



Automated Defect Identification for Tri-structural Isotropic Fuels (AUDIT)

October 2022

Changing the World's Energy Future

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Dr. Joe Oncken
Idaho National Laboratory
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About the Presenter

- **Dr. Joe Oncken, Idaho National Laboratory**
 - **Postdoctoral Research Associate**
 - Ph.D. – Mechanical Engineering, Michigan Technological University
 - B.S. – Mechanical Engineering, University of North Dakota
- **Research Interests**
 - Predictive Control System Development and Deployment
 - Machine Learning
- **Co-Authors:**
 - Nancy Lybeck, Ph.D. – Idaho National Laboratory
 - Jeffrey Phillips, Ph.D. – Idaho National Laboratory
 - Scott Niedzialek – BWX Technologies
 - Justin Coleman, Ph.D. – Idaho National Laboratory



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What is TRISO Fuel?

TRi-structural ISOtropic (TRISO) Particle Fuel

- Uranium Oxycarbide (UCO) fuel kernel
- Coated in Pyrolytic Carbon and Silicon Carbide
- Withstands extreme temperatures and prevents fission product release

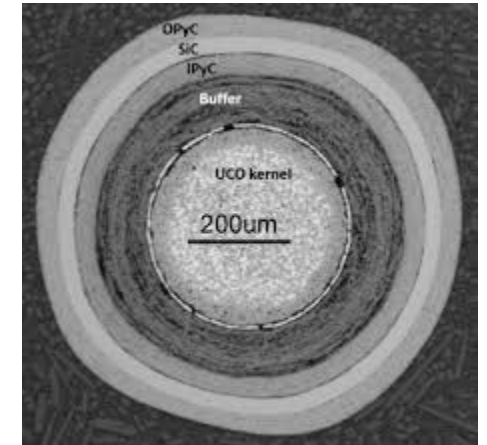


Photo Source: INL/MIS-19-52869-Revision-0

Applications: Advanced Nuclear Reactors

- Small Modular Reactors
 - . X-energy (High Temp Gas-Cooled Reactor)
 - . Kairos Power (Fluoride Salt-Cooled High Temp Reactor)
- Microreactors
 - . US DoD Microreactor (BWXT)

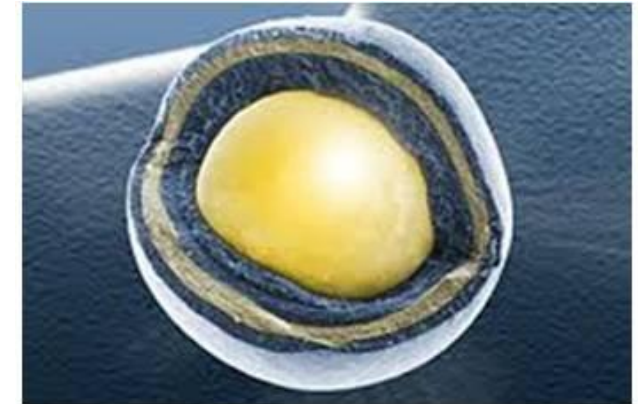
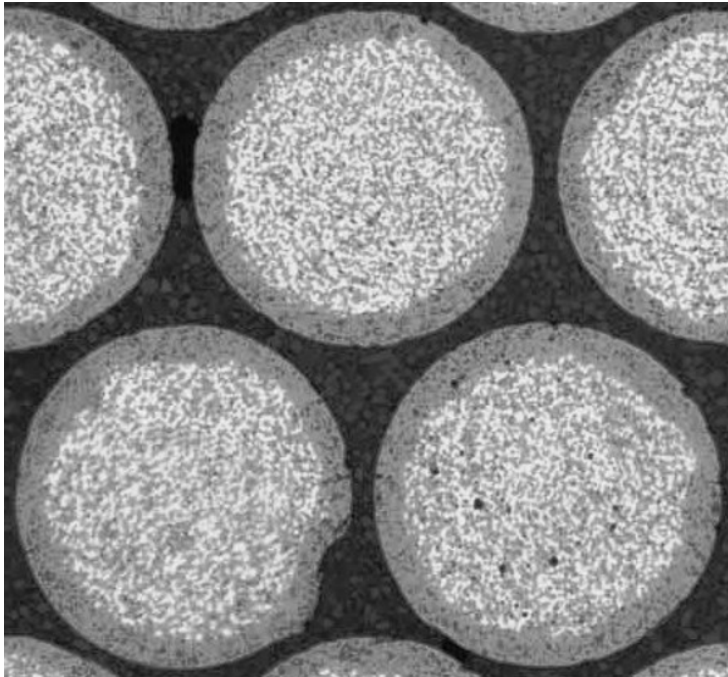


