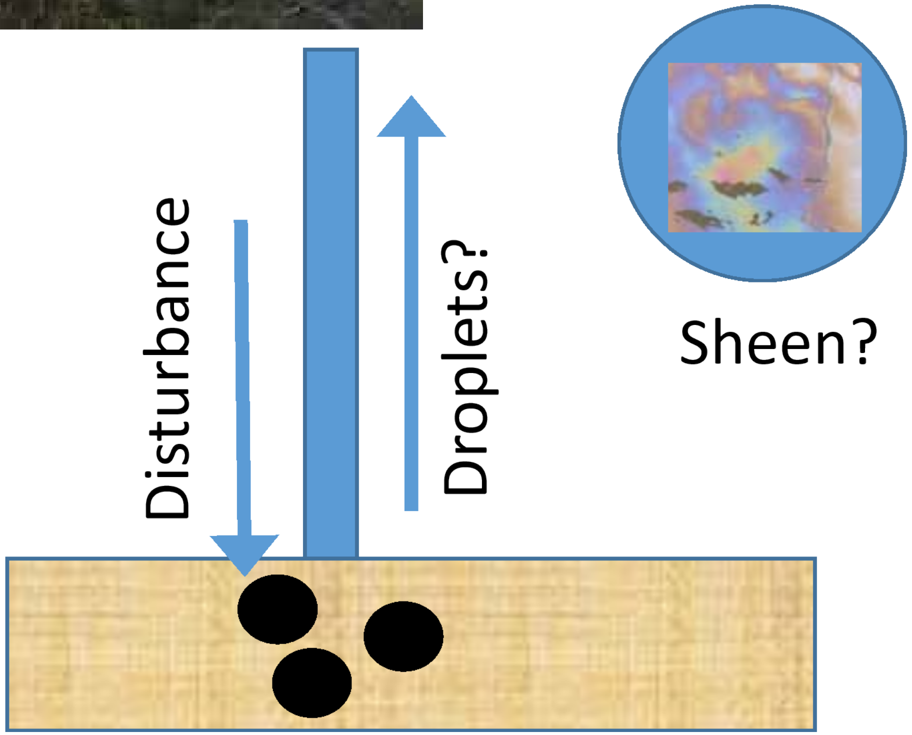
Detecting "Sheening Potential"

- Potential to form a sheen when a subaquatic sediment is disturbed
  - Animal or human disturbance
  - Weather disturbances
  - Flow disturbances
  - Ebulition



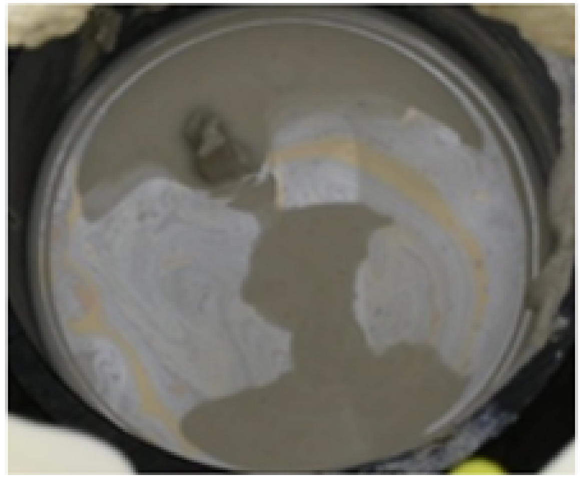
Autonomous Sheening Potential Detection





But we need a detector!!

Challenges to creating an algorithm for oil sheen detection



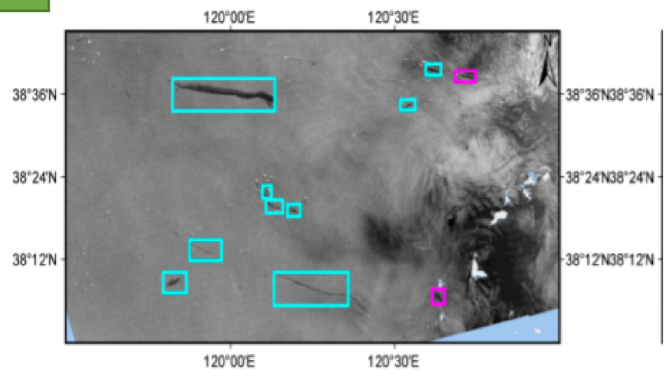
Detection algortihm development challenges

Solution

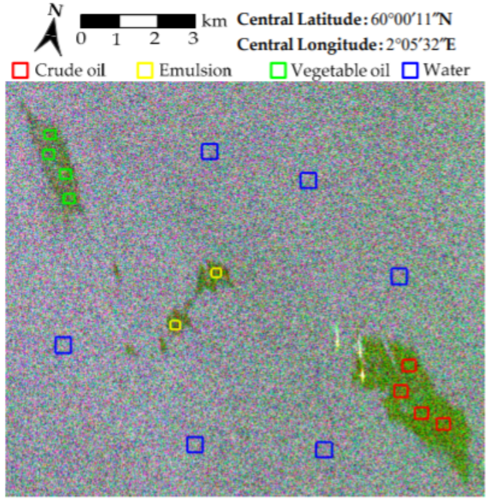
- Lack of data → Prepare a dataset by lab simulation
- How to learn from data → CNN + Transfer learning

Types of oil sheen images available cannot work for us

Satellite images

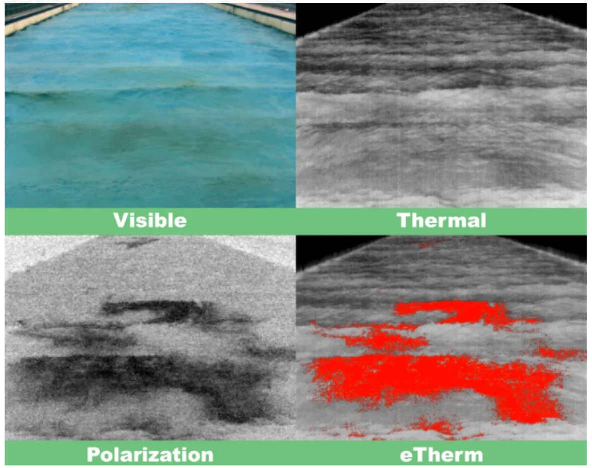


(a)



color-coded image of the Radarsat-2 polarimetric SAR image

Thermal images

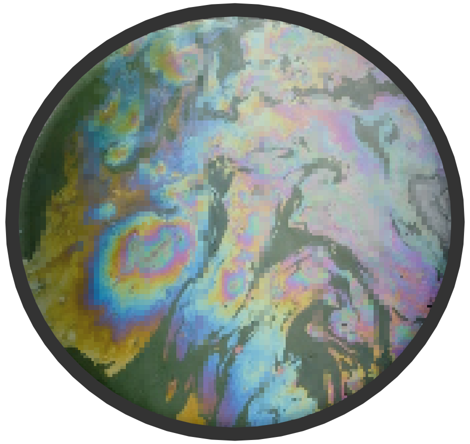


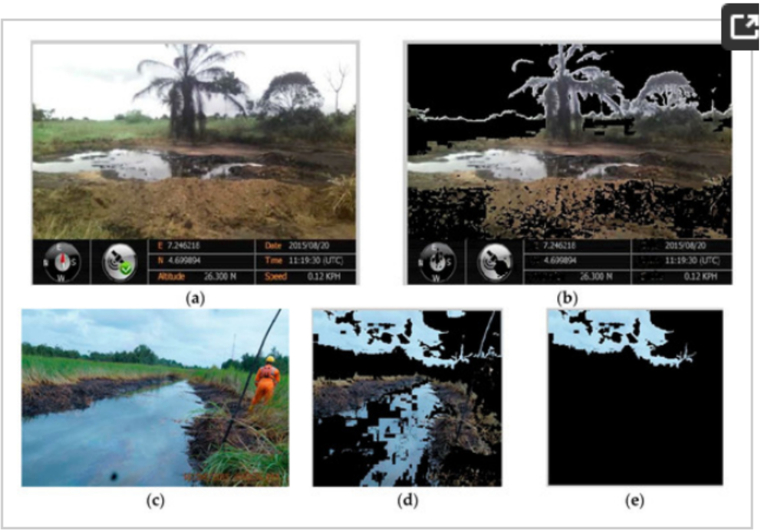
Apply

Lab images

Training Test

Visible images



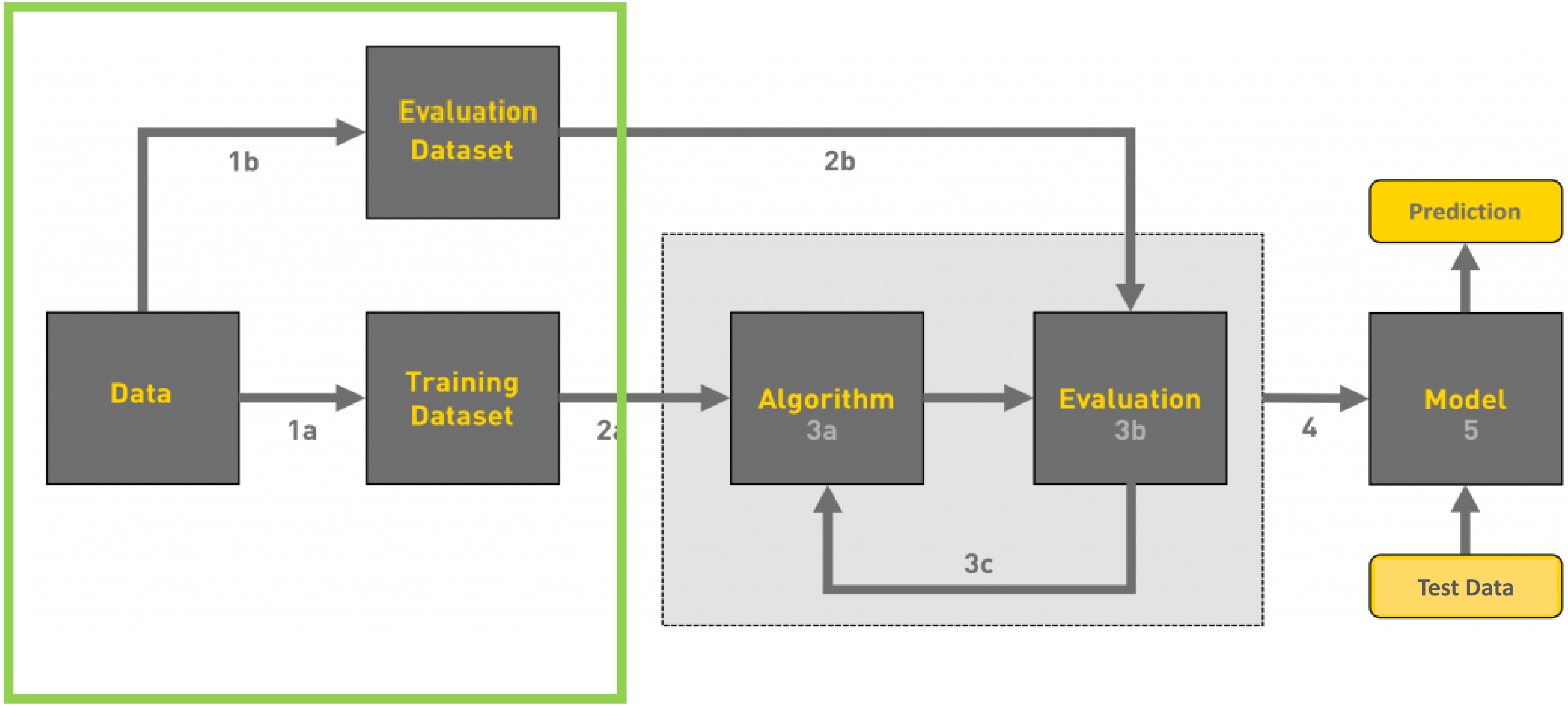


Contents

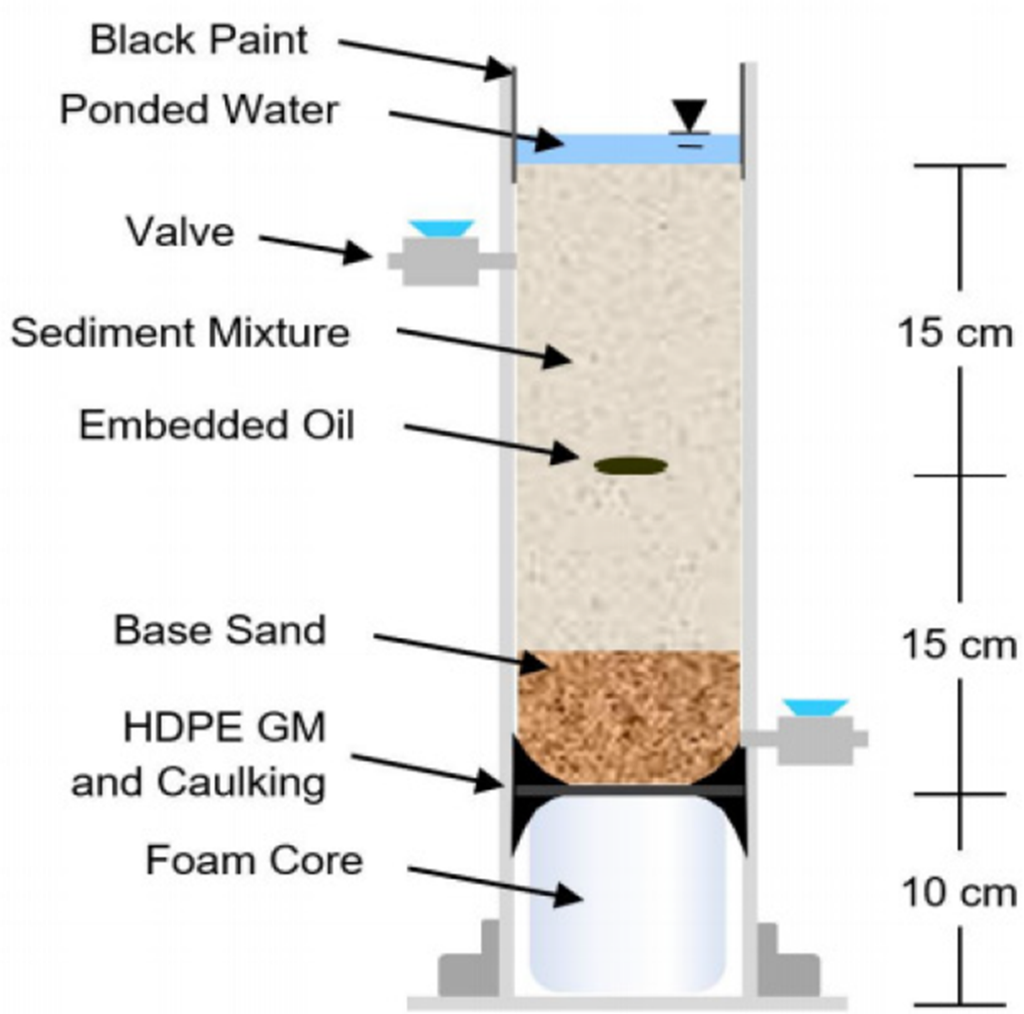
- Context & Motivation
- Methodology & Evaluation
- Conclusion & Future work

Methodology & Evaluation

Oil Sheen Detection Project Workflow



Experimental Setup



Sheening Video

Methodology

- Image classification

- Images (frames) from the videos are described and classified as having a sheen or not.

