U.S. ARMY RESEARCH, DEVELOPMENT AND ENGINEERING COMMAND

Deep Learning for Future Army Systems

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OVERVIEW

- Why are we looking at Deep Learning?
- What is deep learning?

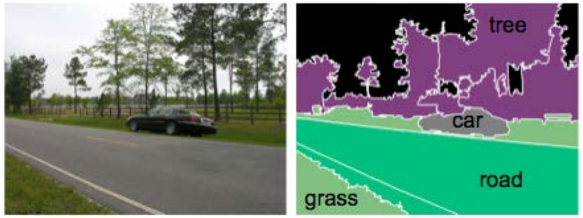
- We are applying it to the study of a diverse set of future Army systems:

1. Detecting crack damage from ultrasound for Sustainment and Future Vertical Lift
2. Intrusion detection / malware analysis (Network / C3I)
3. Classification of radio modulation (Network / C3I)
4. Health monitoring of ground vehicles for Next Gen. Combat Vehicle
5. Monitoring of additive manufacturing for sustainment (NGCV & FVL)

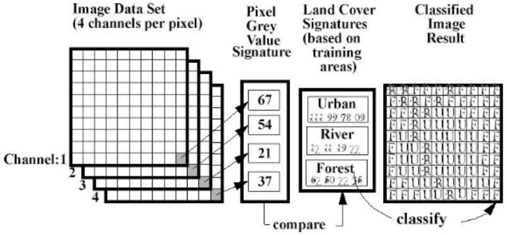
There has been rapid advances in machine learning…

- Game-playing AI – DeepGo can **beat top humans**

- Semantic segmentation: Towards **self-driving cars**



- **Image classification** with ~95% accuracy



- **Language translation**: "Error reduction by 55 to 85%"

Google Translate

CAN DEEP LEARNING HELP US?

- **What Army problems can be solved with DL?**
- Can we trust these black box methods?
- Can DL fit within our power/size constraints?
- Can DL be easily fooled?
- DL usually needs lots of data, **can we overcome this challenge?**

At ARL, we are looking at all of these questions.

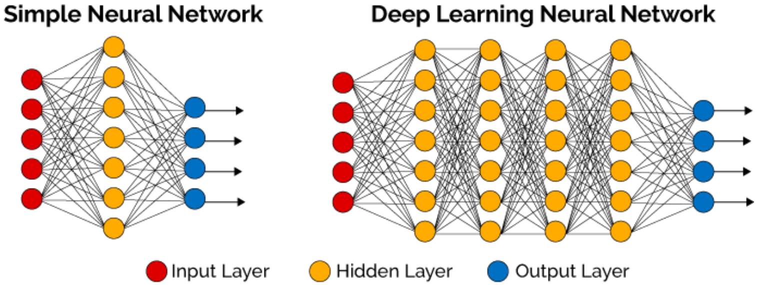
Lee, Michael, et al. *Current and Future Applications of Machine Learning for the US Army*. No. ARL-TR-8345. US Army Research Laboratory Aberdeen Proving Ground United States, 2018.

DEEP LEARNING

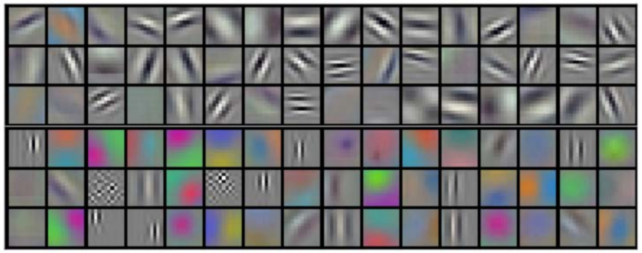
- Optimize the **parameters** of a complicated function that **transforms** some **input** (e.g., picture of a cat) into some **output** (e.g., 'label: cat')

→ "cat"