Photo Source: <https://www.energy.gov/ne/advanced-reactor-technologies>



TRISO Fissure Problem

Good Uncoated UCO Kernel



Fissured Uncoated UCO Kernel

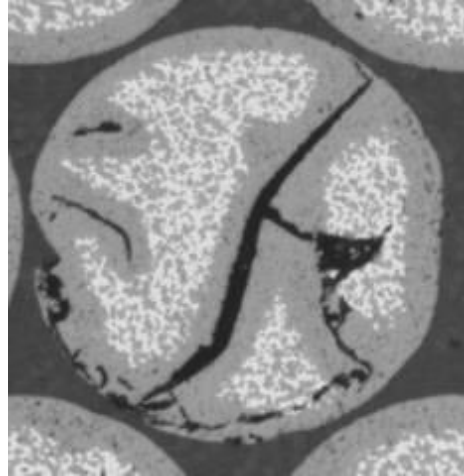


Photo Source: INL/EXT 19 53720

Post-TRISO Coating Fissured Kernels

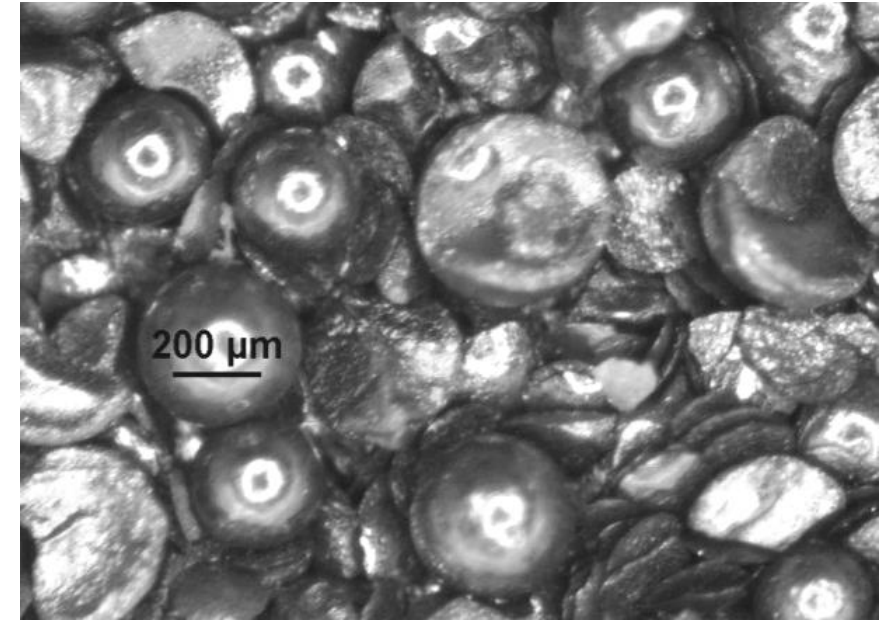


Photo Source: INL/EXT 19 53720

TRISO Fissure Problem

- Potential for fissured kernel to crack in subsequent processing.
- Unacceptable thinning of the coating layers in the dimple crater.
 - Not an adequate barrier against fission-product release.
- Short radius of curvature along the rim.
 - Creates stress concentration which could lead to coating failure.
- Too similar in size to “good” kernels to be sorted post-coating.