- Manual classification of all of the videos

Oil: 400 µL OIL-3
Deposit: Consolidated
Tool: Water Injection
Video/Photo No: 0664 (2)

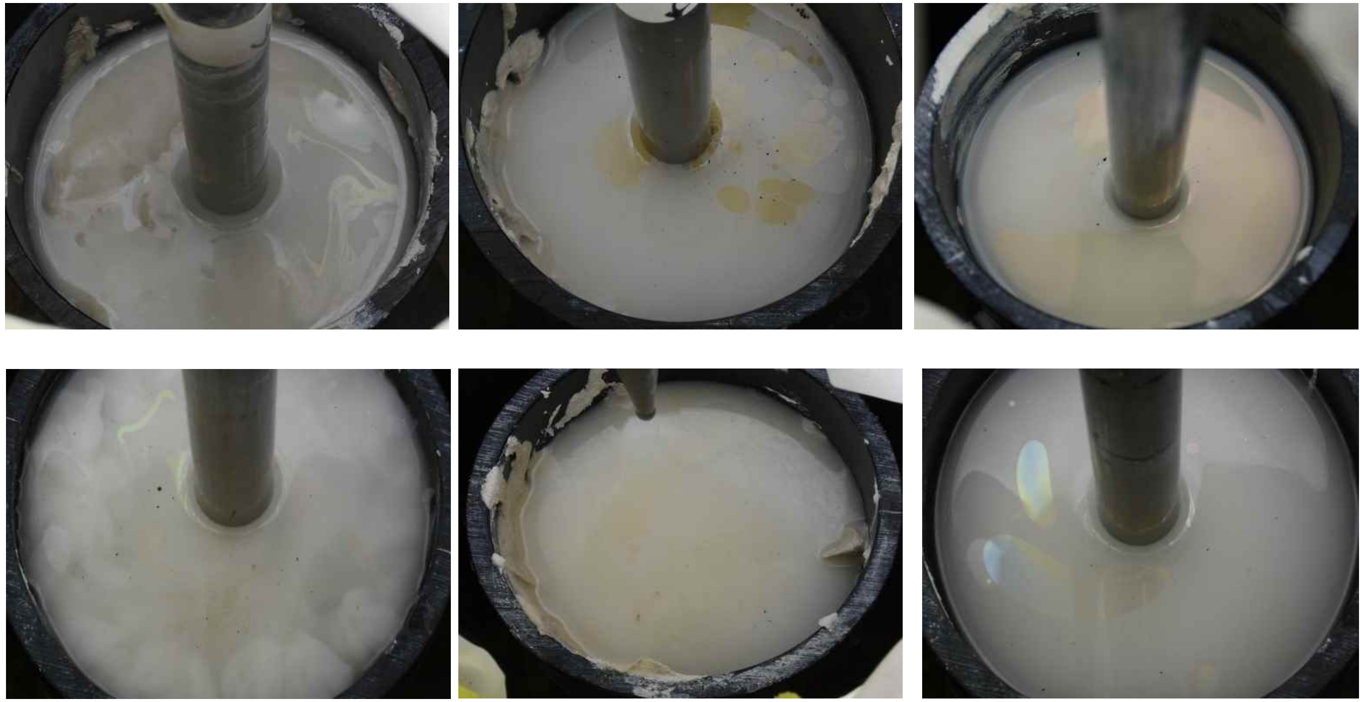
Photo Description: Specks of silver and rainbow sheens or reflective sediment appeared as tool was removed. Very small amount of either miniscule spots of true oil or oil-particle aggregate also appeared.

Oil: 400 µL OIL-2
Deposit: Consolidated
Tool: Rod Drop with Manual Agitation
Video/Photo No: 0684 (5)

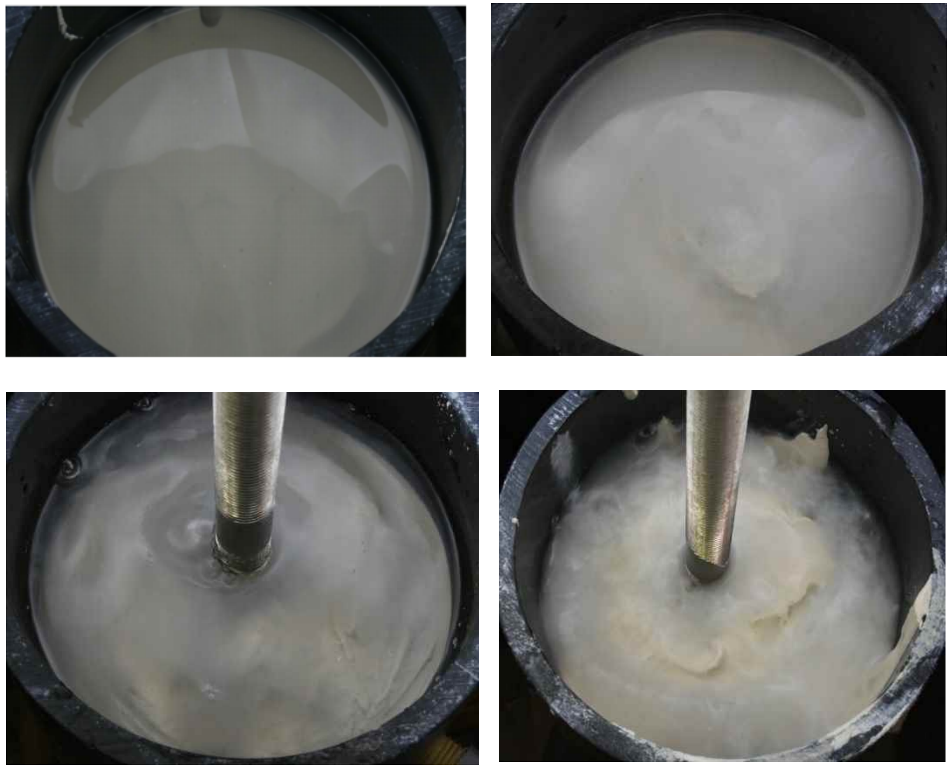
Photo Description: After the manual agitation (tool allowed to rest in column as surface was observed), more picks of true oil and oil sheens appeared covering approximately 75% the surface in rainbow sheens.

Methodology & Evaluation

- Dataset – video frames from lab simulation of sediment disturbance experiment



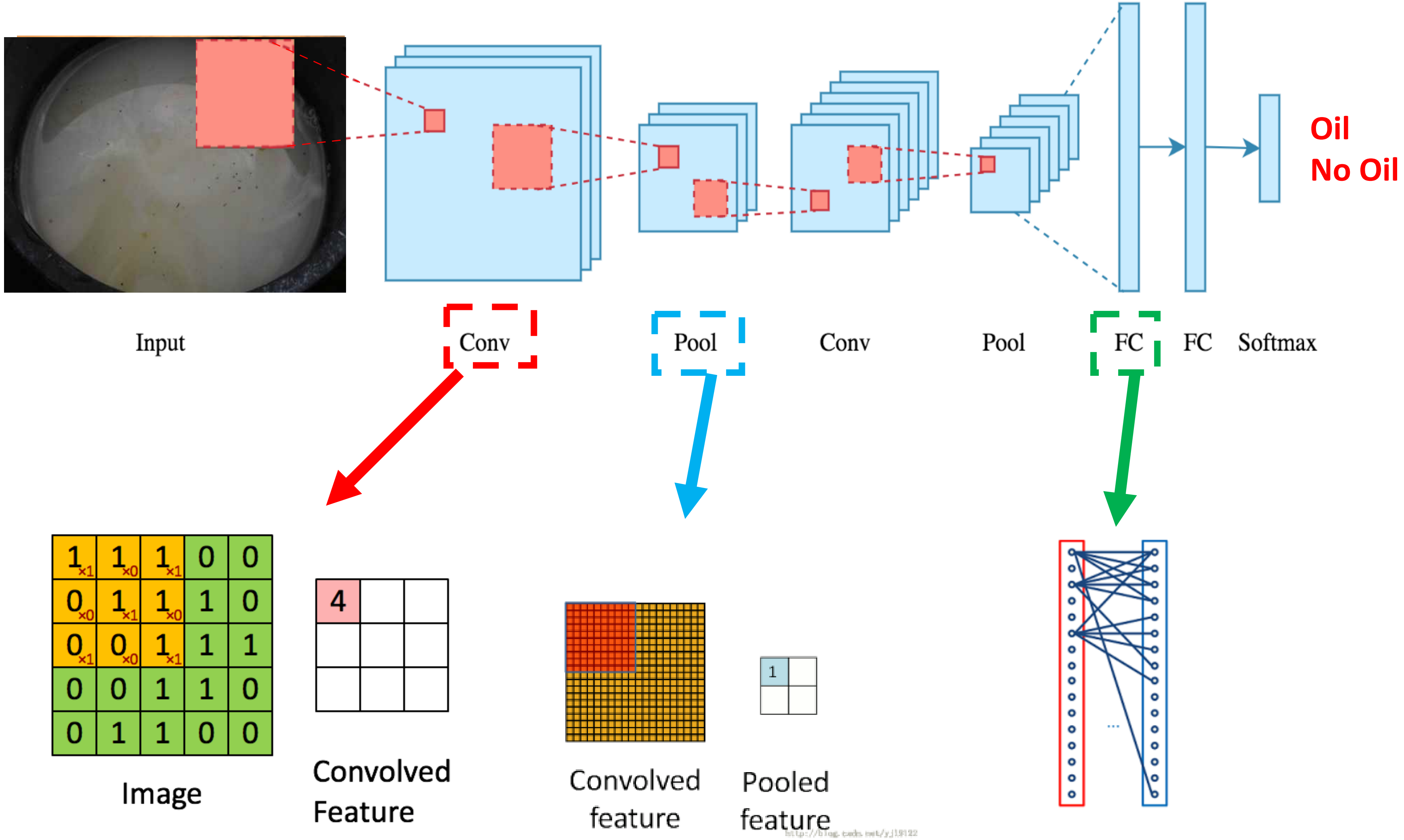
Example Oil sheen images



Example No oil sheen images

Methodology

Convolutional neural network (CNN), commonly applied to analyzing visual imagery



Extract visual and spatial features by kernels

Down-sampling operation

Combined learnt features together to make decision

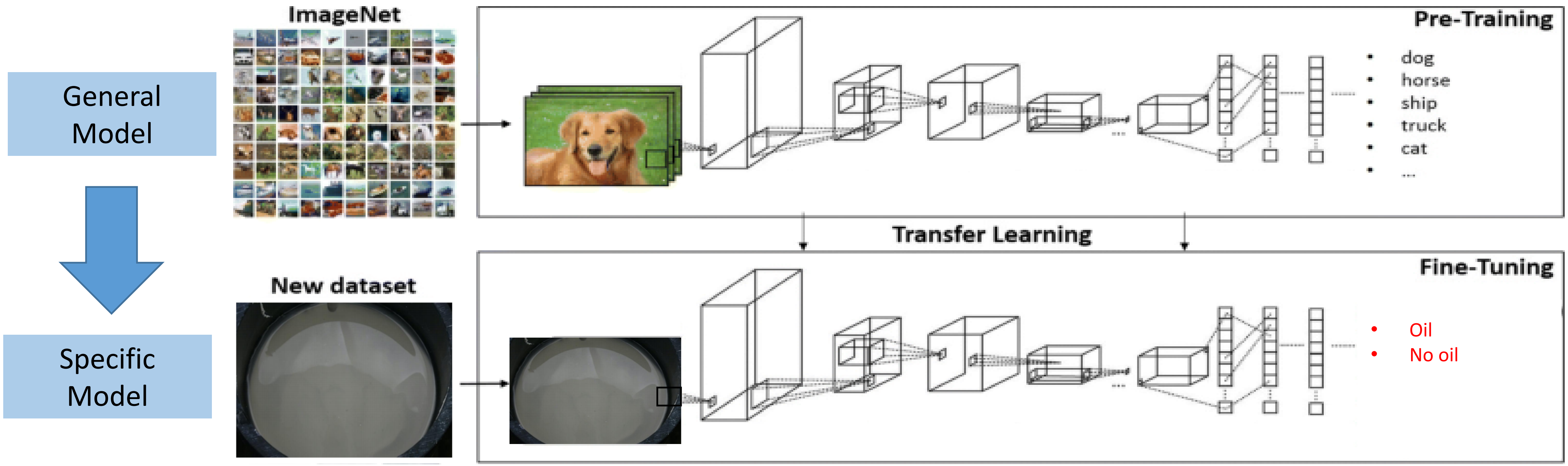
CNN 3 major components:

1. Convolutional layer: Extract visual and spatial features by kernels

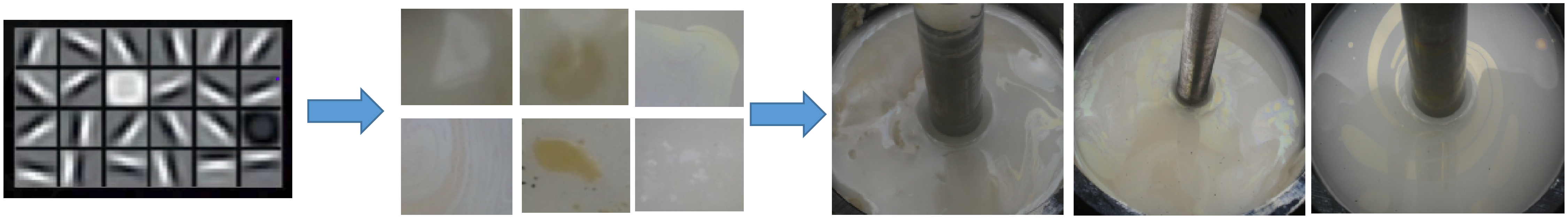
2. Pooling layer: reduce the size of feature by down-sampling operation

