

FIU

Applied Research
Center



DOE-FIU Cooperate Agreement Annual Research Review – FIU Year 3

Nuclear Waste Identification and Classification using Deep Learning

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*Worlds
Ahead*

Advancing the research and academic mission of Florida International University

Overall Needs:

- Understand and identify the presence of nuclear waste within multiple, different environments in real time.
- Develop and use deep learning models to facilitate computer vision operations without needing experience with deep learning.

Objectives:

- Research and explore the development of different deep learning solutions.
 - ✓ There are many algorithms that aim to solve the same or similar problems, each with its own advantages and disadvantages.
- Develop models in such a way that they can be integrated with other code.
 - ✓ Once the models that identify and classify objects are developed, it might be of interest to forward the results to another system like a robot system.
- Deploy developed algorithms to enhance AAML functionality.
 - ✓ Algorithms developed for a dataset can be abstracted to function on similar datasets.



FIU Year 3 Highlights:

Implemented YOLOv7 model for Object Detection.

- ✓ For a given object, the model predicts the object's class, bounding box, and its confidence on the prediction.
- ✓ It reaches a high mAP on the test set.
- ✓ The model is designed to detect objects in real time using a CPU.
- ✓ It requires labeled data to learn how to detect objects.
- ✓ Since it learns from bounding box, it struggles to learn how to detect thin and/or long objects where the background is most of the box.

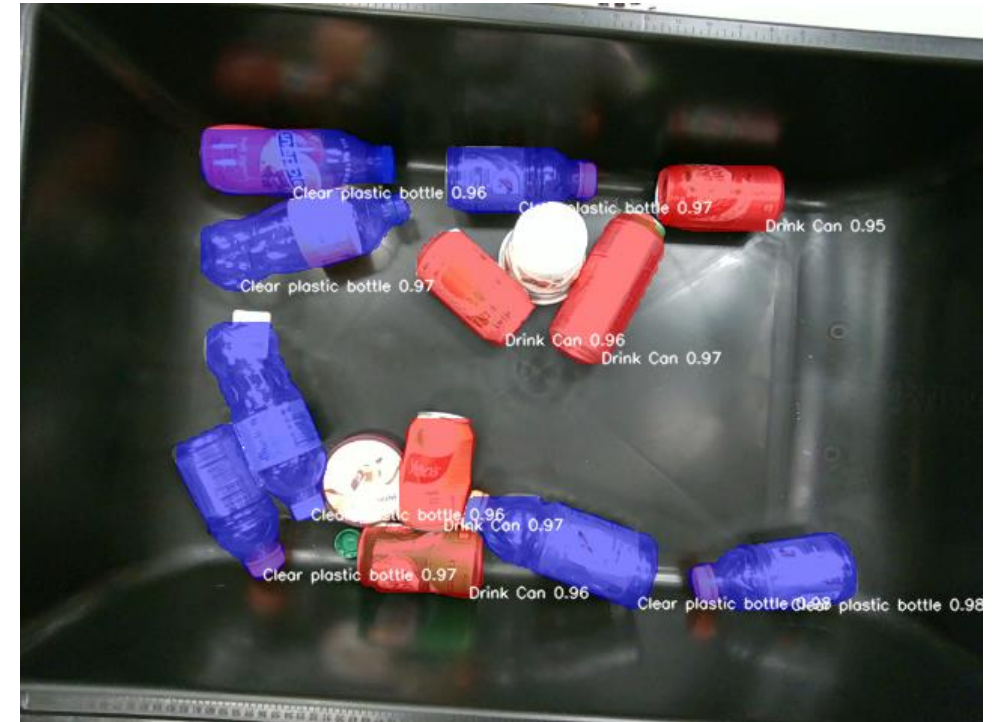


Example of the predictions results for a given image

FIU Year 3 Highlights:

Implemented YOLOv7 model for Instance Segmentation.