- A neural network with multiple "hidden" layers



- Uses a mix of convolutional and pooling (downsampling) layers

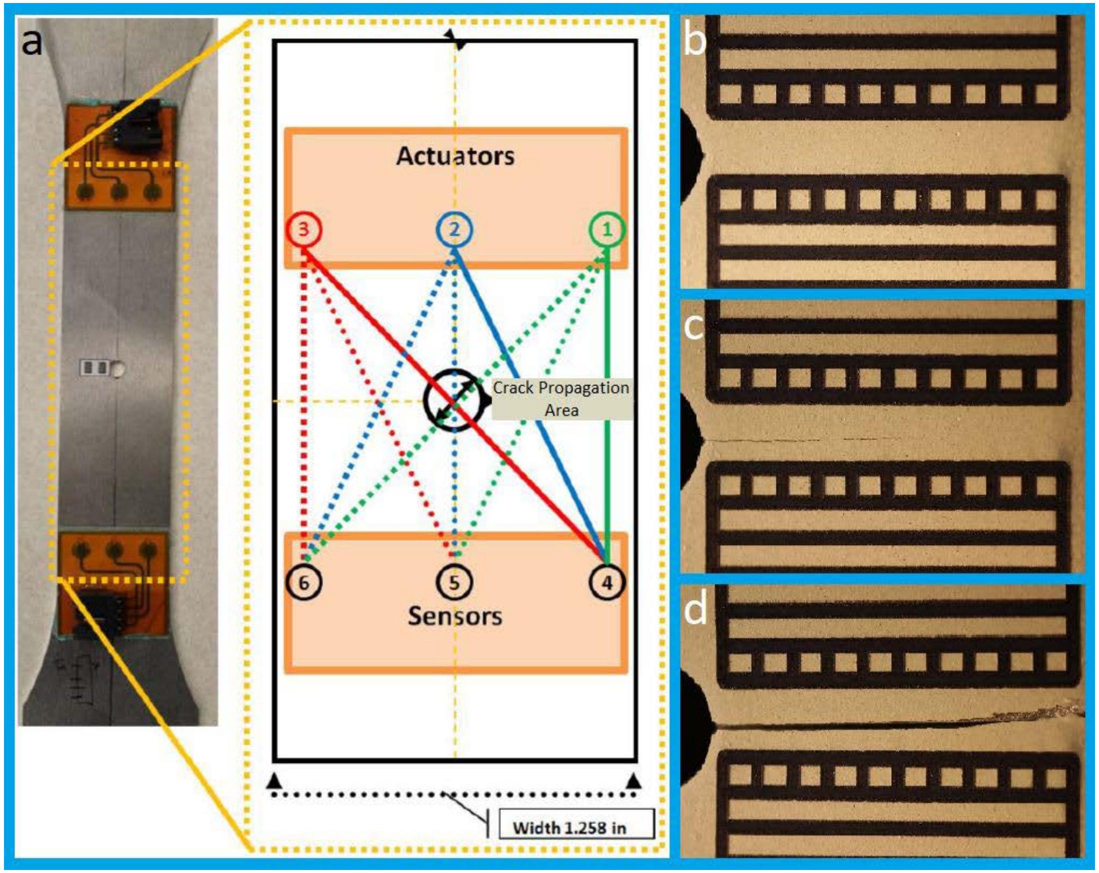


Convolutional filters

PROJECT #1: DETECTING CRACK DAMAGE FROM ULTRASOUND

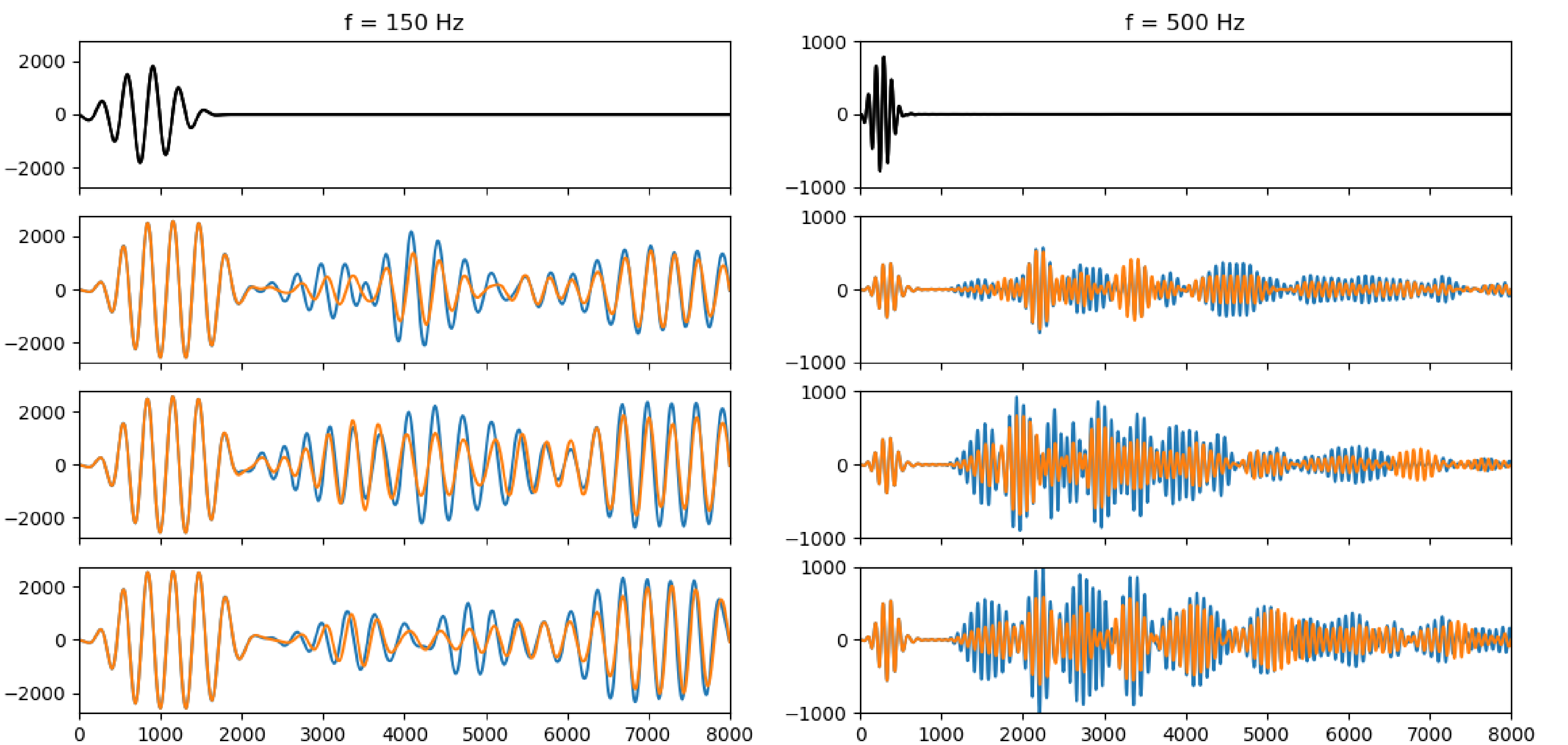
Sustainment Goal:

1) Detect the damage before it even becomes visible.
2) Only replace parts when there is damage.



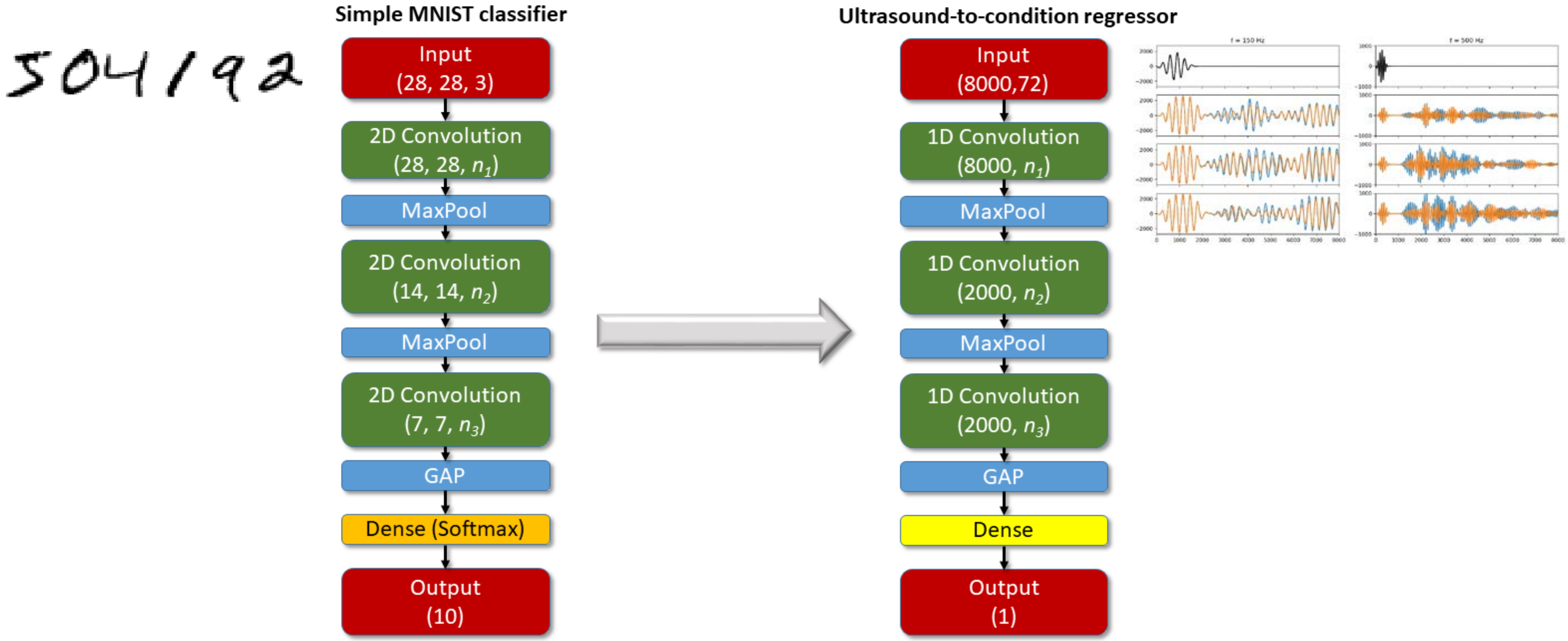
DETECTING CRACK DAMAGE FROM ULTRASOUND

The signals are complex, but ML can simplify (and automate) the readout.