3. Fully connected layer: Combined learned features together to make decision

Methodology & Evaluation-Transfer Learning

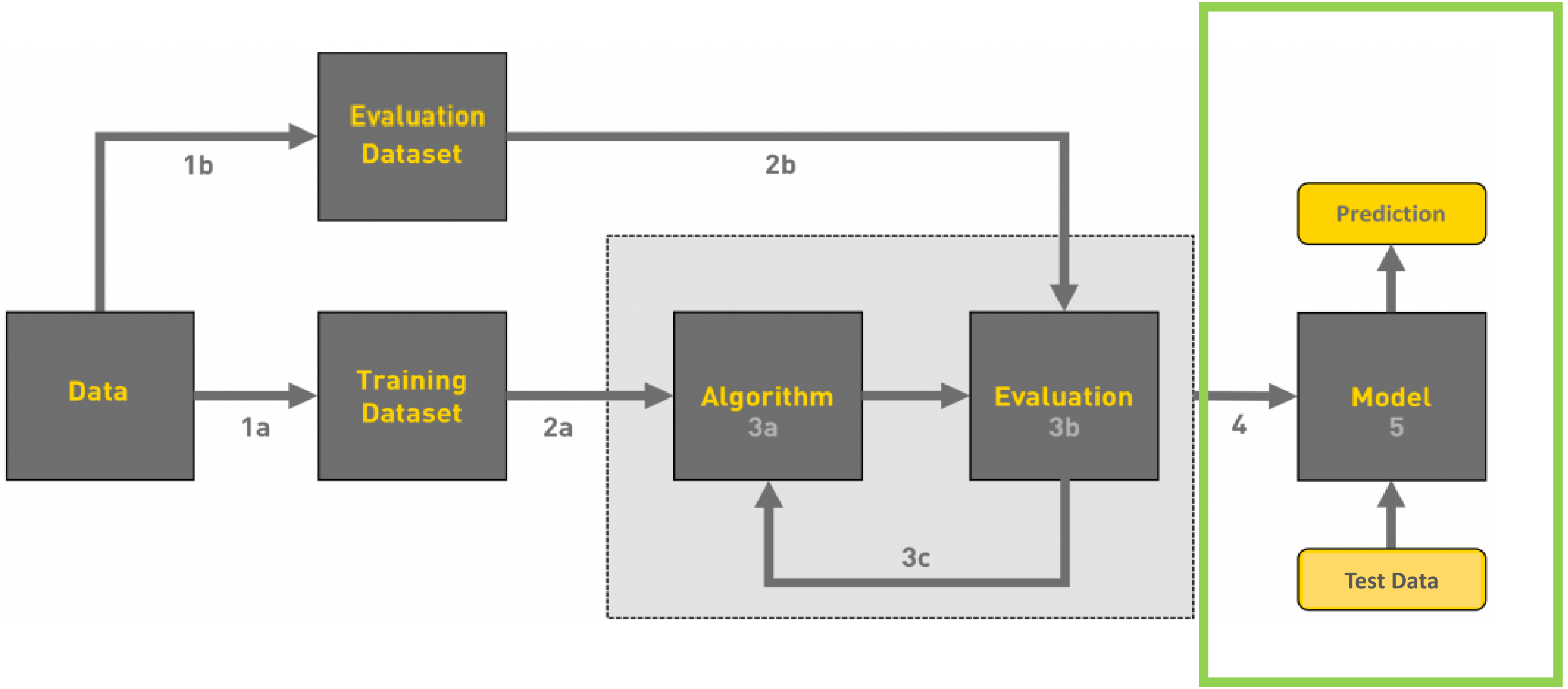


Pooled Features Extracted



Methodology & Evaluation

Oil Sheen Detection Project Workflow

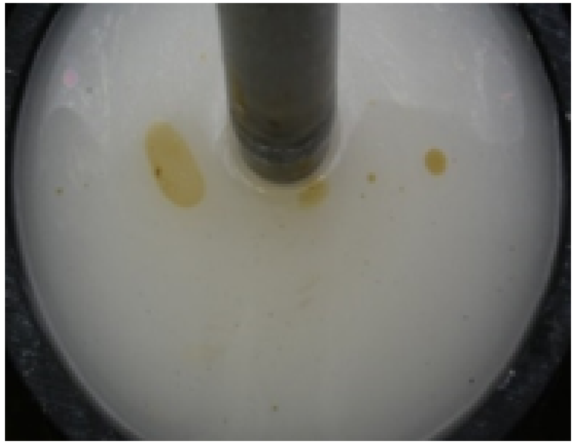


Methodology & Evaluation

Prediction accuracy: 99% (Test dataset)

No oil sheen

No oil sheen



With oil sheen

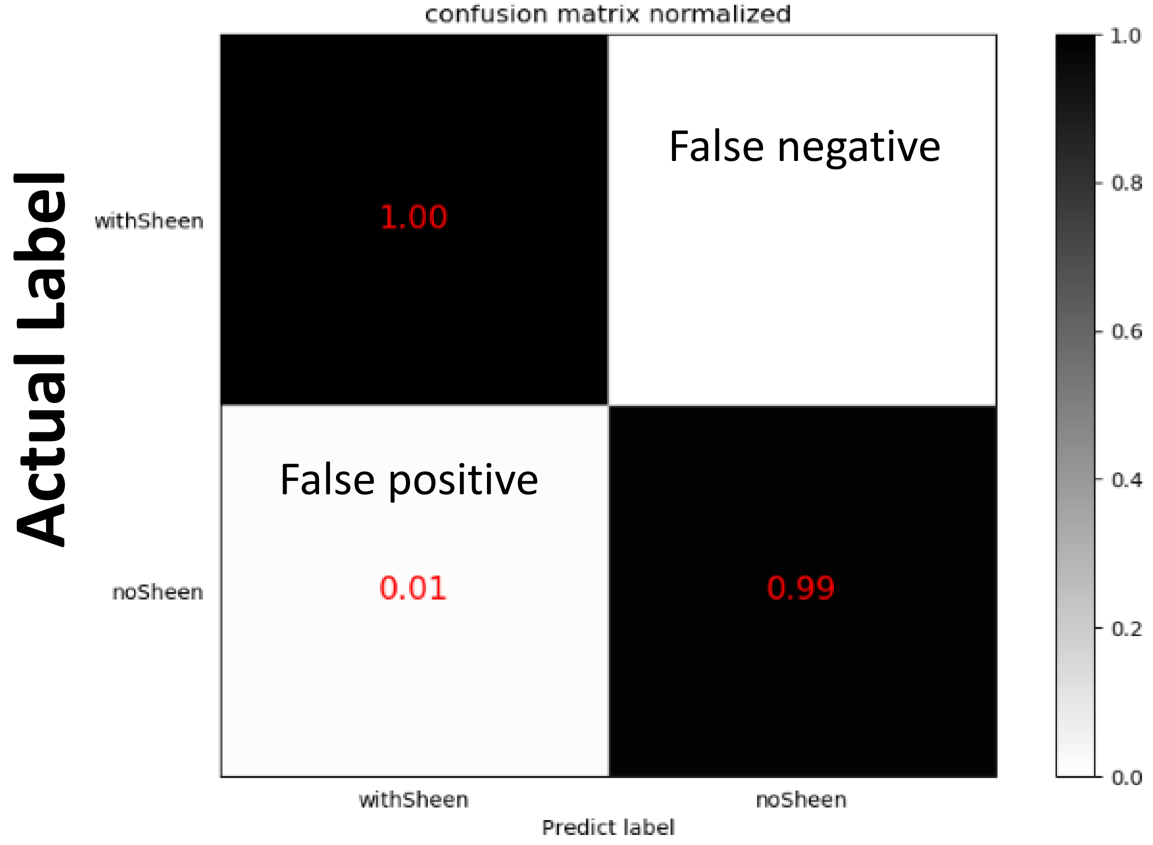
With oil sheen

Prediction results

Oil sheen image ground truth and prediction results

Methodology & Evaluation

Confusion Matrix



Predicted Label

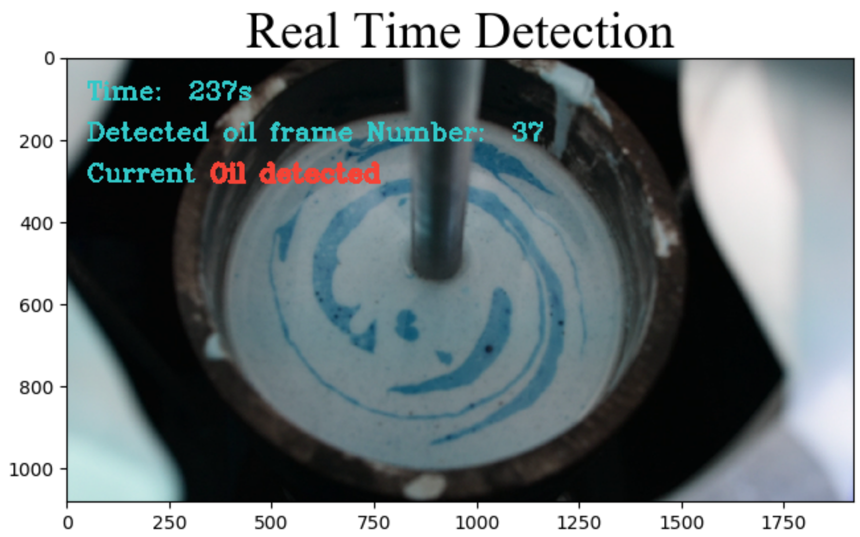
$$\text{Precision} = \frac{\text{True positive}}{\text{True positive} + \text{False positive}}$$

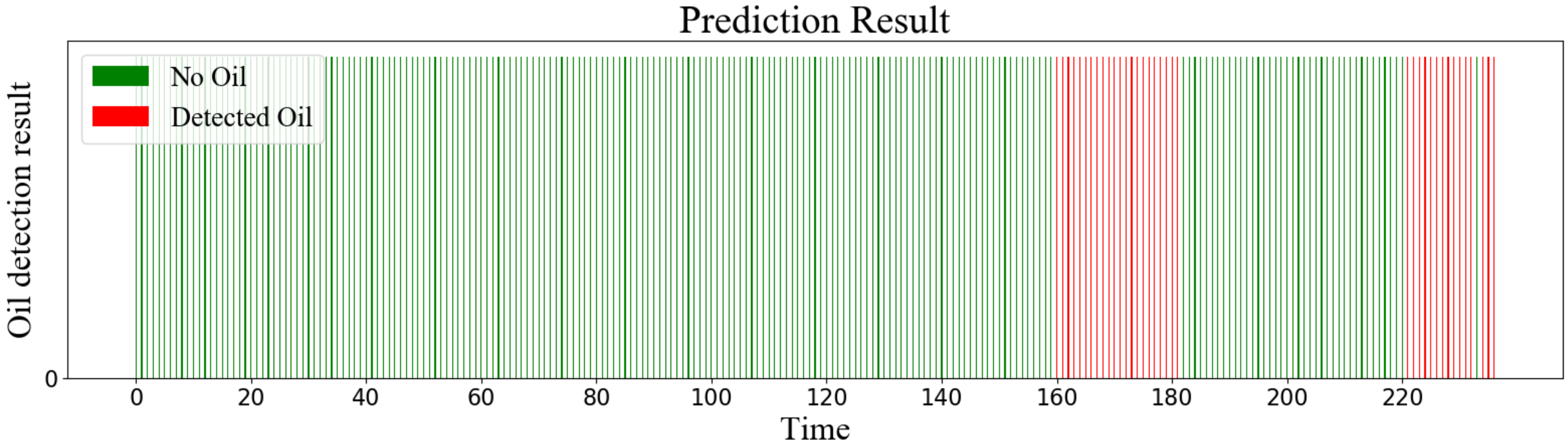
$$\text{Recall} = \frac{\text{True positive}}{\text{True positive} + \text{False negative}}$$

$$\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

	Precision	Recall	F1-score
Model	0.98	1.0	0.99

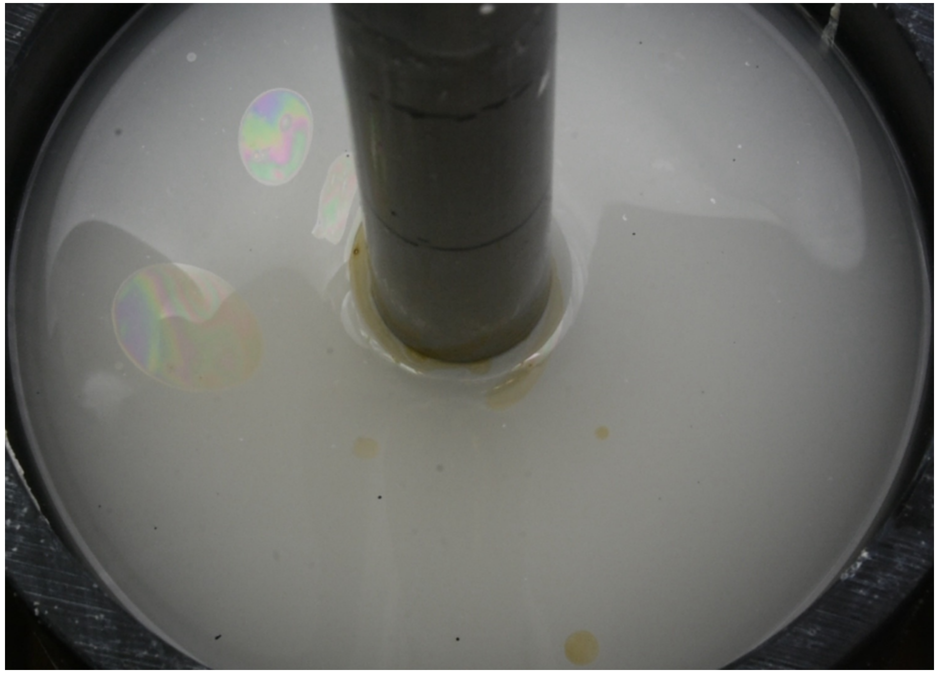
Methodology & Evaluation

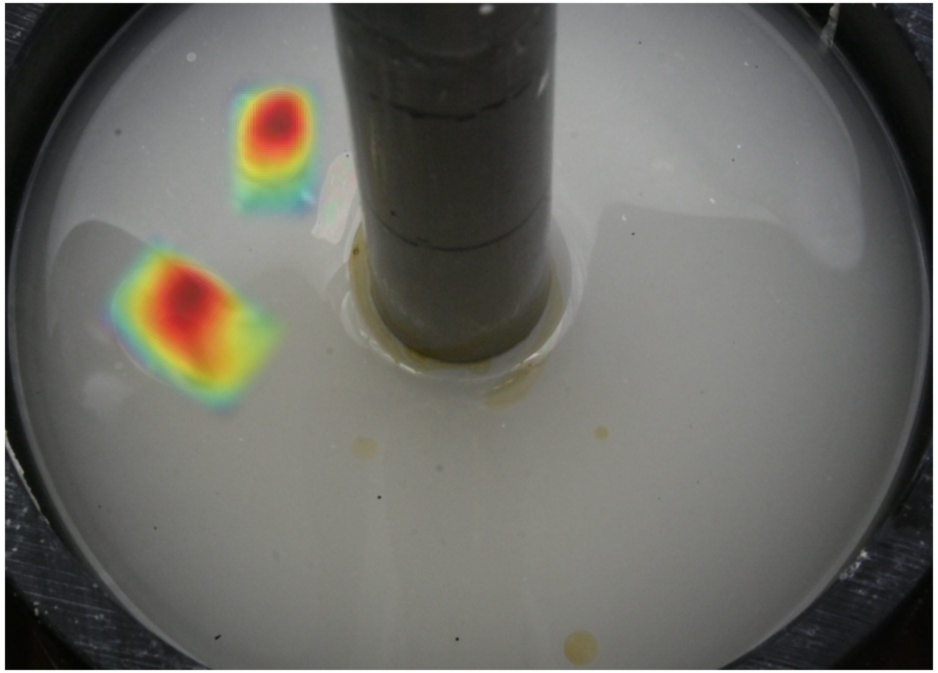




Future work

1. Test algorithm in the field
2. Develop a deployable system
3. Continue to add more images/video and improve the algorithm