- ✓ For a given object, the model predicts the object's class, segmentation mask, and its confidence on the prediction.
- ✓ It reaches a high mAP on the test set.
- ✓ The model is designed to detect objects in real time using a CPU, though it is slower than the Object Detection version.
- ✓ It requires labeled data to learn how to detect objects.
- ✓ It can detect thin and/or long objects better than the previous version



Example of the predictions results for a given image

FIU Year 3 Highlights:

Implemented STEGO model for Unsupervised Semantic Segmentation.

- ✓ For a given image, the model predicts a set of clusters and the segmentation mask for each cluster.
- ✓ The model is not designed to detect objects in real time using a CPU. However, by keeping a sufficiently small image size, it is possible to reach real-time inference speeds. There is a tradeoff with mAP.
- ✓ It does not require labeled data to learn how to detect the clusters.
- ✓ Sometimes it is unfeasible to convert the cluster masks into a polygon format because a cluster can contain one or more objects.

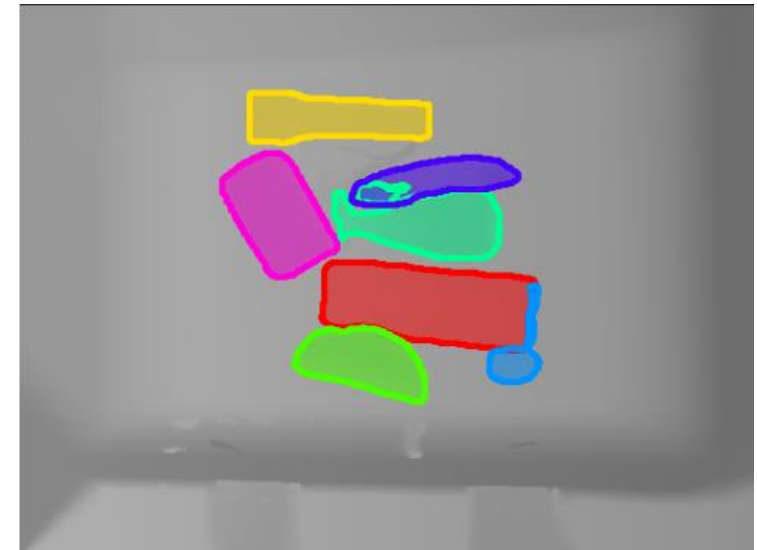


Example of the predictions results for a given image

FIU Year 3 Highlights:

Implemented Mask R-CNN model for Disparity Image Segmentation.

- ✓ For a given disparity image, the model predicts an object's segmentation mask and its confidence that it is a foreground object.
- ✓ The model is not designed to detect objects in real time using a CPU. However, by keeping a sufficiently small image size, it is possible to reach real-time inference speeds. There is a tradeoff with mAP.
- ✓ It does require labeled data to learn how to detect the clusters. It can only detect foreground vs background objects.
- ✓ Struggles with nested objects.