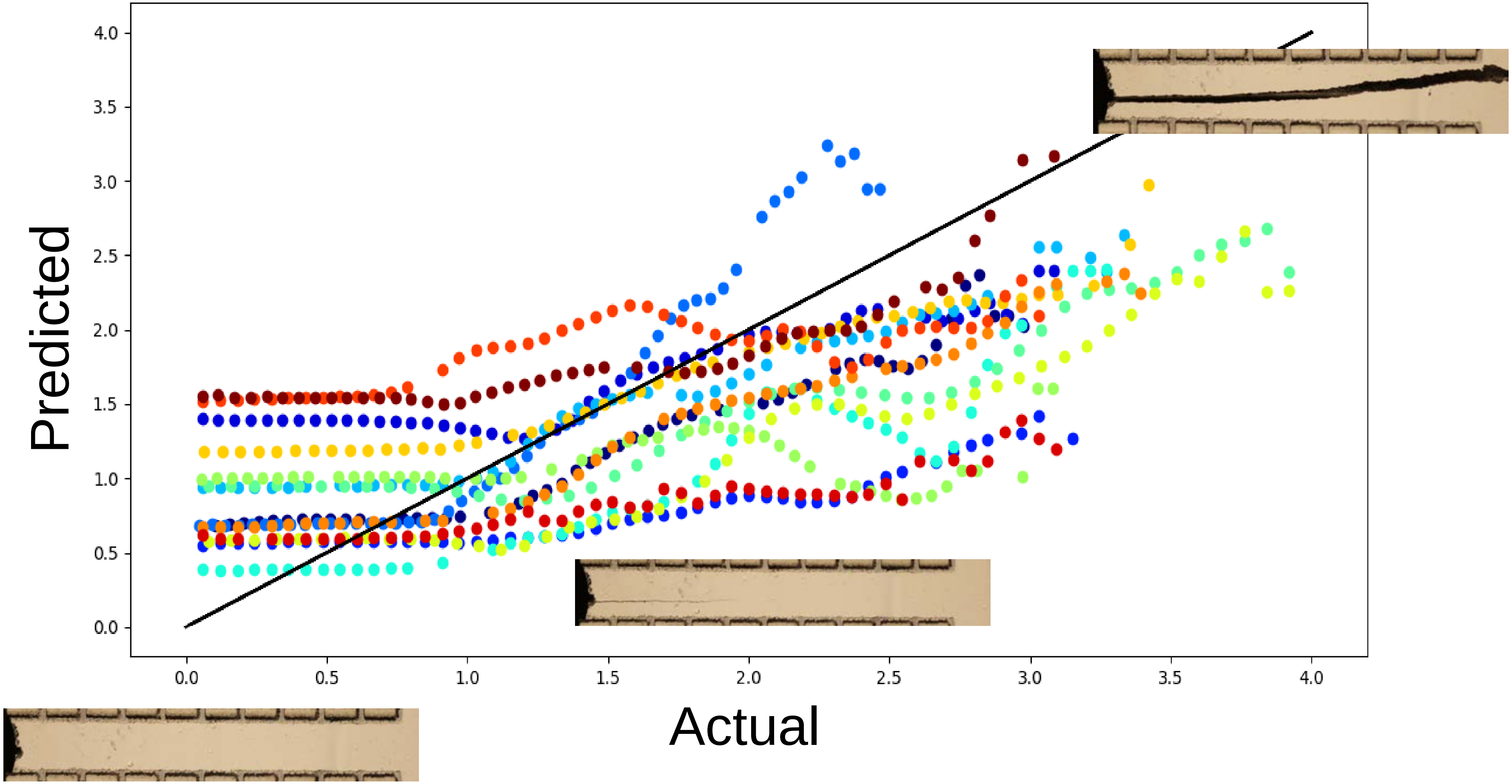


DETECTING CRACK DAMAGE FROM ULTRASOUND

In the same way that the Post Office automatically reads zip codes, convert probe signals to crack damage indicator.