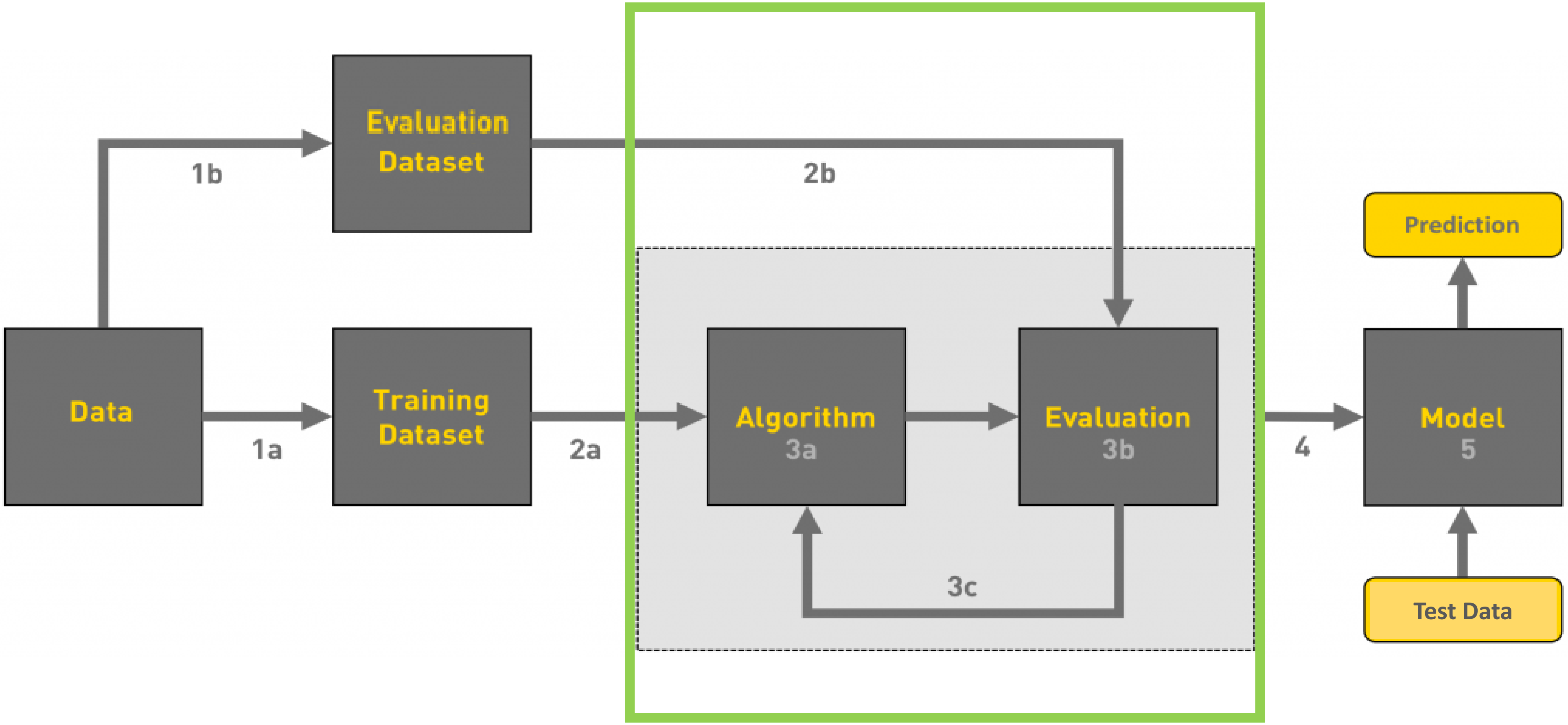


Thank you!

Backup slides

Methodology & Evaluation

Oil Sheen Detection Project Workflow



Environmental Fields tendency

More data
- Sensors
- Images
- Text

Hard to Model
- Air pollution
- Climate change
- Health impacts

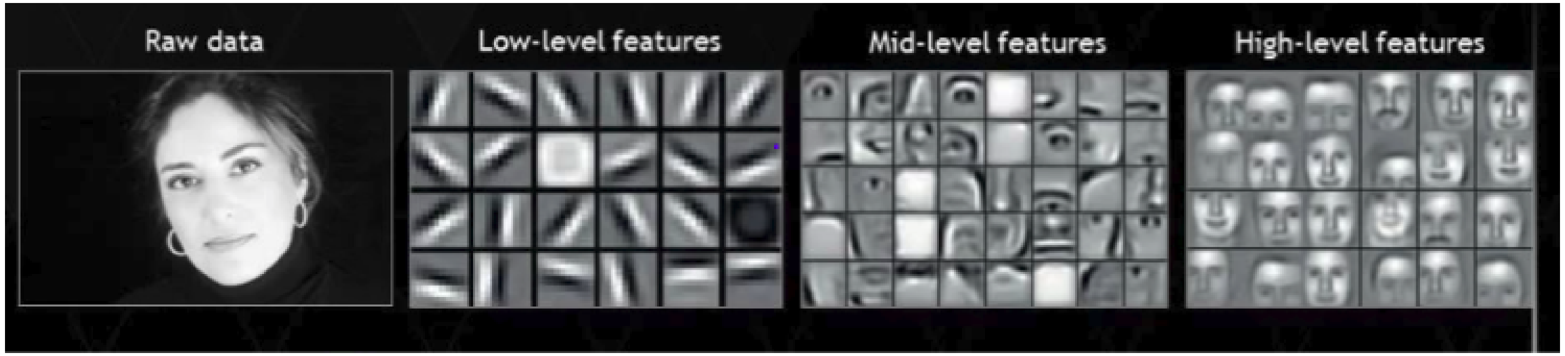
Machine learning

Learn from data
1. Statistical learning
2. Data mining
3. Neural networks

Smarter decision = domain knowledge + learnt knowledge

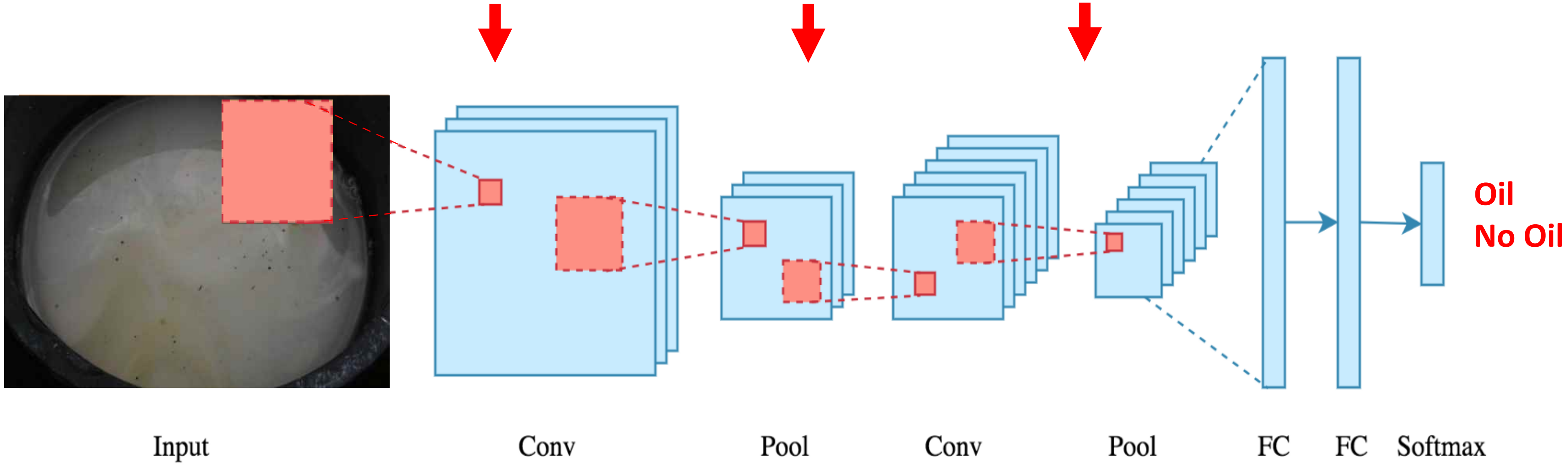
Methodology & Evaluation

E.g. Face detection



...

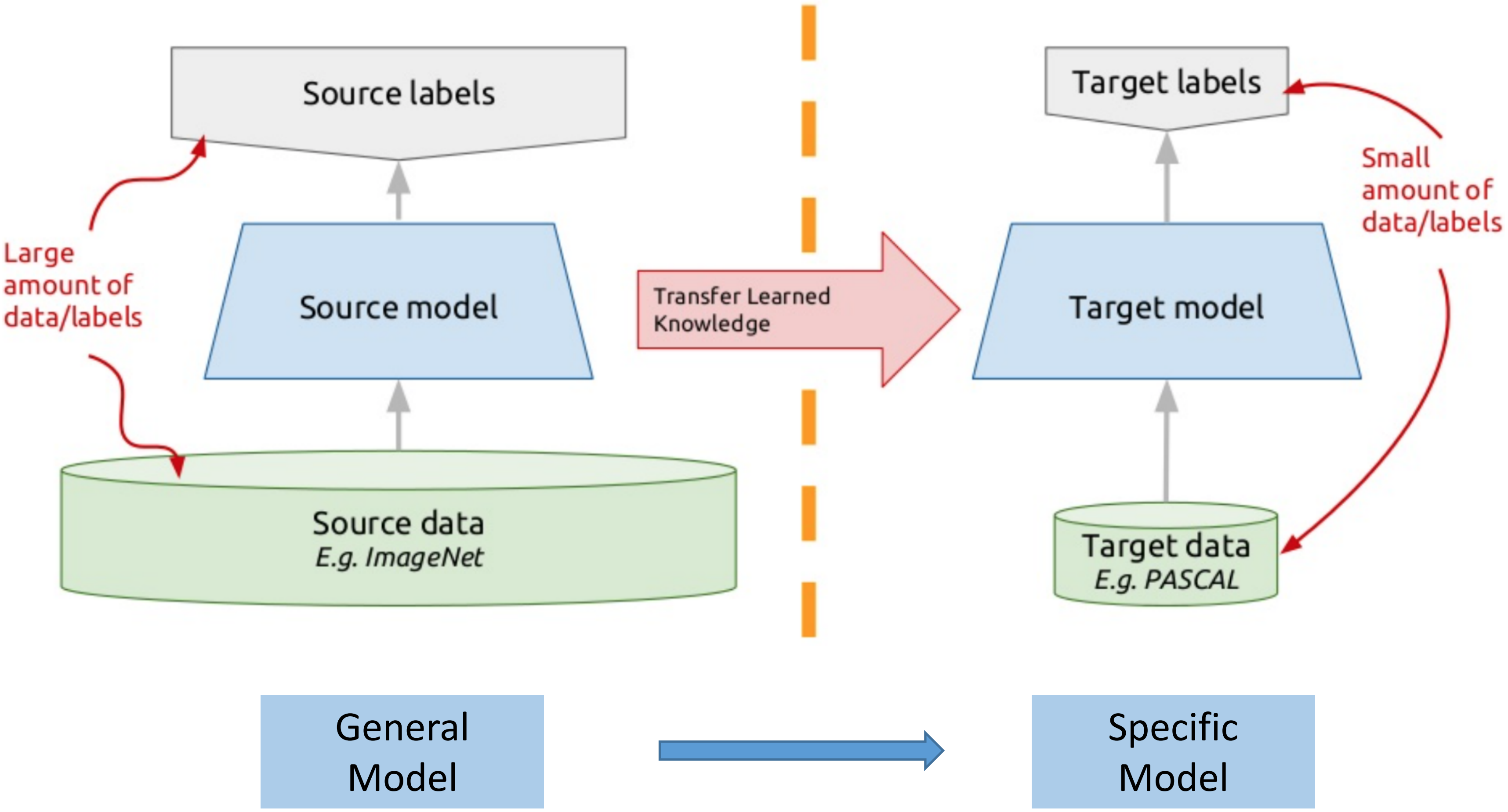
Face
No face



What kind of feature are CNN looking for?