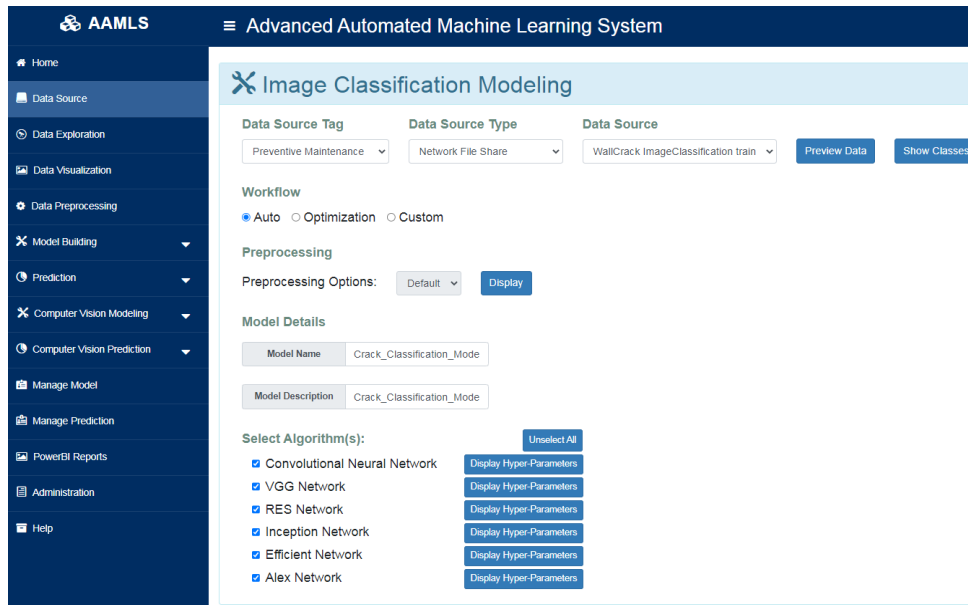


Example of the predictions results for a given disparity image. The top image is used for comparison purposes only.

FIU Year 3 Highlights:

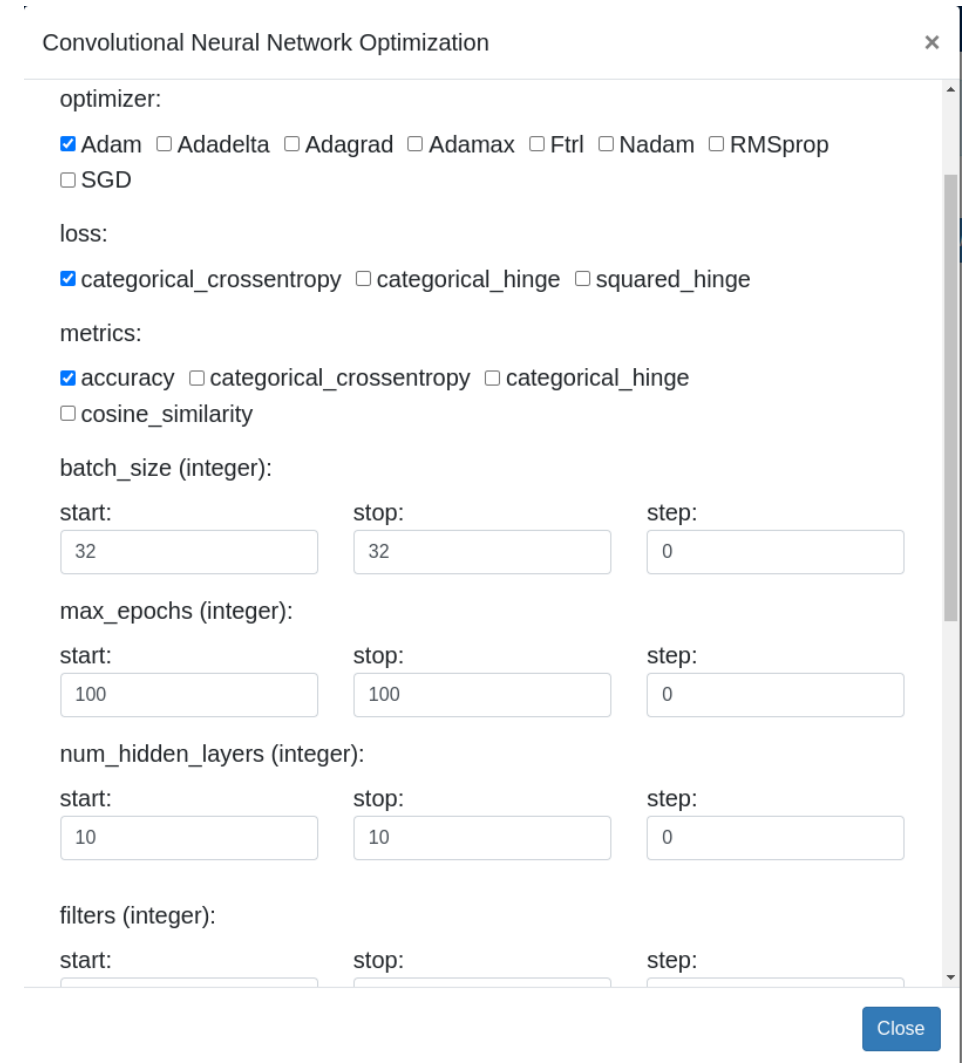
Implemented Image Classification Models.