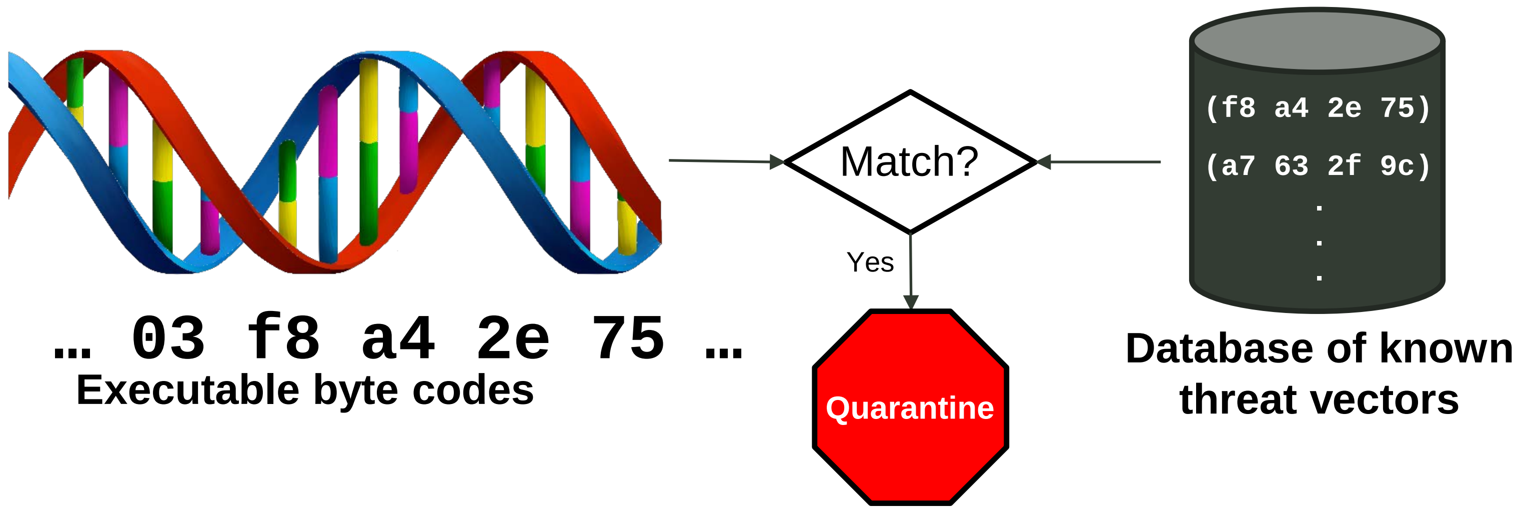
DETECTING CRACK DAMAGE FROM ULTRASOUND



Learn more: Hyatt, John S., Eliseo Iglesias, and Michael Lee. *Convolutional Neural Networks for 1-D Many-Channel Data*. No. ARL-TR-8372. US Army Research Laboratory APG, MD, US, 2018.

PROJECT #2: INTRUSION DETECTION & MALWARE ANALYSIS

- Traditionally, threat vectors to a computer system are detected by **matching strings** from a known threat database (e.g., antivirus software).

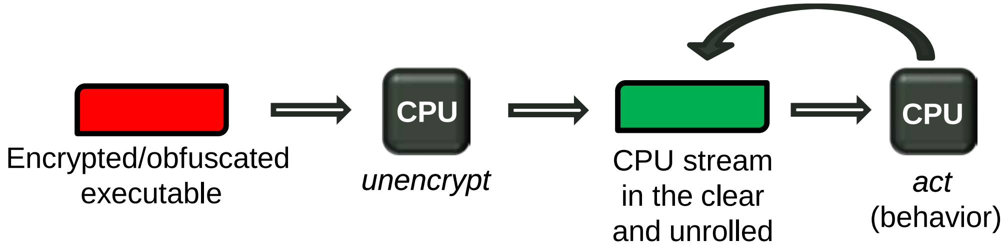


- New threats, however, are either **encrypted** or are **uniquely developed** for targeted attacks on a particular asset.

- Therefore, we have to look **beyond a threat's DNA** (i.e., executable code) to **detect** and **understand** it.

ML FOR INTRUSION DETECTION

Strategy:

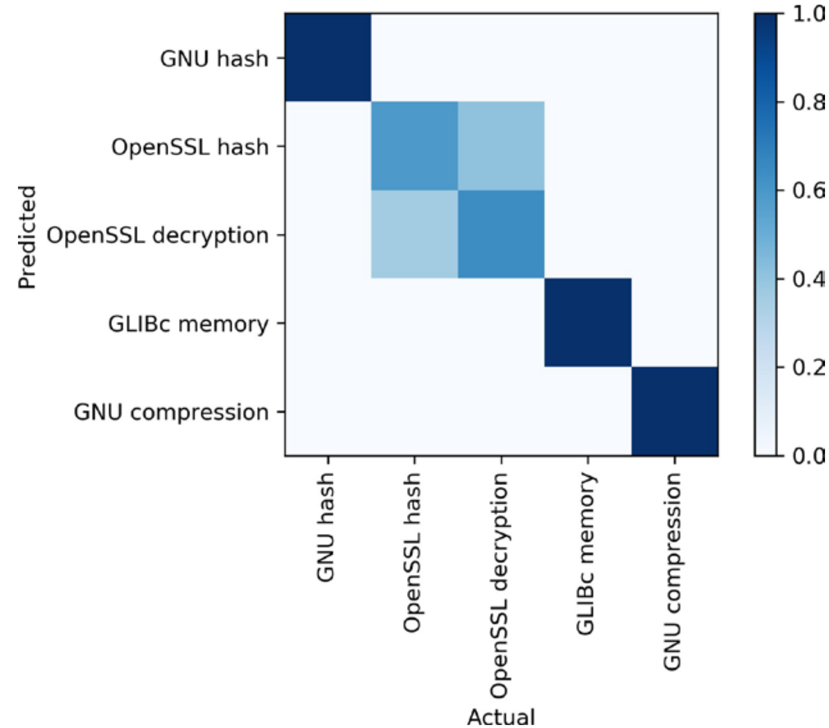


Questions:

- Are CPU instruction streams sufficient to distinguish good and bad activities?
- Does all data need to be fed in? (i.e., could the processing of data be **intermittent** – realistic scenario)
- Can **novel threat activities be detected**?

USING CONVOLUTIONAL NN TO CLASSIFY PROGRAM FUNCTIONS

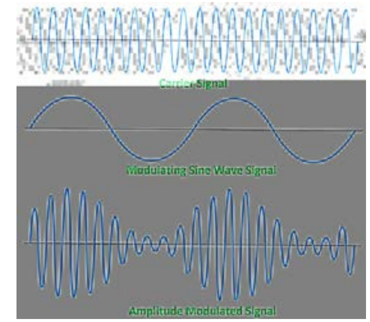
- Input: CPU stream fragments (1000 opcodes each)
- Embedding layer (16-dim vector encodes 100+ unique opcodes)
- Convolution layer #1 (N = 30, size = 11)
- MaxPool (size = 10)
- Dropout (0.2)
- Convolution layer #2 (N = 30, size = 5)
- MaxPool (size = 2)
- Dropout (0.2)
- Convolution layer #3 (N = 30, size = 5)
- MaxPool (size = 2)
- Dropout (0.2)
- Flatten
- Dense layer
- Softmax classifier



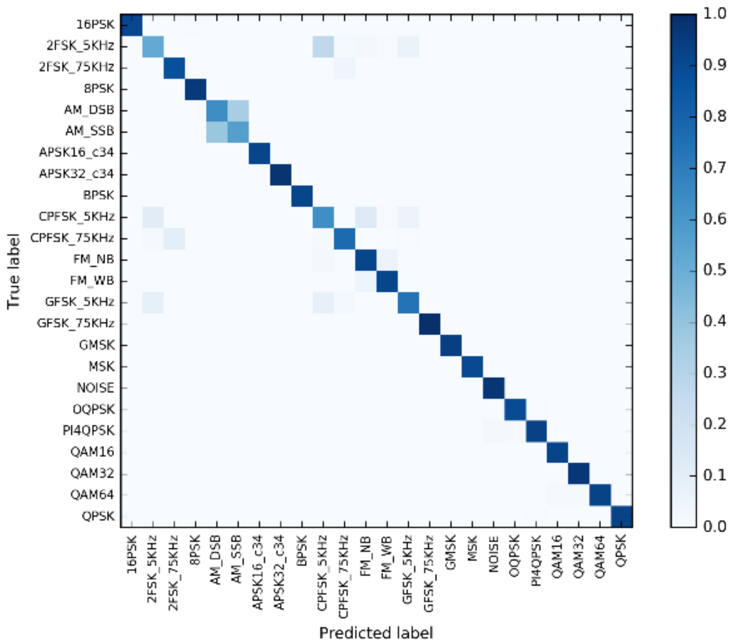
Class	**Programs**
GNU cryptographic hashes[16]	md5sum, sha256sum, sha384sum, sha512sum
OpenSSL cryptographic hashes[16]	-sha128, -sha256, -sha384, -sha512
OpenSSL decryption algorithms[17]	-camellia-256-cbc, -rc2-64-cbc, -aes-256-cbc, -blowfish
GLIBC memory operation tests	test-memcpy, test-memchr, test-memmem, test-memcmp
Compression tools	gzip, xz, bzip2, zip

Lee, MS. "Convolutional neural networks for functional classification of opcode sequences." *Disruptive Technologies in Information Sciences*. Vol. 10652. International Society for Optics and Photonics, 2018.