Post-TRISO Coating Fissured Kernel Cross Section

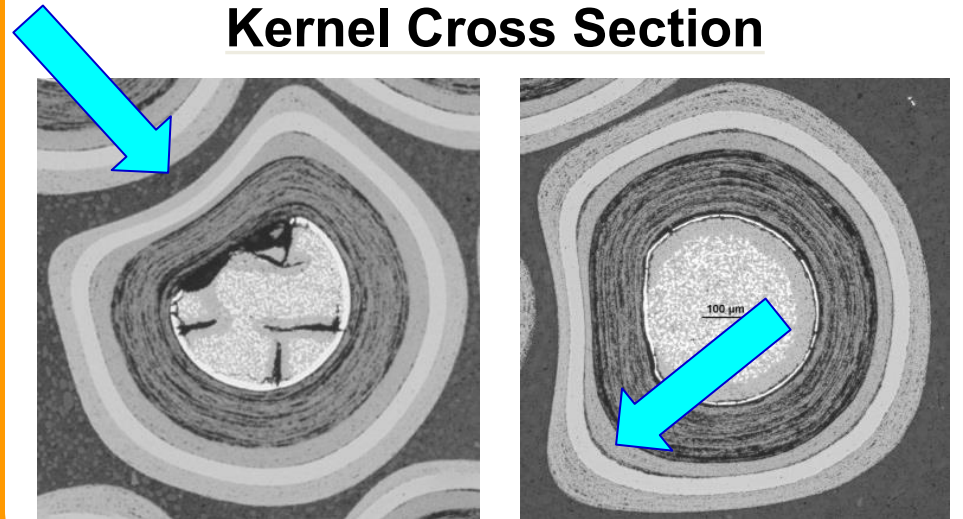


Photo Source: INL/EXT 19 53720



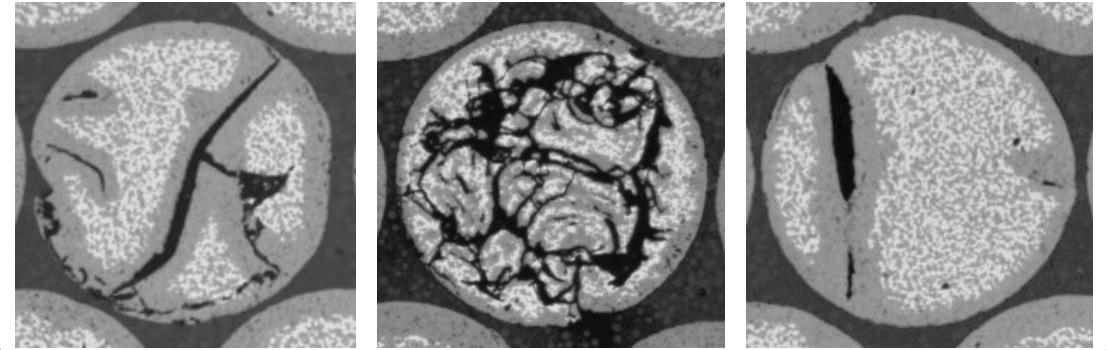
TRISO Fissure Definition

Countable Fissure (CF): Fissure terminates within the oxidic rind at two or more positions along the kernel perimeter. This could be a visible fissure and/or its oxidic lining that transects the kernel, a fissure that branches within the kernel, intersects another fissure within the kernel, or forms an arc that returns to the kernel surface.

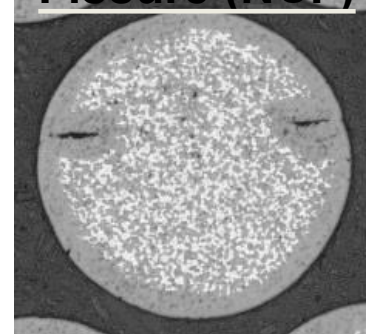
Non-Countable Fissure (NCF): A surface connected void that is lined by an oxidic phase and clearly extends below the mean radius of the oxidic rind. “Clearly” means that it is discernable without the use of tools to measure the oxidic rind thickness or the length of the exposed void. The presence of the oxidic rind around the fissure is evidence that the fissure is (or was) surface connected. Surface connected at one location.

Mounting Artifact: Kernel cracks created as a result of the polishing process used to prepare kernels for inspection. Internal voids, which are non-surface connected and are not surrounded by oxidic rind, in kernel are exposed as a result of the polishing process.

Countable Fissure (CF)



Non-Countable Fissure (NCF)



Mounting Artifact

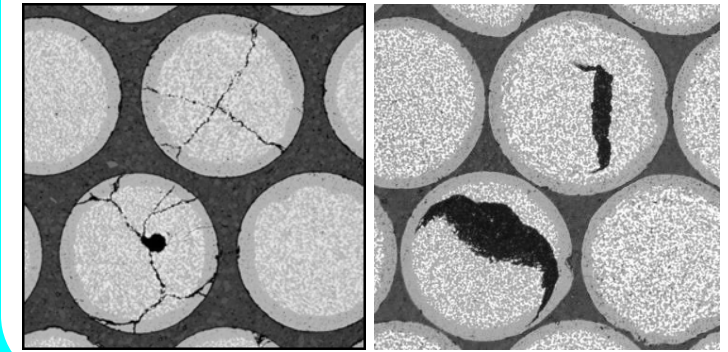
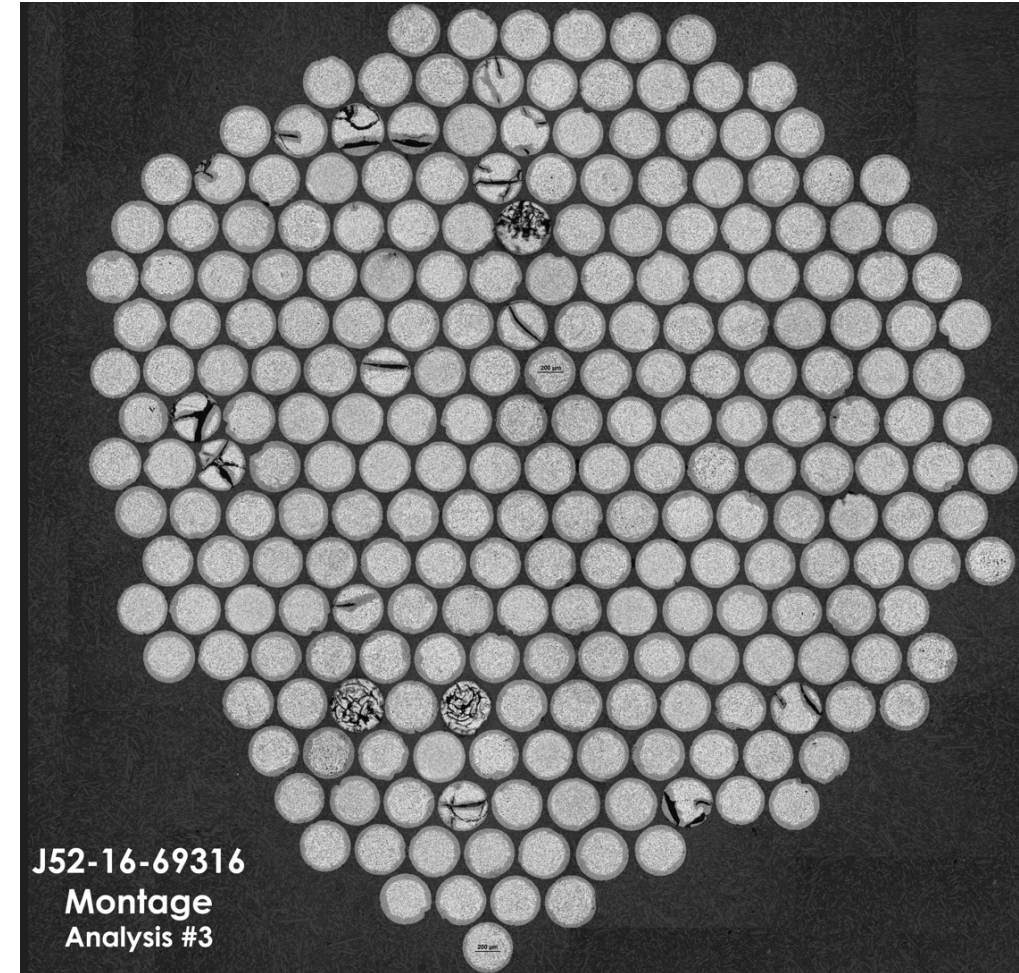