Methodology & Evaluation

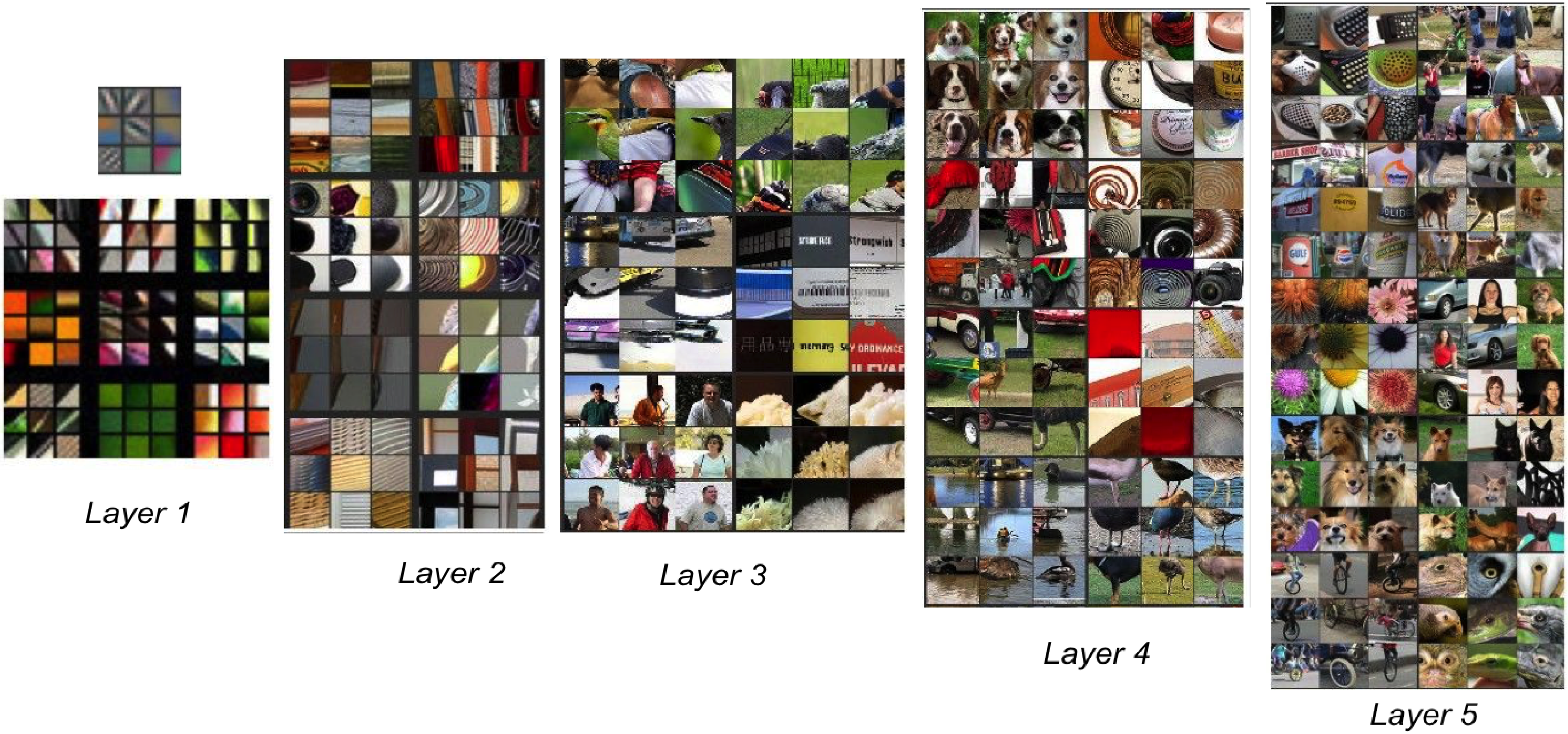
Transfer Learning -- Solve the problem of lack of data



Methodology & Evaluation

- General feature extractor

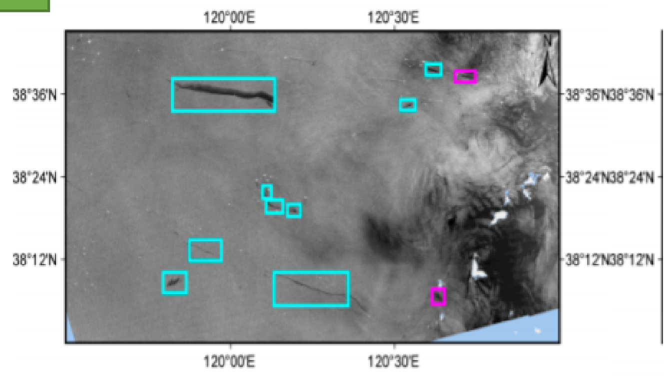
ImageNet: 14,197,122 images, 1,000 classes



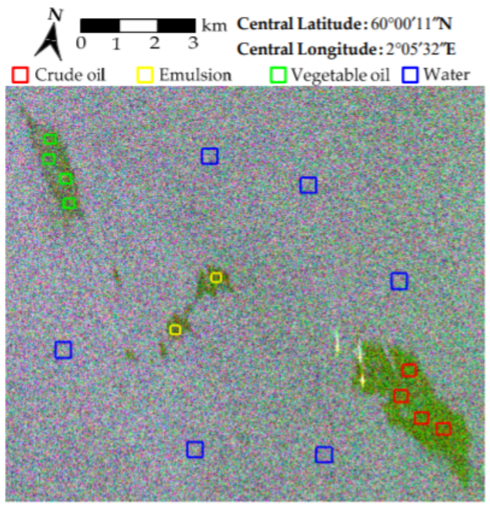
Context & Motivation

oil detection

Satellite images

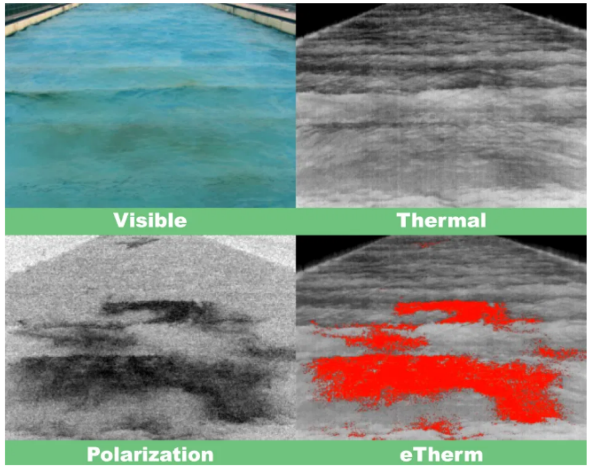


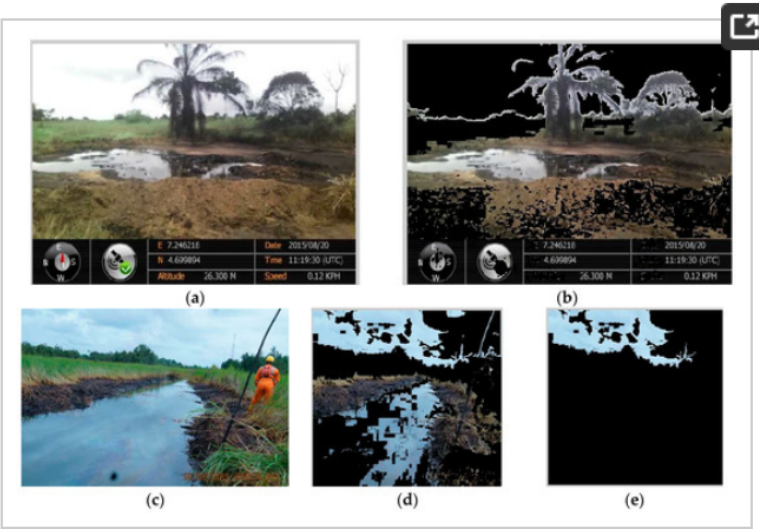
(a)



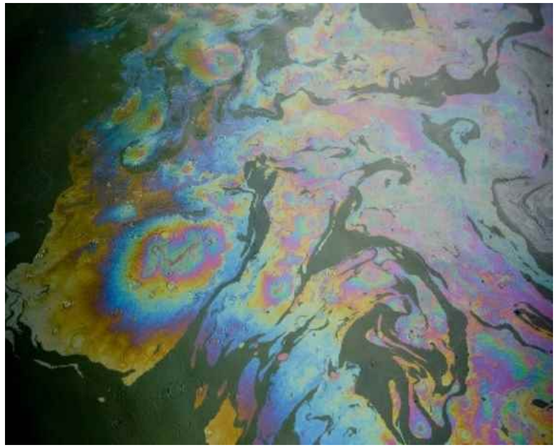
color-coded image of the Radarsat-2 polarimetric SAR image

Thermal images



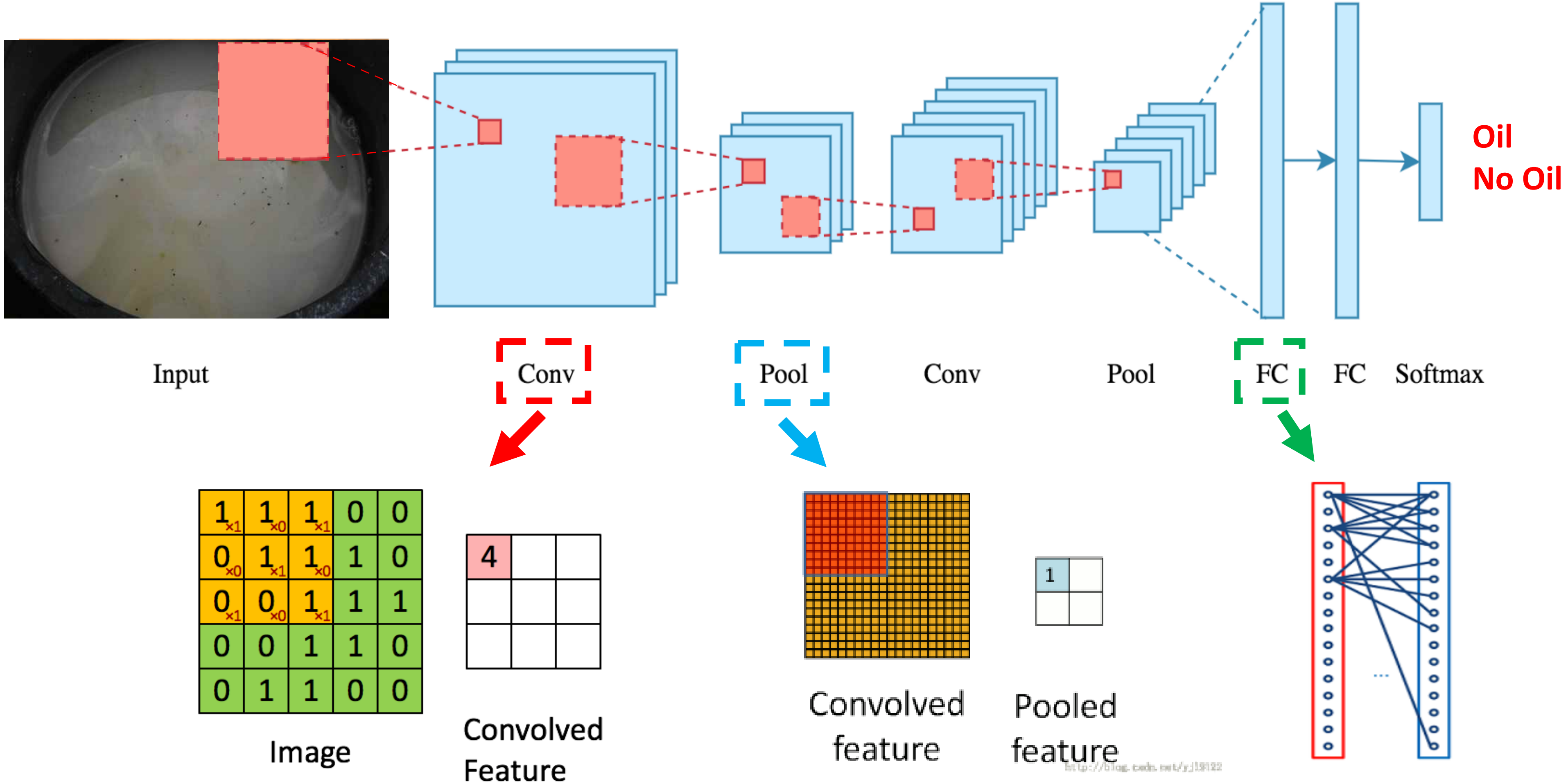


Visible images



Methodology & Evaluation

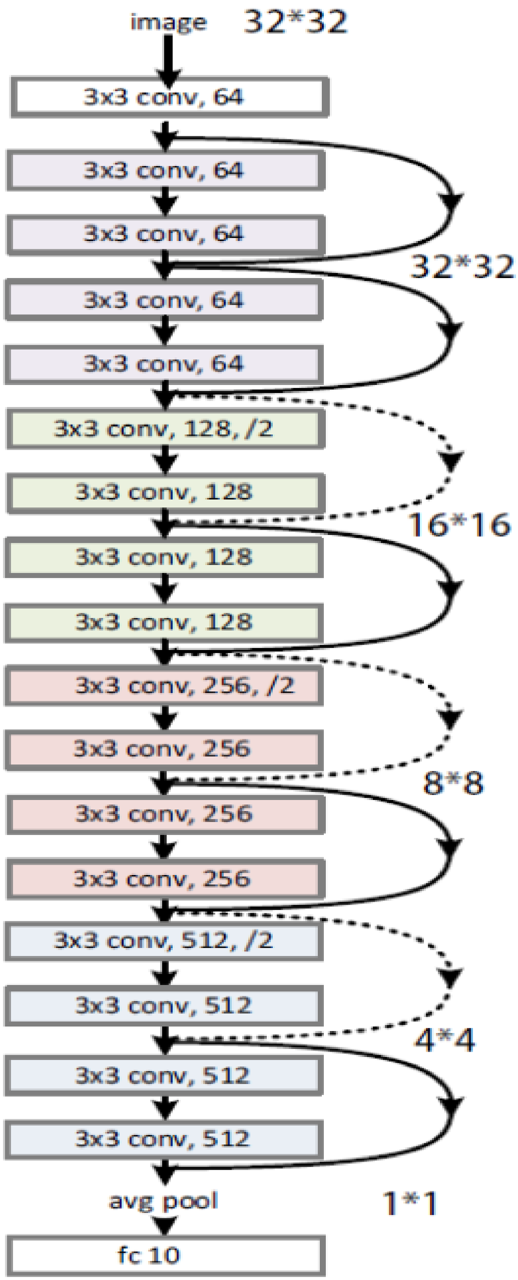
Convolutional neural network (CNN)



Extract visual and spatial features by kernels

Down-sampling operation

Combined learnt features together to make decision

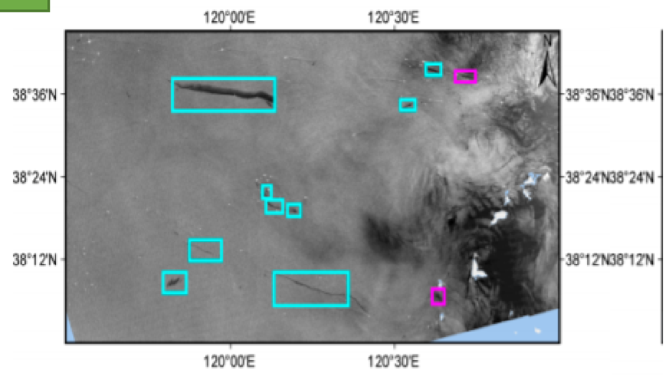


ResNet-18 Architecture

Conclusion & Future work

Data space of oil sheen

Satellite images



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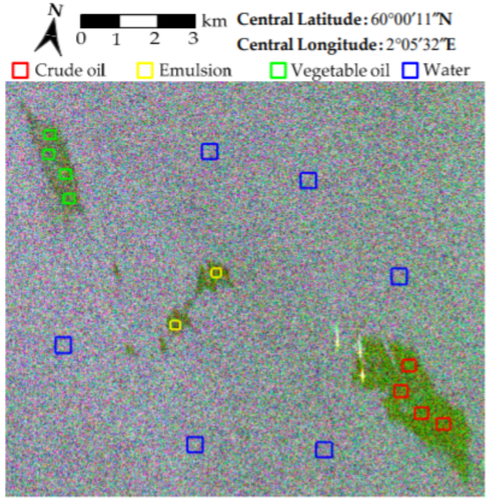

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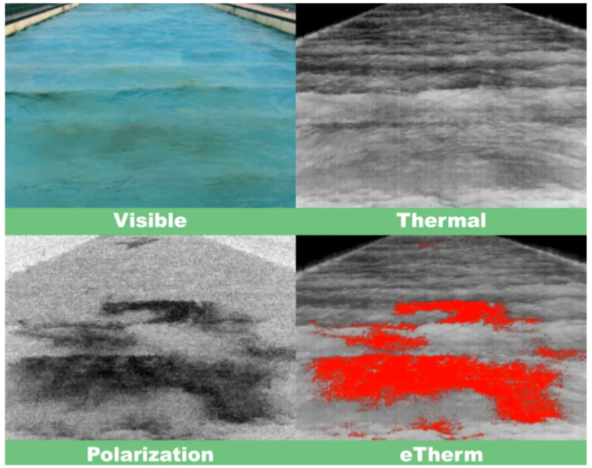
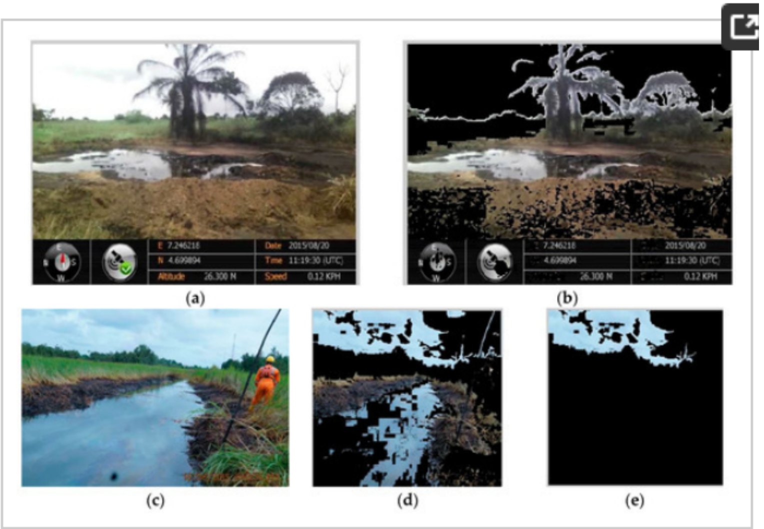


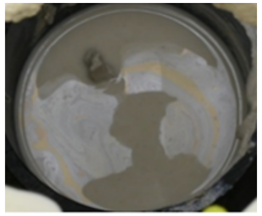


Drop?