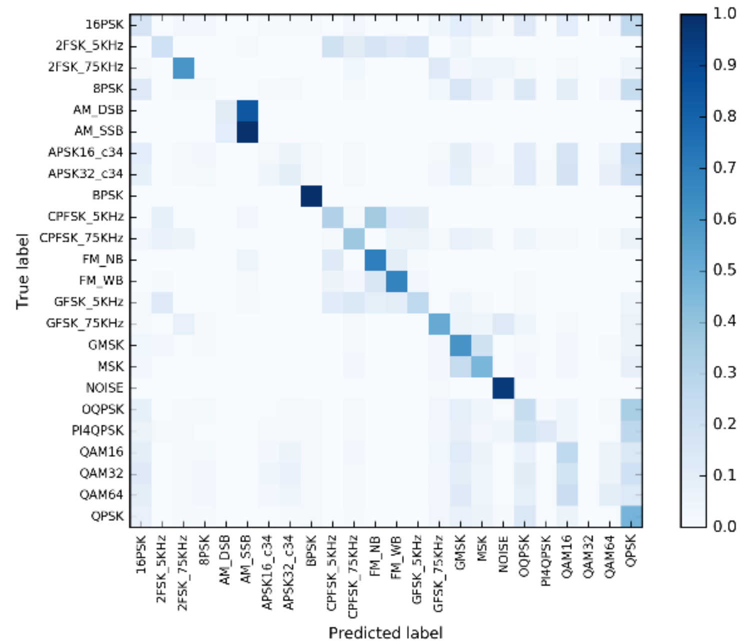
#3: CLASSIFICATION OF DIGITAL RADIO MODULATION



- **Goals:**
  - Detect adversary RF modulation, use smart jamming
  - Detect adversarial interference, choose best mitigation strategy



SNR = 10 dB
“Clean signal”

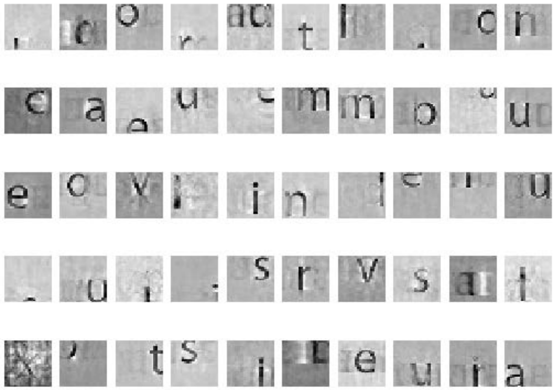


SNR = -10 dB
“Noisy signal”

Army Rapid Capabilities Office Challenge:
24 modulation classes, 6 signal-to-noise ratios

FEATURE EXTRACTION & DETECTION W/ LIMITED DATA

We developed a neural network that **extracts** and **detects** **shift(phase)-invariant** features from a <u>**single data sample**</u>.