- Added models like VGG, ResNet, InceptionNet, EfficientNet, AlexNet, and a custom model.
- Implemented the ability to customize the models with different number of layers, activation functions, etc.



The screenshot shows the AAML interface with the following components:

- Header:** AAML | Advanced Automated Machine Learning System
- Left Sidebar:** Home, Data Source, Data Exploration, Data Visualization, Data Preprocessing, Model Building, Prediction, Computer Vision Modeling, Computer Vision Prediction, Manage Model, Manage Prediction, PowerBI Reports, Administration, Help.
- Main Content Area:**
 - Image Classification Modeling**
 - Data Source:** Preventive Maintenance (Tag), Network File Share (Type), WallCrack ImageClassification train (Source). Buttons: Preview Data, Show Classes.
 - Workflow:** Auto (selected), Optimization, Custom.
 - Preprocessing:** Default (selected), Display.
 - Model Details:** Model Name: Crack_Classification_Mode; Model Description: Crack_Classification_Mode.
 - Select Algorithm(s):**
 - Convolutional Neural Network (Display Hyper-Parameters)
 - VGG Network (Display Hyper-Parameters)
 - RES Network (Display Hyper-Parameters)
 - Inception Network (Display Hyper-Parameters)
 - Efficient Network (Display Hyper-Parameters)
 - Alex Network (Display Hyper-Parameters)



The screenshot shows the 'Convolutional Neural Network Optimization' configuration window with the following settings:

- optimizer:**
 - Adam
 - Adadelta
 - Adagrad
 - Adamax
 - Ftrl
 - Nadam
 - RMSprop
 - SGD
- loss:**
 - categorical_crossentropy
 - categorical_hinge
 - squared_hinge
- metrics:**
 - accuracy
 - categorical_crossentropy
 - categorical_hinge
 - cosine_similarity
- batch_size (integer):**
 - start: 32
 - stop: 32
 - step: 0
- max_epochs (integer):**
 - start: 100
 - stop: 100
 - step: 0
- num_hidden_layers (integer):**
 - start: 10
 - stop: 10
 - step: 0
- filters (integer):**
 - start: [empty]
 - stop: [empty]
 - step: [empty]