Photo Source (All): INL/EXT 19 53720

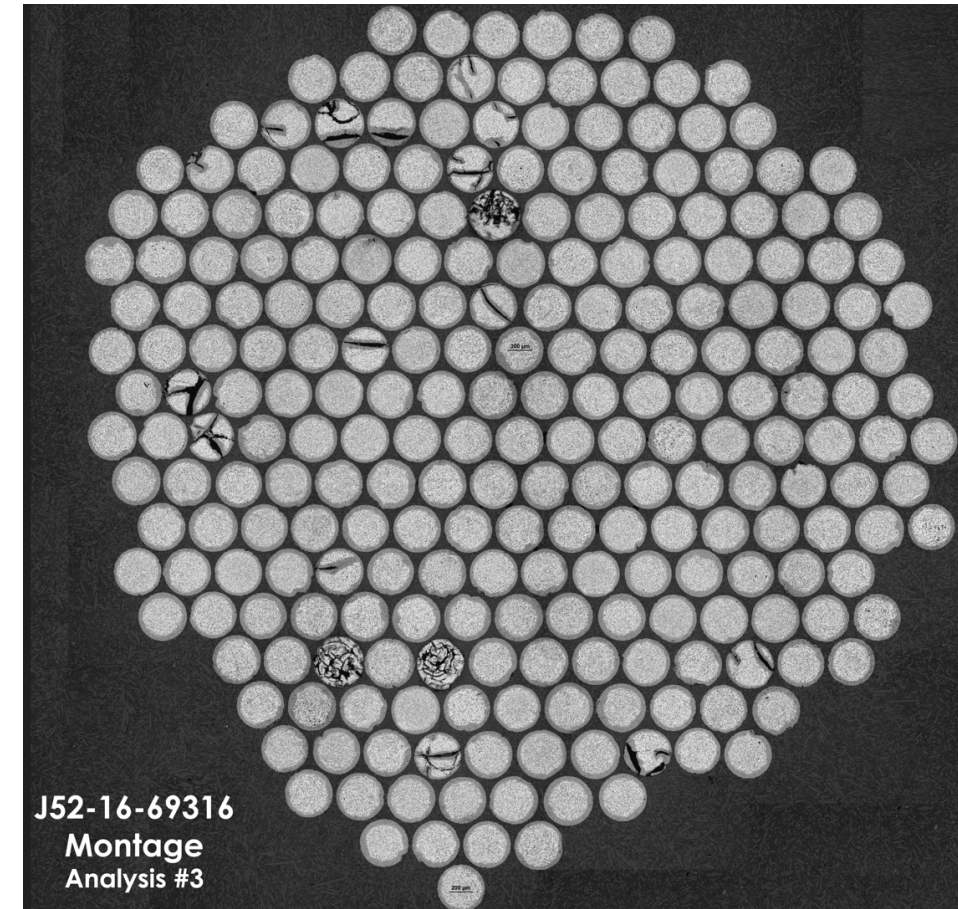
Identifying TRISO Fissures

- **Important Specification:**
 - the maximum # of CFs allowed that maintain overall fuel integrity
- **Metrics Needed:**
 - Total Kernel Count
 - Fissured Kernel Count
- **Problems with Manual Approach:**
 - Time consuming
 - Tedious
 - Subject to human error (miscounting)



Automated Defect Identification for TRISO Fuels (AUDIT)

- **Can we automate this process?**
- **Utilize image processing and machine learning to gather:**
 - _ **Total Kernel Count**
 - _ **Identify Fissured Kernels**
 - _ **Distinguish between countable and non-countable fissures**



Automated Defect Identification for TRISO Fuels (AUDIT)