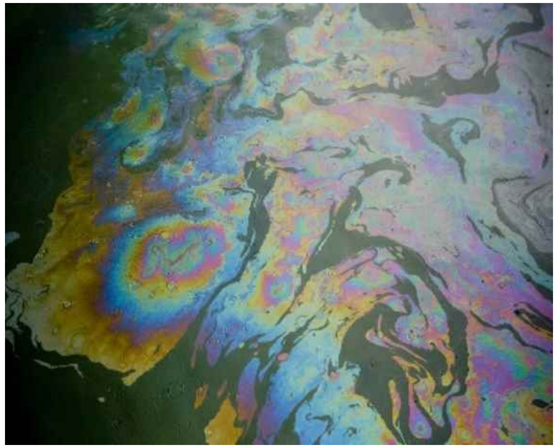
Lab images

Drop 1%

Training Test

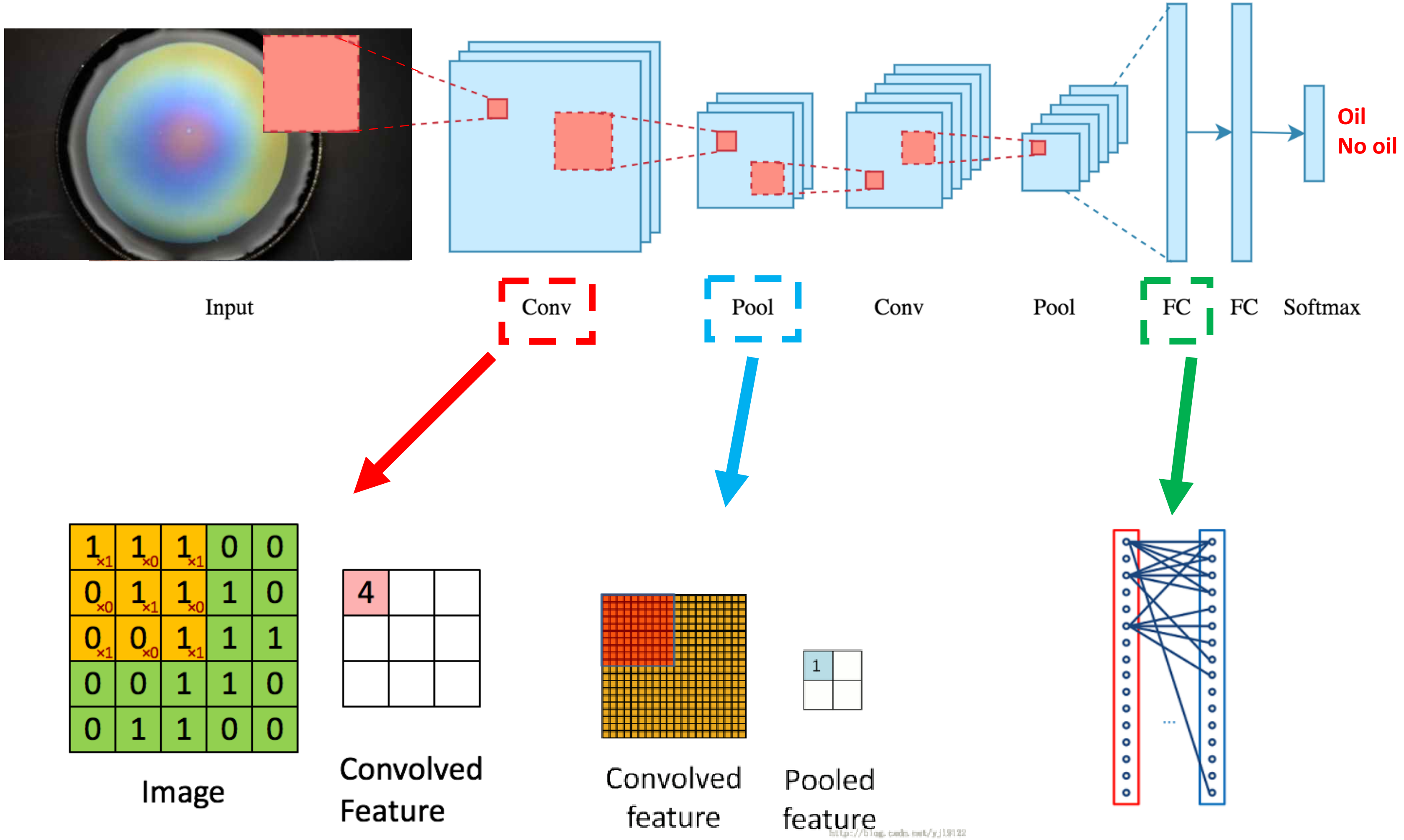


Visible images



Methodology

Convolutional neural network (CNN) is a class of deep neural networks(NN), most commonly applied to analyzing visual imagery (Good at image classification)



Extract visual and spatial features by kernels

Down-sampling operation

Combined learnt features together to make decision

Advantage of CNN:

1 Local connection and parameter sharing: reduce the requirement of tons of parameters

2 Shift invariant: Capture spatial information make your model generalize better

Current Model – Intro

Hypothesis: Linear regression

$$h_\theta(x) = \theta_0 + \theta_1 x$$

Parameters:

$$\theta_0, \theta_1$$

Cost Function:

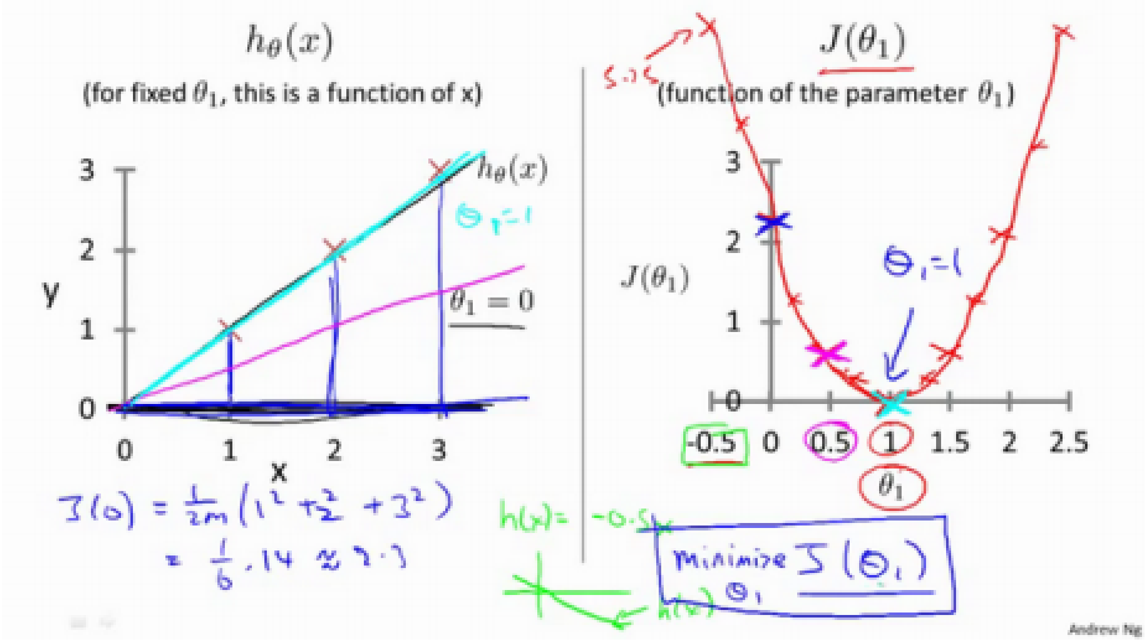
$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$$

Goal: $\underset{\theta_0, \theta_1}{\text{minimize}}\ J(\theta_0, \theta_1)$

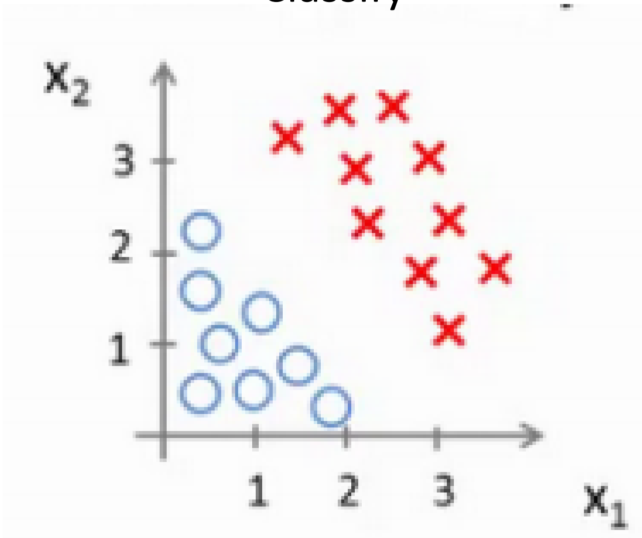
repeat until convergence {

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$$

}



Classify



Current Model – Intro

Gradient descent for neural networks

Parameters: $W^{[1]}$, $b^{[1]}$, $W^{[2]}$, $b^{[2]}$
$(n^{[1]}, n^{[0]})$ $(n^{[1]}, 1)$ $(n^{[2]}, n^{[1]})$ $(n^{[2]}, 1)$

$n_x = n^{[0]}$, $n^{[1]}$, $n^{[2]} = 1$

Cost function: $J(W^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}) = \frac{1}{m} \sum_{i=1}^{n} \mathcal{L}(\hat{y}, y)$

$a^{[2]}$

Gradient descent:

Repeat {

Compute predicts $(\hat{y}^{(i)}, i = 1 \ldots, m)$

$dW^{[1]} = \frac{\partial J}{\partial W^{[1]}}$, $db^{[1]} = \frac{\partial J}{\partial b^{[1]}}$, ...

$W^{[1]} := W^{[1]} - \alpha \, dW^{[1]}$

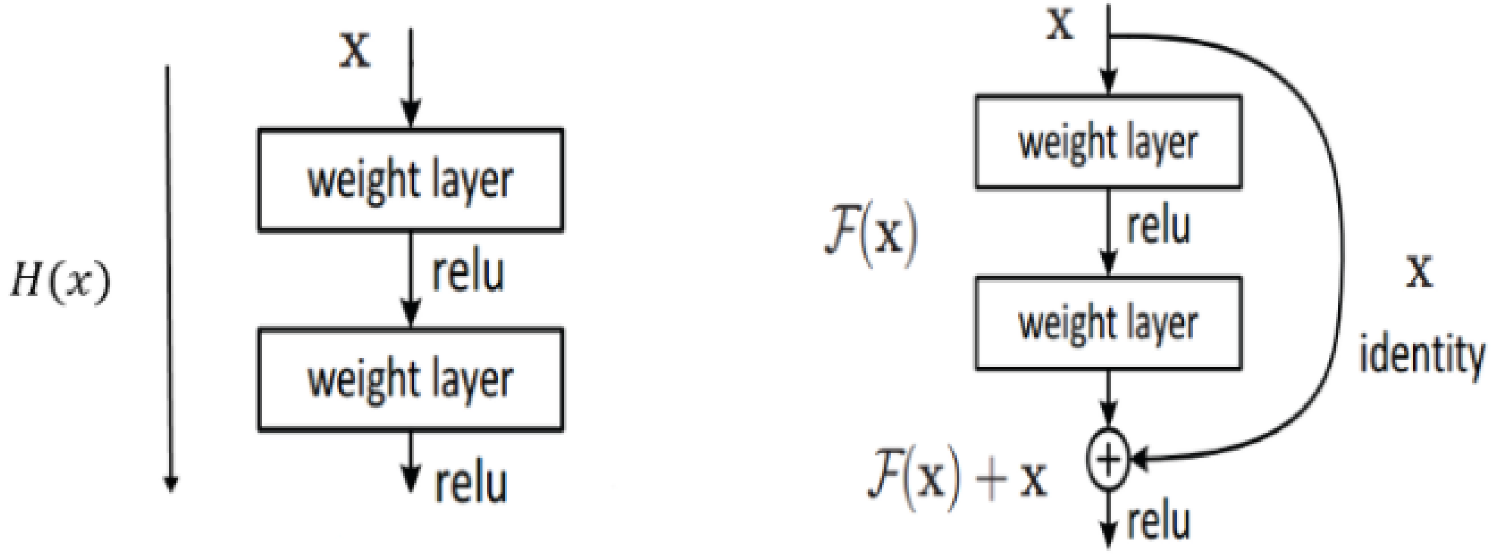
$b^{[1]} := b^{[1]} - \alpha \, db^{[1]}$

