

# Autonomous Fault Detection Using Artificial Intelligence Applied to CLAS12 Drift Chamber Data

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Christian Peters

# Motivation

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- > Most crucial elements of a physical experiment?
  - > Methods of measurement, e.g. drift chamber at CLAS12
  - > Need to be highly precise
  - > Essential for success
- > Problem: Extreme conditions often lead to faults
  - > Distortions in measurement accuracy
  - > Have to be detected and filtered out during runtime
- > Too much data to be processed by a human
  - > An *autonomous* approach of fault detection is required

# Motivation

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- > Emerging field lending itself particularly well to the task:
  - > The domain of Artificial Intelligence (AI)
  - > Deep Learning, Convolutional Neural Networks (CNNs)
- > Goal: Apply methods of AI to the problem of fault detection
  - > Experimental context: CLAS12 drift chamber
- > Baseline software: deeplearning4j (DL4J) library
  - > Will be used to implement the fault detection system

# The CLAS12 Drift Chamber

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- > Subsystem of the CLAS12 particle detector
  - > Electron beam hits target inside the detector's center
  - > Drift Chamber (DC) is used to measure the results (particle momentum)
- > Hierarchical arrangement of multiple wires grouped together as wire chambers
  - > Wires are used to detect particle presence
  - > Particle hits wire → wire gets activated

# The CLAS12 Drift Chamber

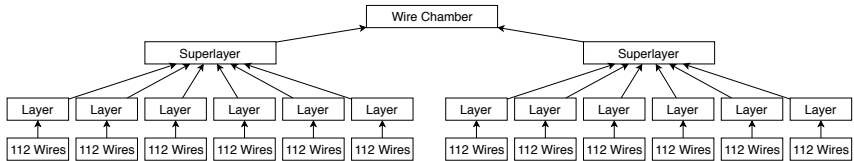


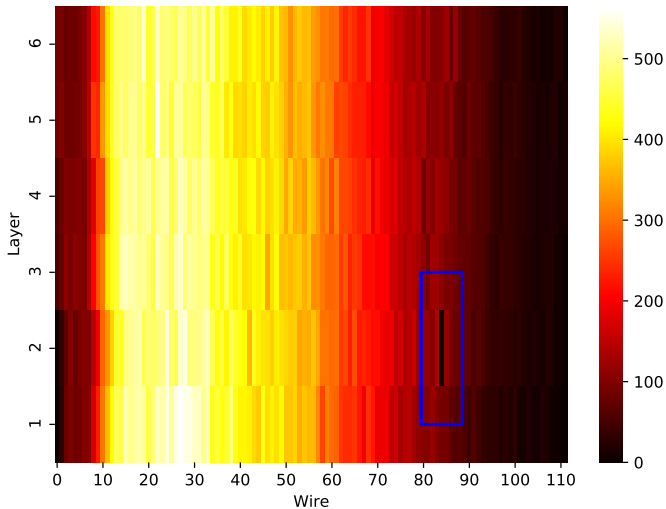
Figure: The hierarchical structure of a single wire chamber.

# Drift Chamber Faults

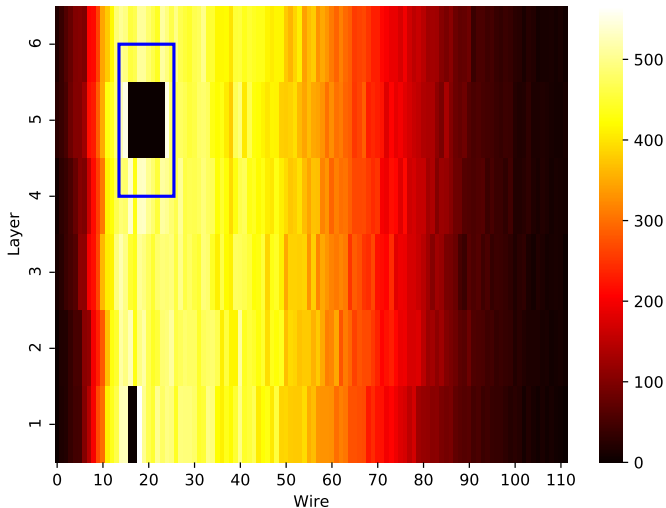
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- > Drift chamber operates under extreme conditions
  - > Huge amounts of radiation
  - > Components can get damaged during an experiment
  - > Single wires or collections thereof stop working
- > Wire activations can be visualized as heatmaps
  - > Easier to detect faults