Image Processing

- . Filtering
- . Segmentation
- . Kernel Identification
- . Kernel Extraction

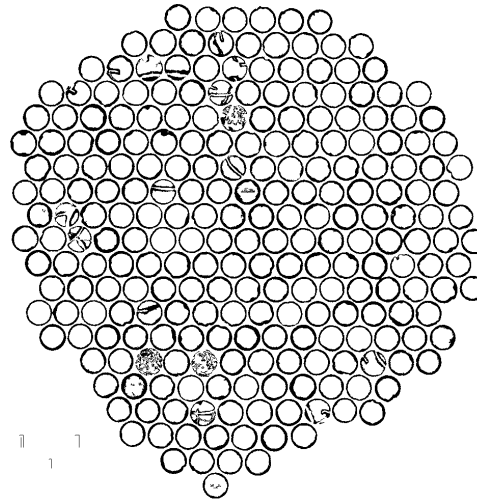
Machine Learning

- . Input is all kernels extracted from micrograph
 - . Convolutional Neural Network
 - . Sorts Good vs. Any Fissure
- . Input is only kernels labeled “Fissured” by Network 1
 - . Convolutional Neural Network
 - . Sorts Countable Fissure from Non-Countable Fissure



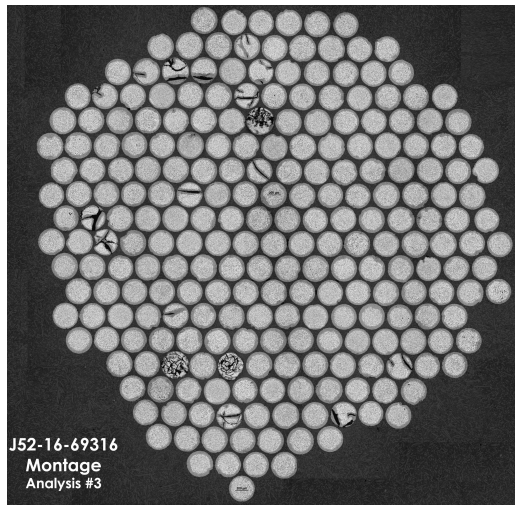
Image Preprocessing Steps

Extracted Rind



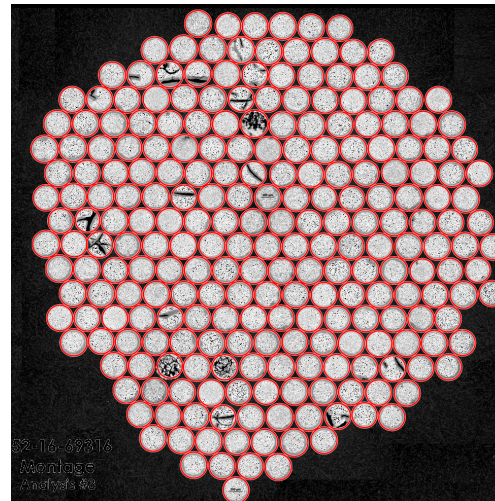
Adjust Resolution,
Filter Image, and
Extract Rind

Original Micrograph



Identify and
Count Kernels

Identified Kernels



Separate
Kernels

Good Kernels



Non-Countable Fissures



Countable Fissures



- . Kernel Count
- . Kernel Location



Training Results: Network 1

Data Classes

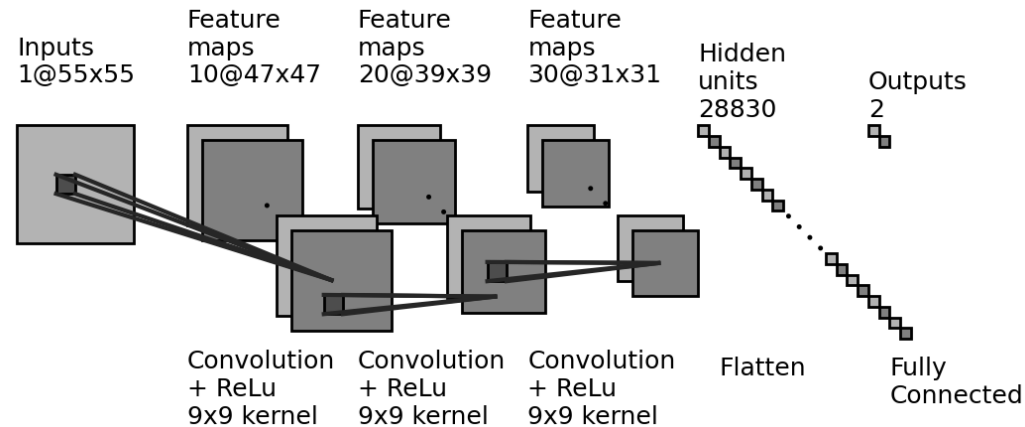
Good Kernels



Fissured Kernels



Convolutional Neural Network Layers



Training Data


Class	Count
Good	8136
Original Fissured Count	262
Oversampled Fissured Count	8122

- Oversampling of fissured kernel class used to balance data set.
- Data augmentation, including random rotation and translation, applied to prevent overfitting of oversampled kernels.