$W^{[2]} := \ldots$ $b^{[2]} := \ldots$

}

Andrew Ng

Current Model – Resnet18



Normal CNN vs CNN with Residual Connection

$$a^{[l+2]} = g(z^{[l+2]} + a^{[l]})$$

$$= g(\cancel{W^{[l+2]} a^{[l+1]} + b^{[l+2]}} + a^{[l]}) = g(a^{[l]})$$

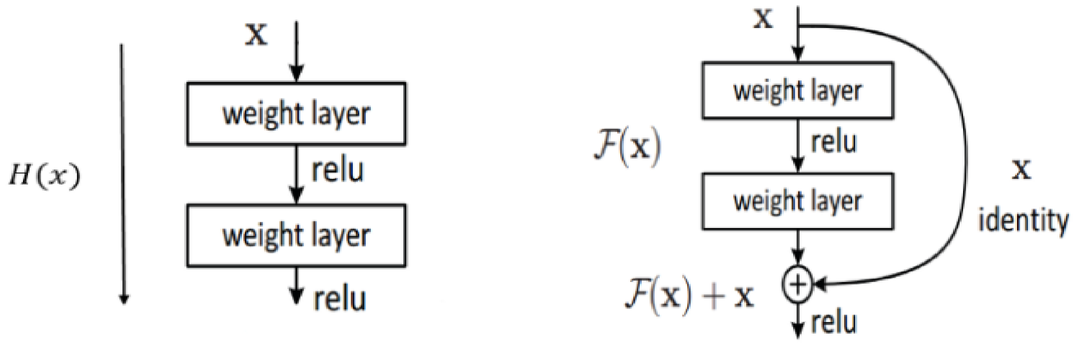
$$= a^{[l]}$$

If $W^{[l+2]}=0$, $b^{[l+2]}=0$

Approach

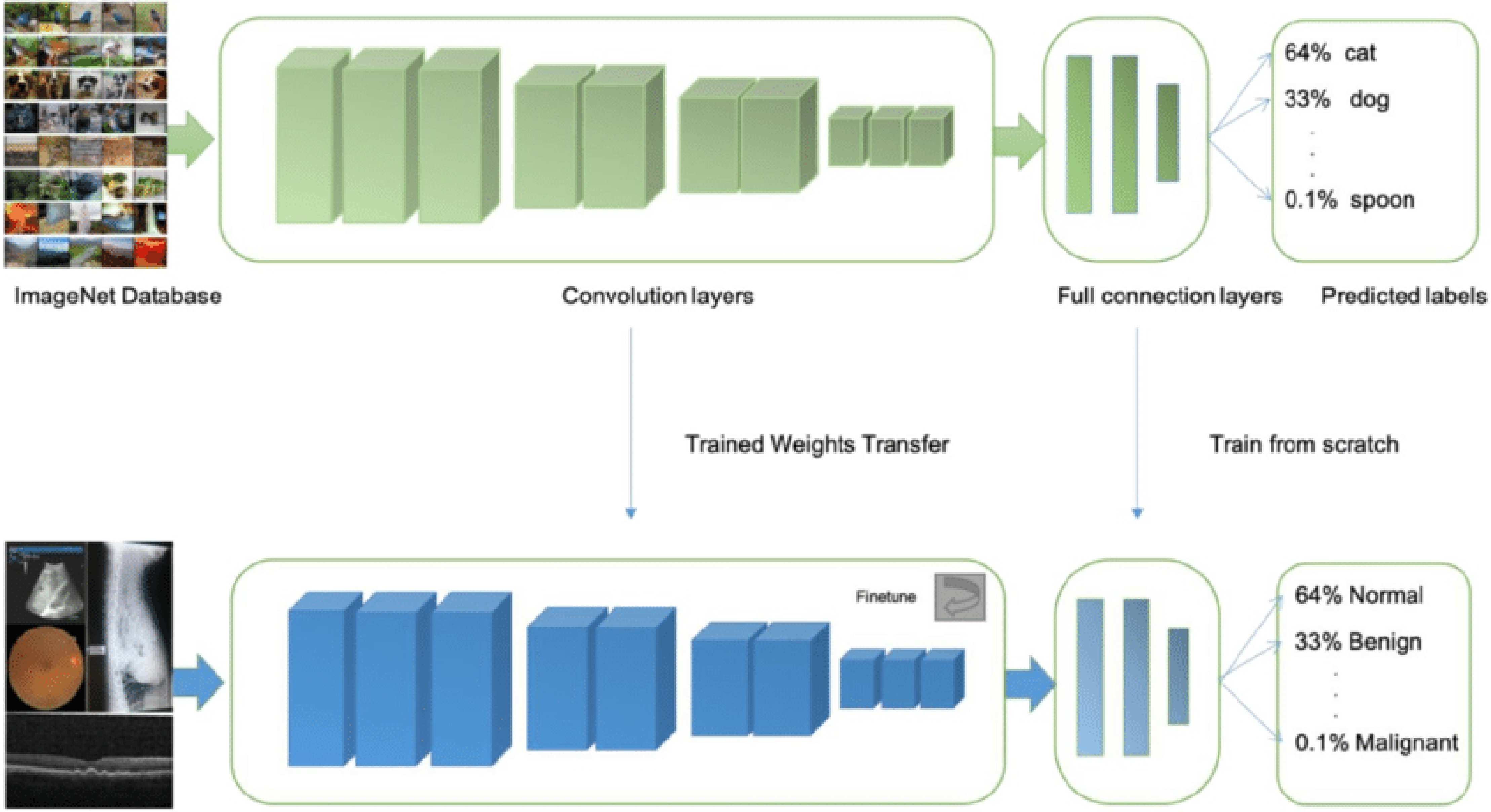
Image-based model

By using the Residual Block, the vanishing gradient problem can be solved. With Residual Block, the gradients can flow directly through the skip connections backwards from later layers to initial filters, by adding layers are identity mapping. The existence of this constructed solution indicates that a deeper model should produce no higher training error than its shallower counterpart.

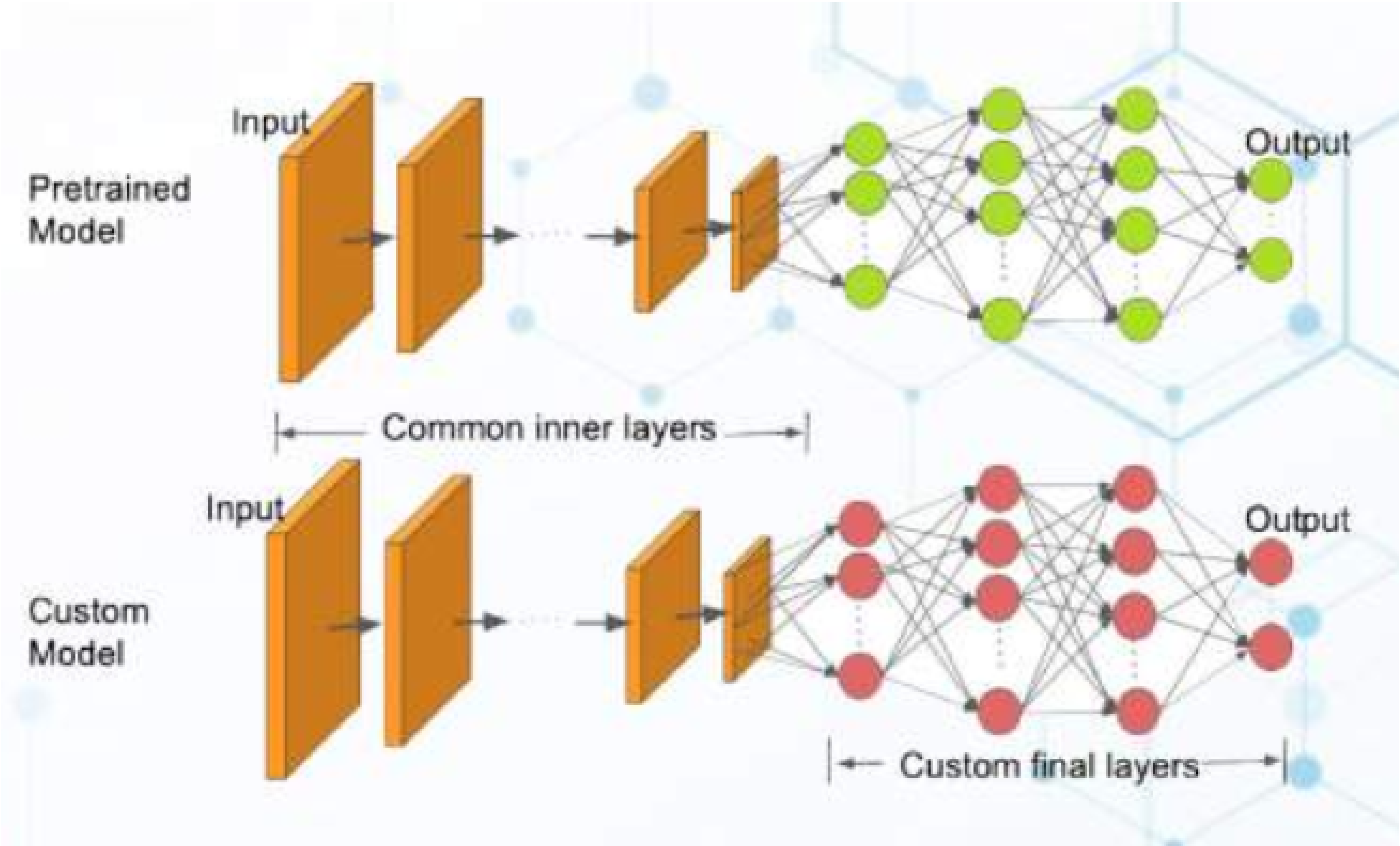


Normal CNN vs CNN with Residual Connection

Current Model – transfer learning



Current Model – Resnet18



Approach

Model Evaluation

1. Accuracy

2. Classification confusion metrics

3. Precision

$$\text{Precision} = \frac{\text{True positive}}{\text{True positive} + \text{False positive}}$$

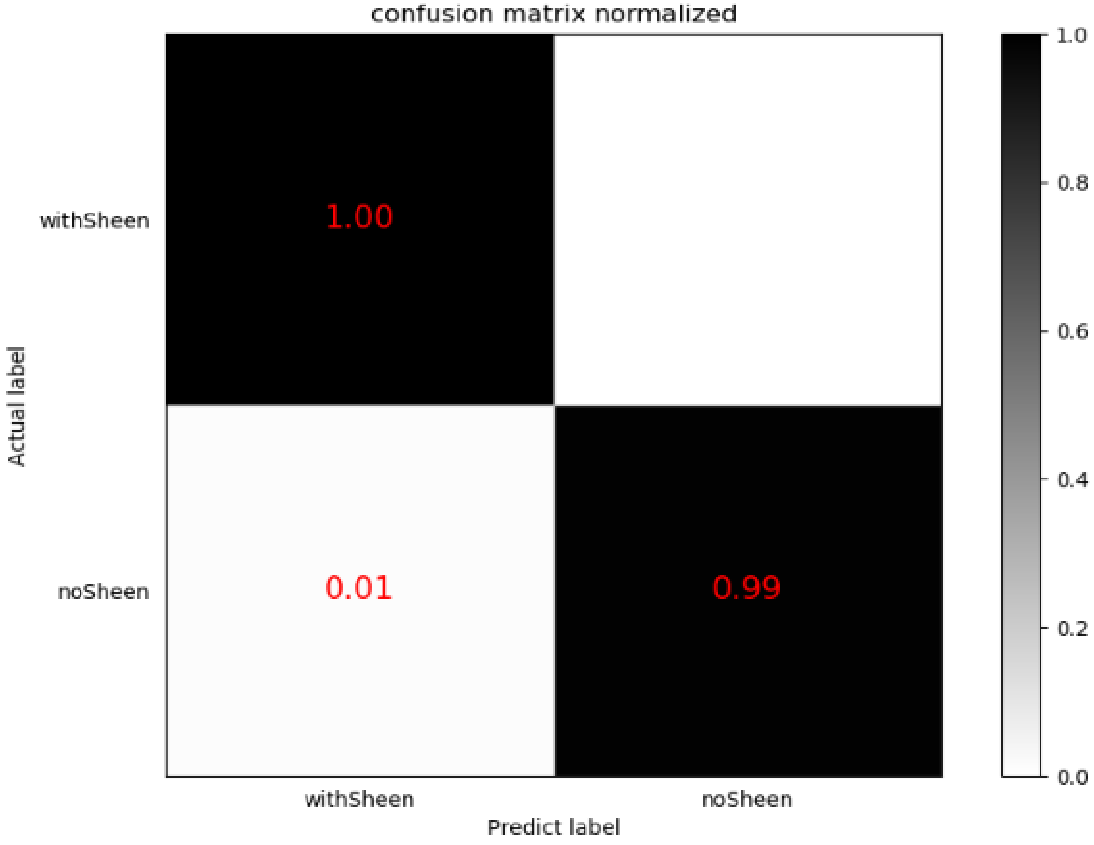
4. Recall

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive} + \text{False negative}}$$