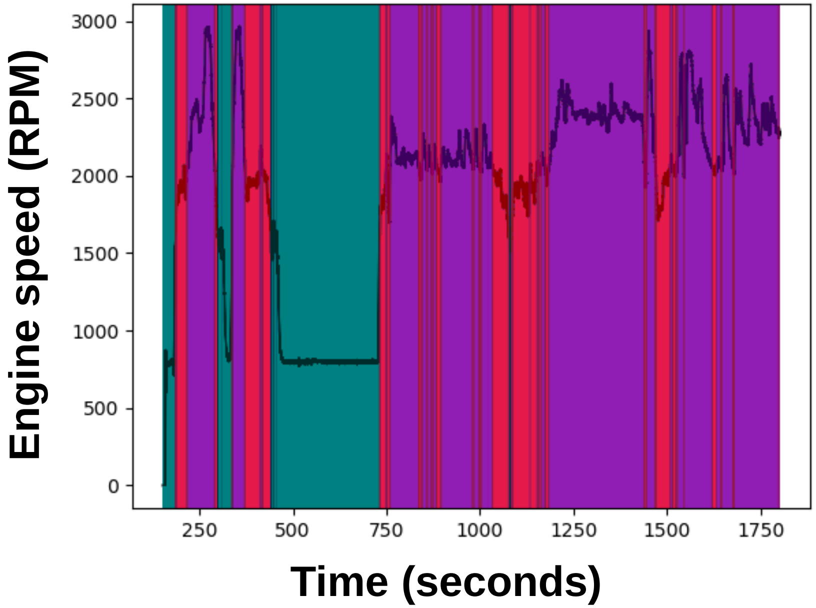
Learned features

#4: HEALTH MONITORING OF GROUND VEHICLES

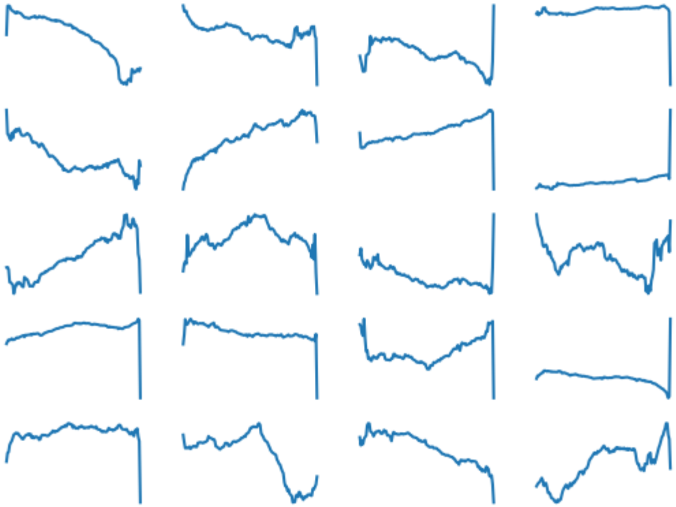
- **Identify useful indicators** in data collected from Army Multi-Purpose Vehicle testing.
- **Detect anomalous** events.
- Devise **automated** strategies to detect these anomalies.

#4: ANOMALY DETECTION IN AMPV DATA

Labelled engine speed data



Learned features



#5: MONITORING FOR ADDITIVE MANUFACTURING

- Additive manufacturing holds promise for making parts in the field.
- However, we need assurances that these parts are up to our standards.
- Deep learning will enable
  - Closed-loop monitoring (repair issues on-the-fly)
  - Certification by real-time assessment

#5: MONITORING FOR ADDITIVE MANUFACTURING

Layer #60

Layer #42

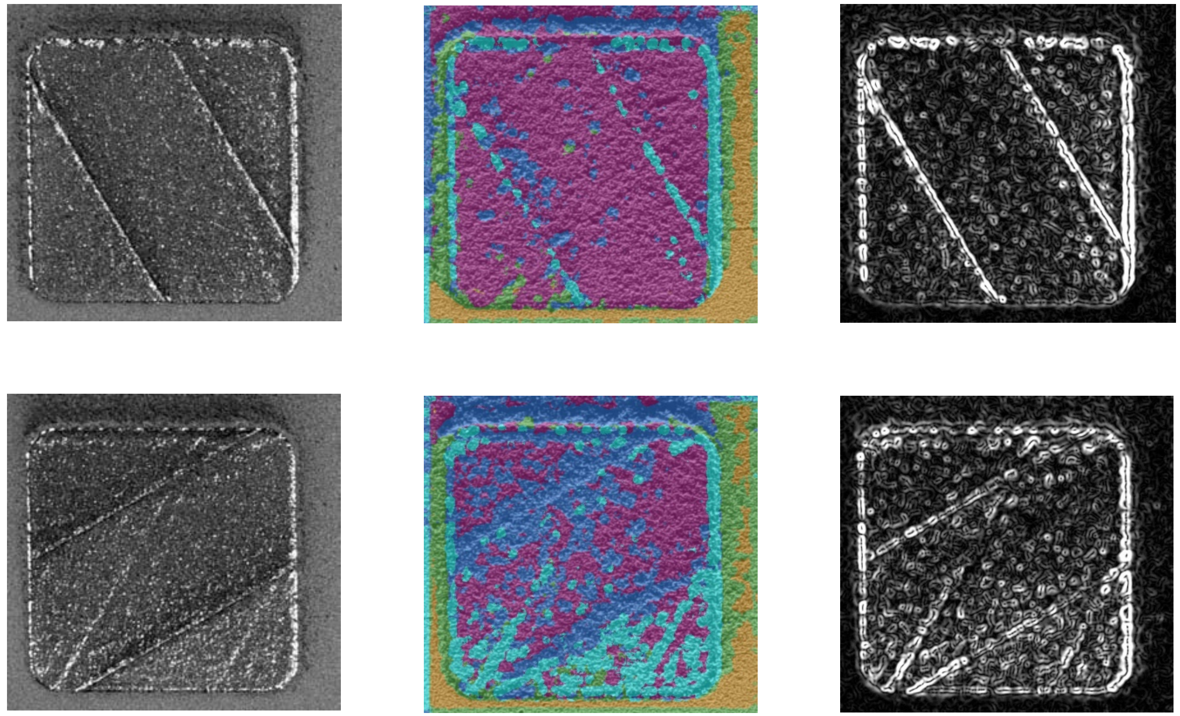


Image **Autoencoder** **Simple edge detection**

FUTURE WORK

Project	Future efforts
Malware detection	More programs (incl. malware); Real-time monitoring; autonomous cyber agents
Radio classification	ML-based demodulation in the presence of interference
AMPV	Data mining with various ML algorithms
Additive manufacturing	Complex builds, intended and unintended defects
<Your Idea Here>	???