Training Results: Network 1

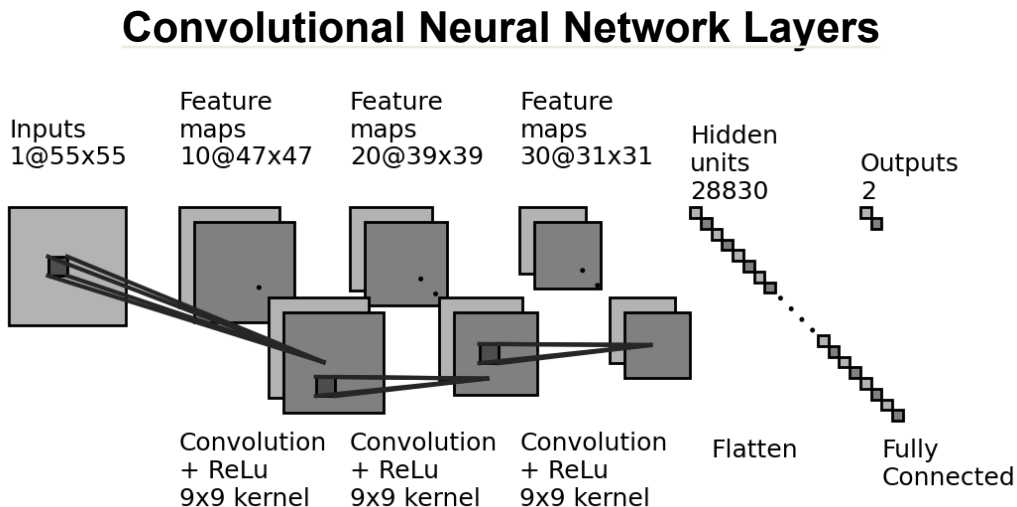
Data Classes

Good Kernels



Fissured Kernels





Training Data

Class	Count
Good	8136
Original Fissured Count	262
Oversampled Fissured Count	8122

Test Data Confusion Matrix

	Actual Fissured	Actual Good
Predicted Fissured	108	66
Predicted		

Precision = 0.62 → 62% of identified fissures are actual fissures.

Recall = 0.96 → 96% of all fissures are identified as fissures.

Training Results: Network 1

Data Classes

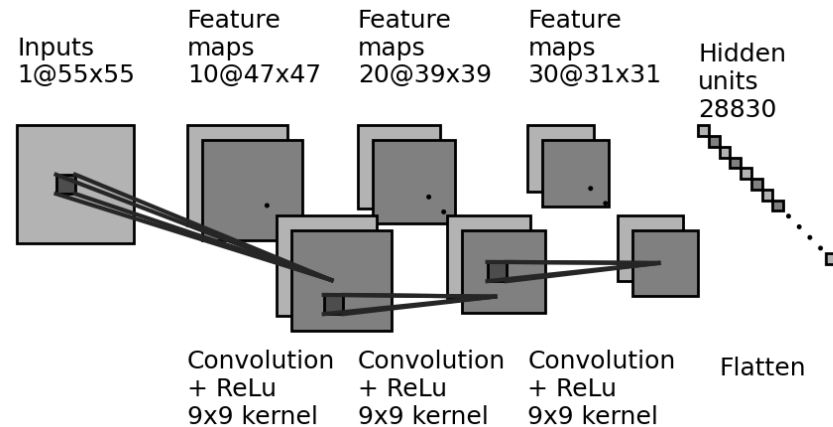
Good Kernels



Fissured Kernels



Convolutional Neural Network Layers



Training Data

This performance is acceptable as it is preferable to capture all possible fissures even at the expense of mis-labeling some good kernels as fissured.

Test Data Confusion Matrix

	Actual Fissured	Actual Good
Predicted Fissured	108	66
Predicted		

Precision = 0.62

62% of identified fissures are actual fissures.

Recall = 0.96

96% of all fissures are identified as fissures.

Training Results: Network 2

Data Classes

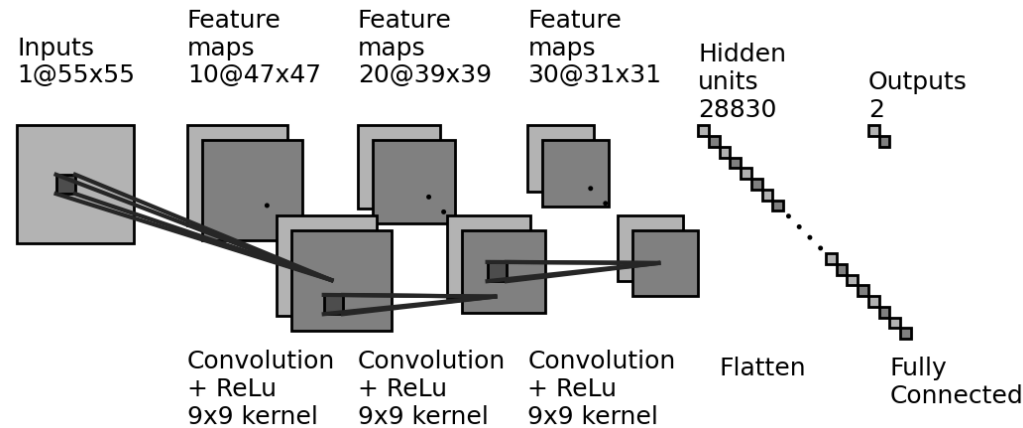
Non-Countable Fissures



Countable Fissures



Convolutional Neural Network Layers



Training Data

Class	Count
Original CF	162
Original NCF	99
Oversampled CF	324
Oversampled NCF	198

- Oversampling of both data classes used to increase the amount of training data which results in better CNN performance.
- Data augmentation, including random rotation and translation, applied to prevent overfitting of oversampled kernels.