5. F1 Score

$$\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

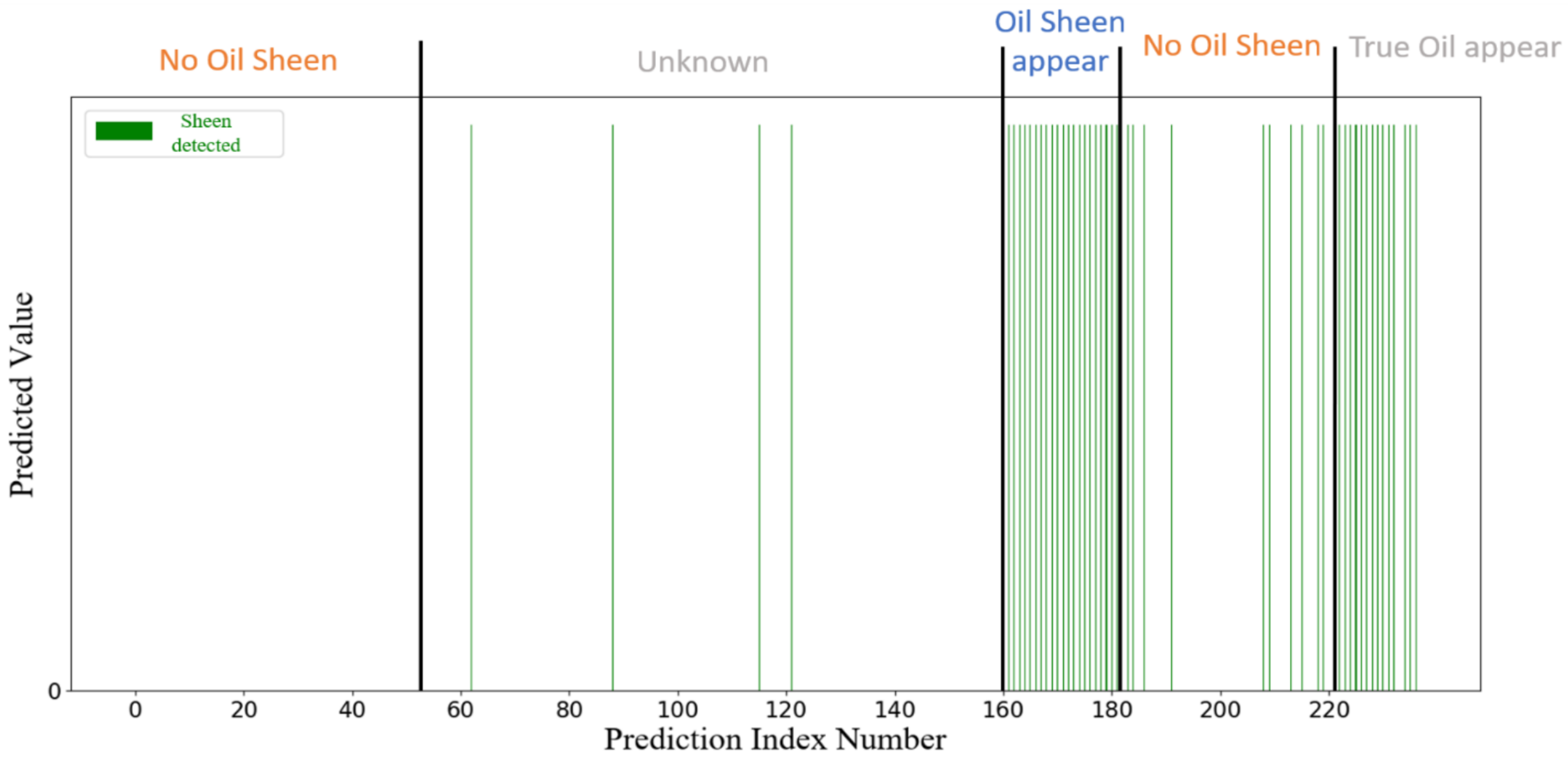
Model Evaluation



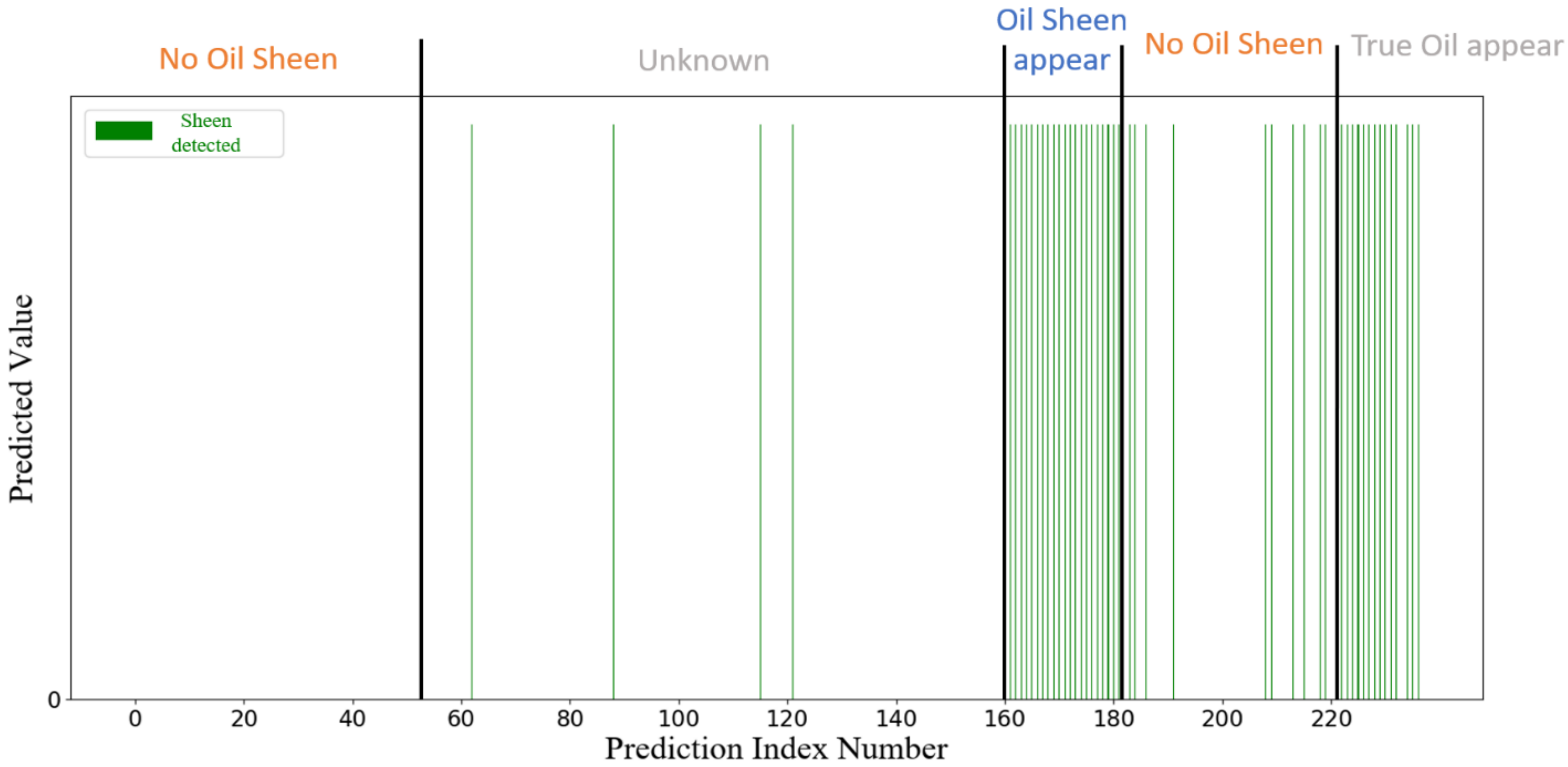
	Precision	Recall	F1-score
Model	0.98	1.0	0.99

Approach

Real-time video oil sheen prediction algorithm

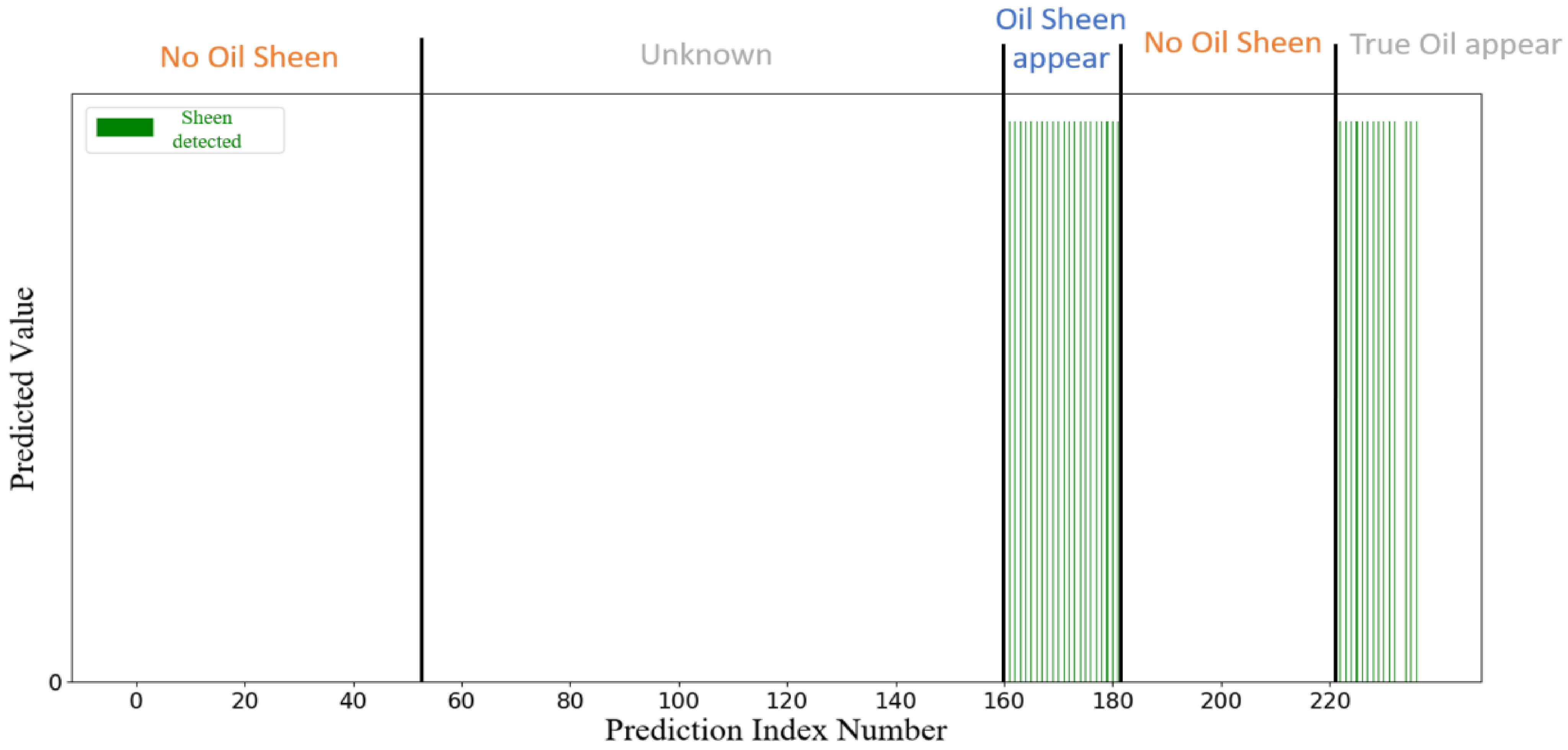


Model Evaluation



(a) Oil sheen prediction result with no filter

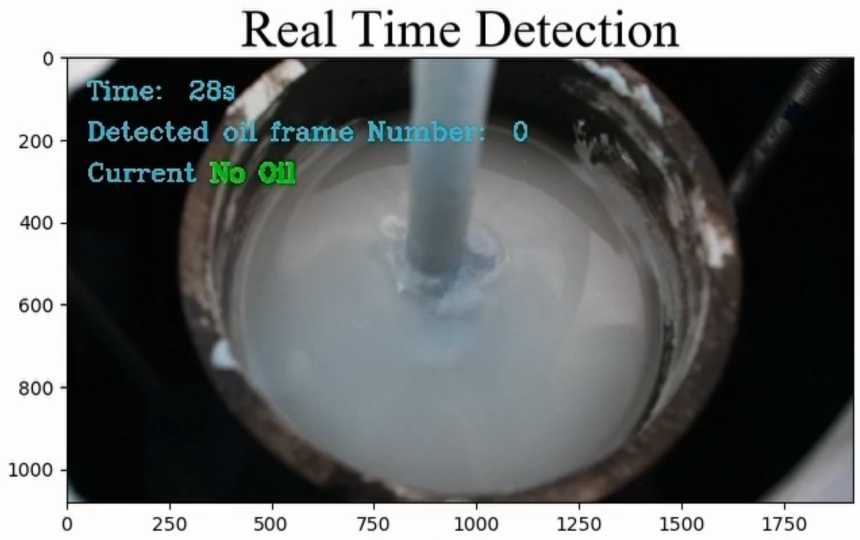
Model Evaluation



(b) Oil sheen prediction result with filter (kernel = 3)

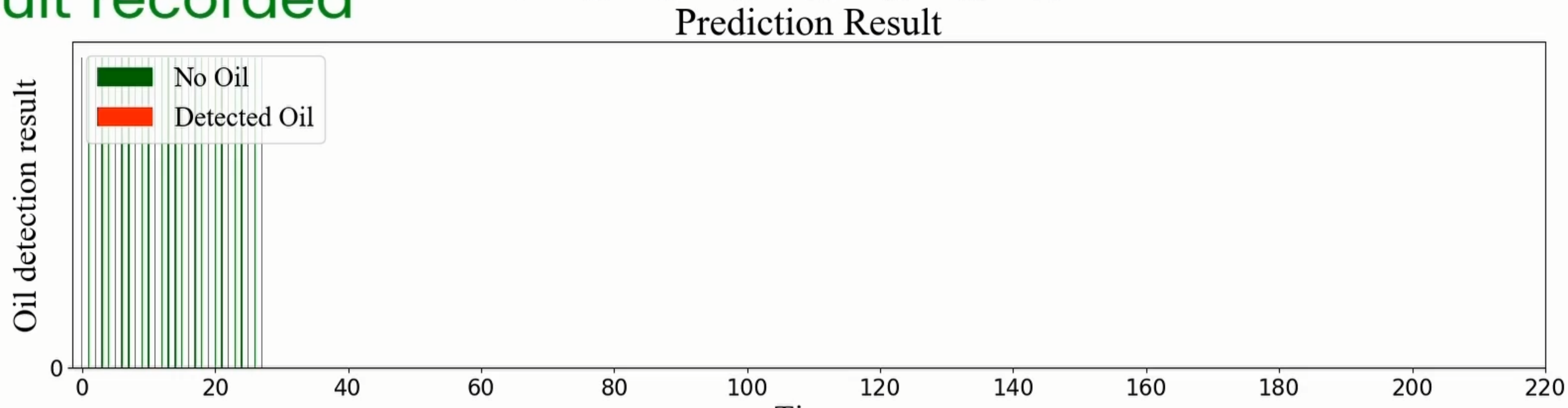
Model Evaluation

Current detection result →



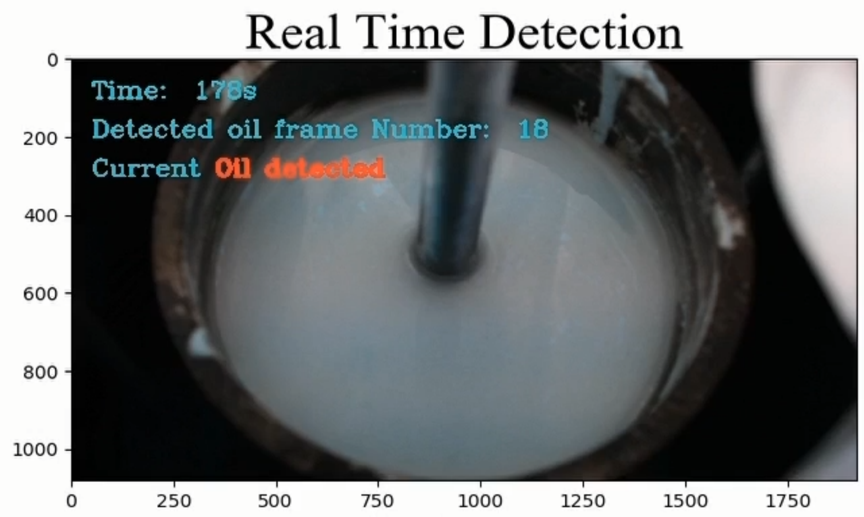
No oil sheen detected

Result recorded



Model Evaluation

Current
detection result →



Oil sheen detected
with filter = 3

Warning will be given when
oil Sheen was detected
in 3 consecutive times

Result recorded