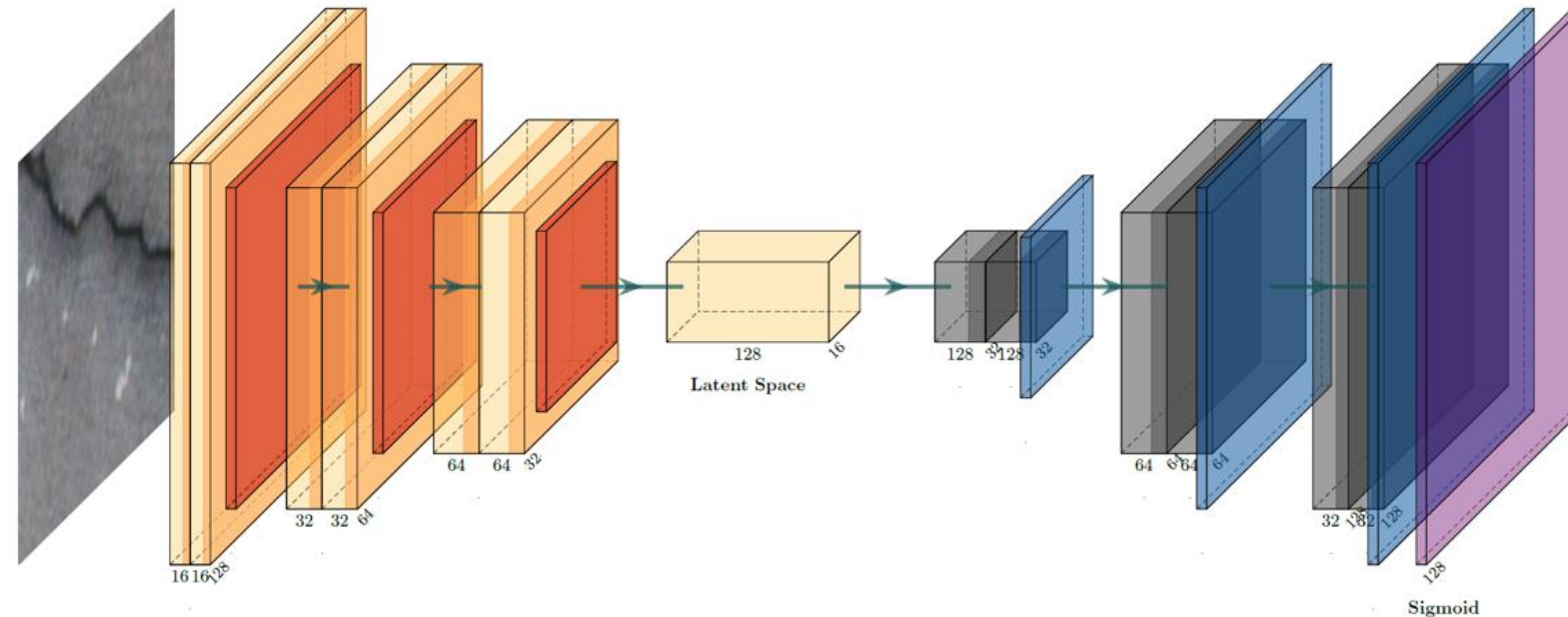
Buttons: Unselect All, Display Hyper-Parameters (for each algorithm), Close.



FIU Year 3 Highlights:

Implemented Anomaly Detection Models.

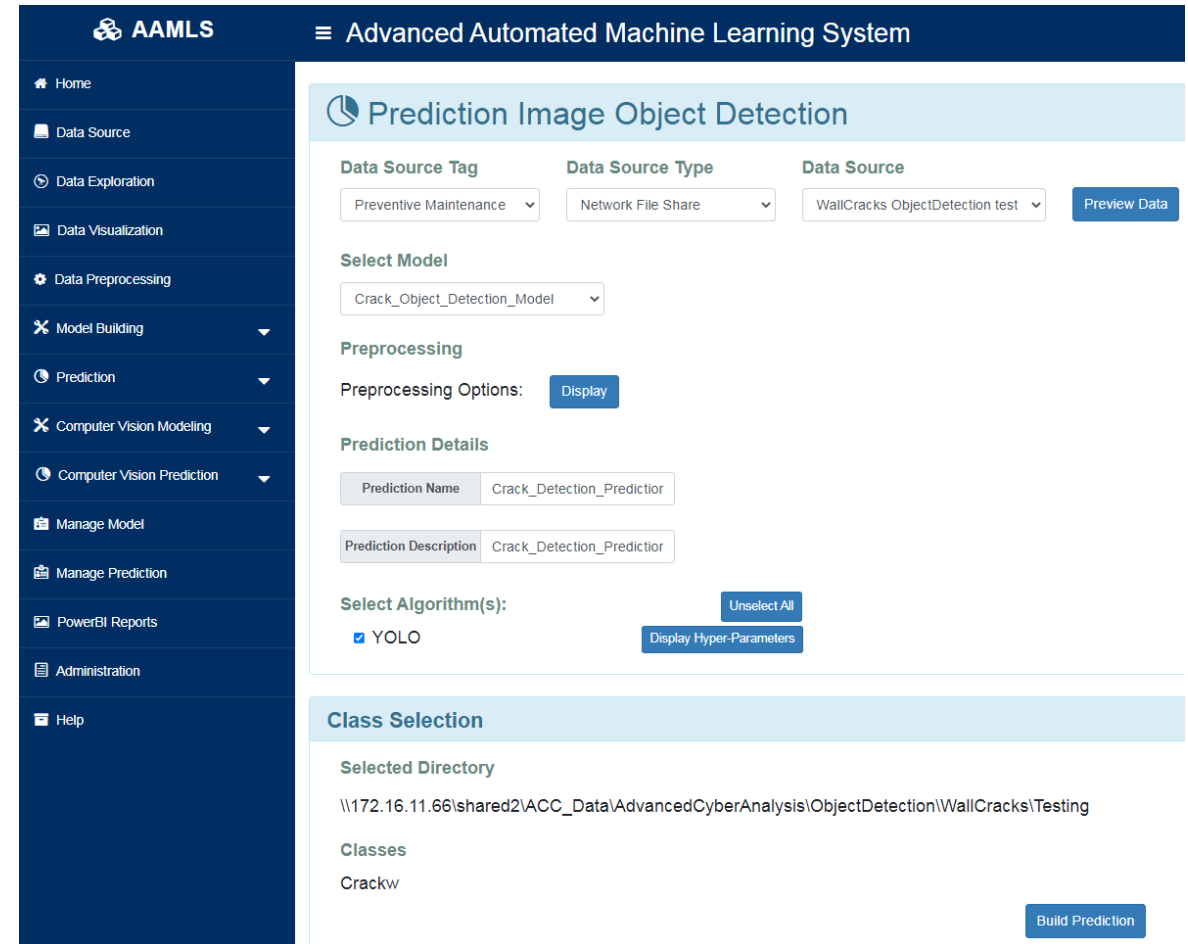
- Added an Autoencoder model that learns how to compress and decompress normal data. When given anomalous data, it fails, and the degree of failure corresponds to how different the anomalous data is from the normal data.
- Implemented the ability to customize the models with different number of layers, activation functions, etc. to enhance the performance of the model on new data.