Training Results: Network 2

Data Classes

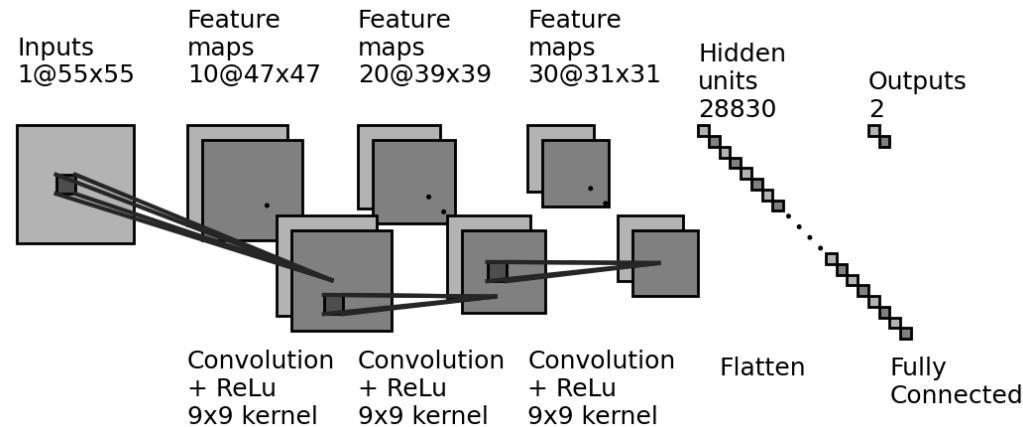
Non-Countable Fissures



Countable Fissures



Convolutional Neural Network Layers



Training Data

Class	Count
Original CF	162
Original NCF	99
Oversampled CF	324
Oversampled NCF	324

Test Data Confusion Matrix

	Actual CF	Actual NCF
Predicted CF	60	8
Predicted NCF	10	34

Precision = 0.88 →

NCF
88% of identified
CFs are actual CFs.

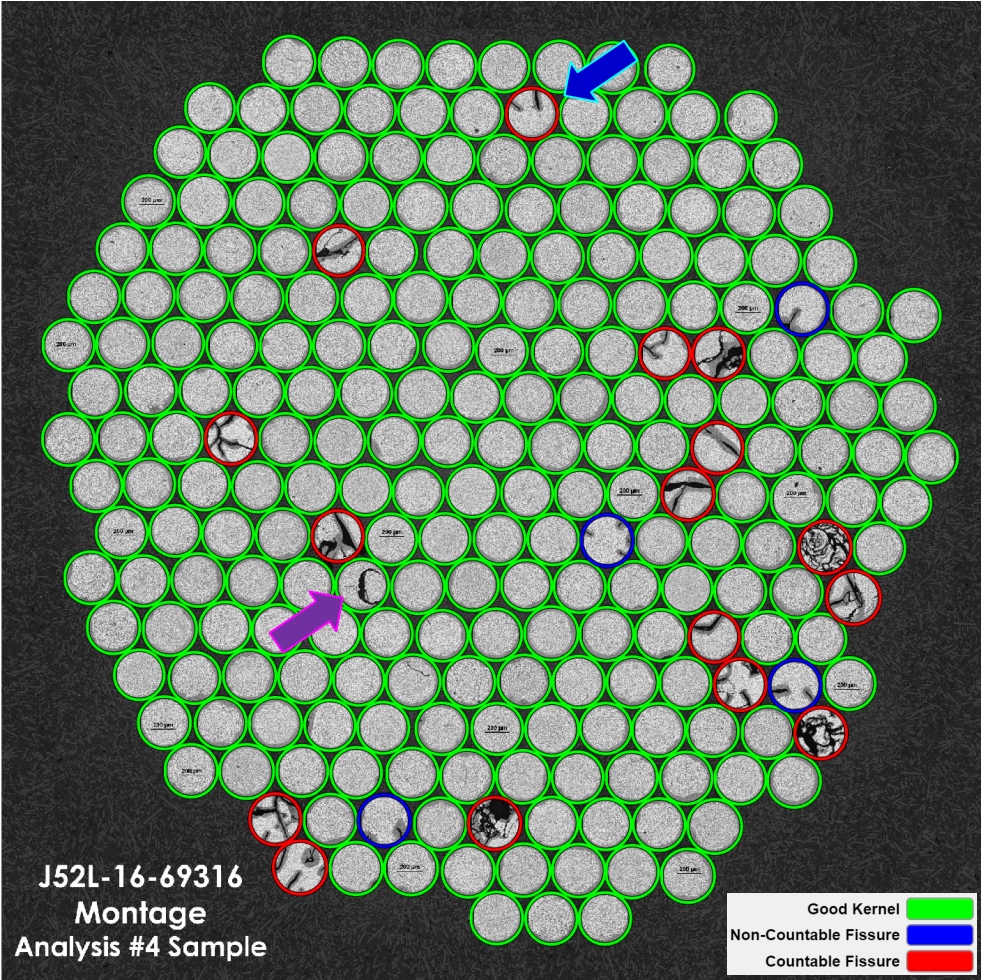
Recall = 0.86 →

86% of all CFs are
identified as CFs.

In-Practice Results 1

- For this example, AUDIT accurately identifies and categorizes nearly all kernels.
- All Good kernels are appropriately labeled.
- One NCF is identified as CF (blue arrow).
- A kernel with an internal void, which is not of interest, is appropriately ignored (purple arrow).

	Total Count	Good Kernels	Non-Countable Fissures	Countable Fissures
Actual Count	242	222	5	15
AUDIT	242	222	4	16

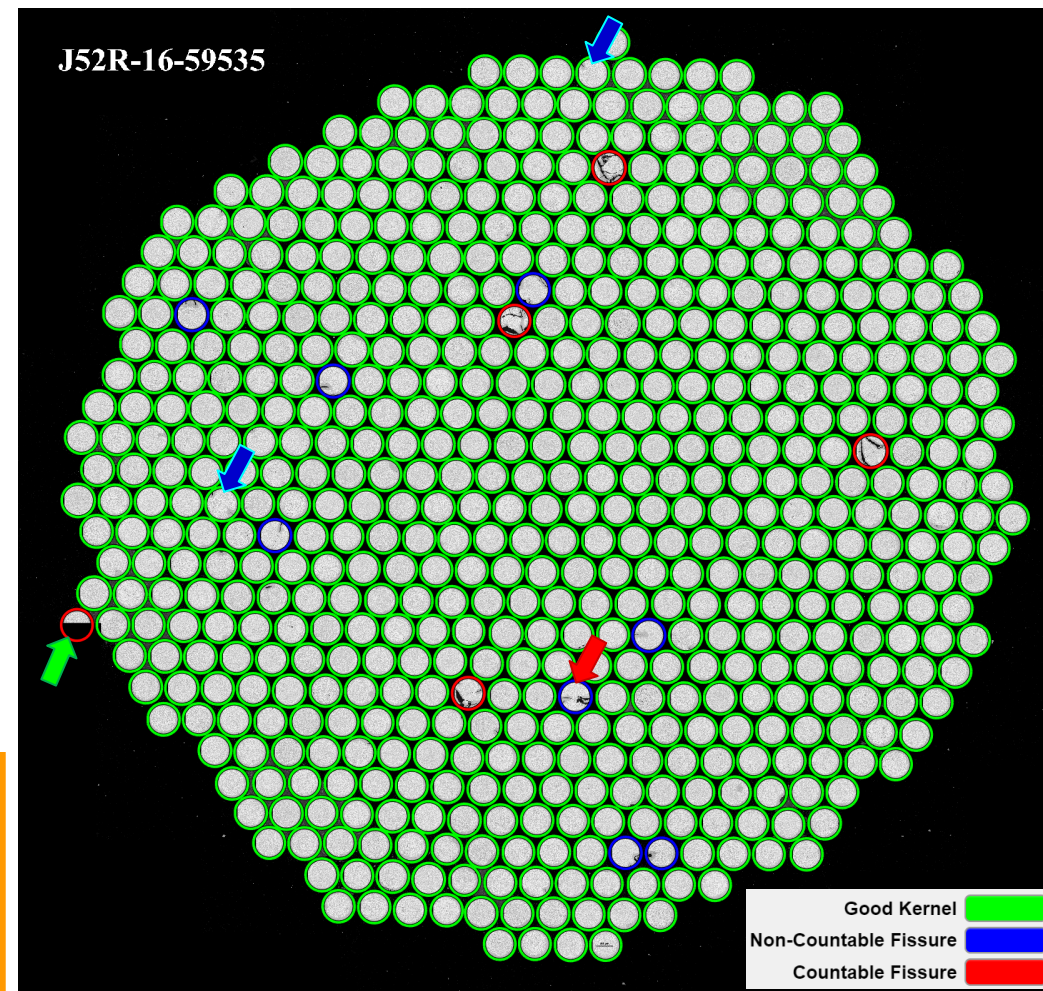


***Kernels in this micrograph were included in training and validation data.**



In-Practice Results 2

- For this example, AUDIT accurately identifies and categorizes the majority kernels.
 - The missed CF is still identified as a fissure.
 - The two NCF's not identified are very minute fissures and do not impact the viability of the batch.
- The precise fissure count is less important than the ability to quickly determine if the batch clearly meets or does not meet specification.
 - For example, if spec is 10 CF per 500 kernels:
 - 4 CFs are identified → the micrograph passes.
 - 8 CFs are identified → inspect manually.



***No kernels in this micrograph were included in training, validation, or test data.**

	Total Count	Good Kernels	Non-Countable Fissures	Countable Fissures
Actual Count	589	575	9	5

A missed CF (green arrow) is caused by a photography error that appears a partial kernel.



Conclusions

- During the manufacture of TRISO nuclear fuel, the potential exists for the UCO kernel to fissure.
- These fissures create an undesirable final product and need to be identified mid-manufacturing process.
- An automated detection application, AUDIT, based on image processing and convolutional neural networks, was developed that aids the inspector in quickly and efficiently identifying and quantifying UCO fissures.
- AUDIT can reliably quantify fissured kernel fractions and greatly reduces the inspection time and required effort.