FIU Year 3 Highlights:

Implemented Object Detection Models.

- Added YOLOv3 model that has high performance and low latency when predicting.
- Implemented the ability to customize the model's confidence and IoU thresholds. Also implemented transfer learning to reduce training time while maintaining a high performance.



The screenshot displays the AAML web interface. The top navigation bar includes the AAML logo and the system name 'Advanced Automated Machine Learning System'. A left sidebar contains a menu with options: Home, Data Source, Data Exploration, Data Visualization, Data Preprocessing, Model Building, Prediction, Computer Vision Modeling, Computer Vision Prediction, Manage Model, Manage Prediction, PowerBI Reports, Administration, and Help.

The main content area is titled 'Prediction Image Object Detection' and contains the following configuration fields:

- Data Source Tag:** Preventive Maintenance
- Data Source Type:** Network File Share
- Data Source:** WallCracks ObjectDetection test
- Select Model:** Crack_Object_Detection_Model
- Preprocessing:** Preprocessing Options: Display
- Prediction Details:**
 - Prediction Name: Crack_Detection_Predictor
 - Prediction Description: Crack_Detection_Predictor
- Select Algorithm(s):** YOLO (checked), Unselect All, Display Hyper-Parameters

Below the configuration fields is a 'Class Selection' section:

- Selected Directory:** \\172.16.11.66\shared2\ACC_Data\AdvancedCyberAnalysis\ObjectDetection\WallCracks\Testing
- Classes:** Crackw

A 'Build Prediction' button is located at the bottom right of the interface.



Future work

- Research and implement an object detection algorithm that has these properties:
 - Does not require labeled data to learn to detect a new object.
 - Has the ability to choose which objects to detect, not just every foreground object.
 - Has real-time or close to real-time inference speeds.

Those properties make up for all the shortcomings of the current solutions. The team plans to research computer vision and natural language processing models to do text-prompted zero-shot object detection. However, the real-time inference speeds will be a challenge.

- Continue to deploy the implemented models on the AAML System.
 - Models on the AAML System can be used for the same tasks, but on different data. This flexibility provides solid solutions to people working on similar problem sets that do not have the time or experience to develop the deep learning solutions themselves.



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Thank You. Questions?