# Dead Wire

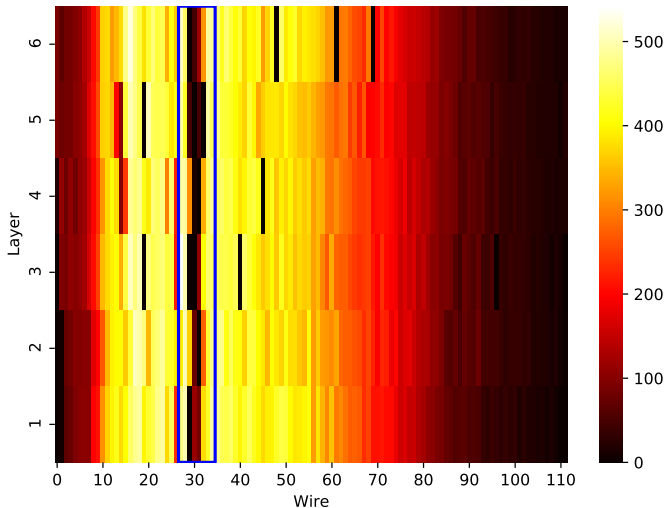


# Dead Pin

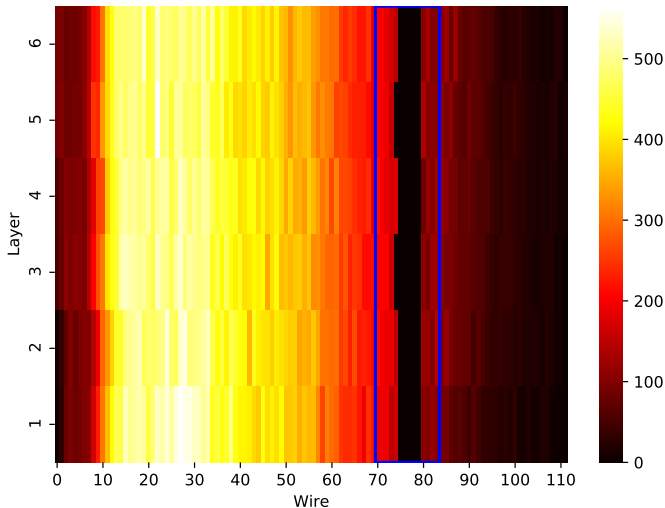




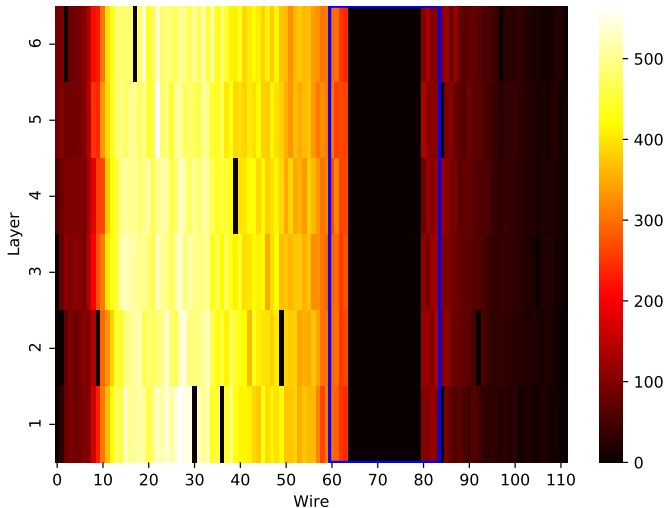
# Dead Connector



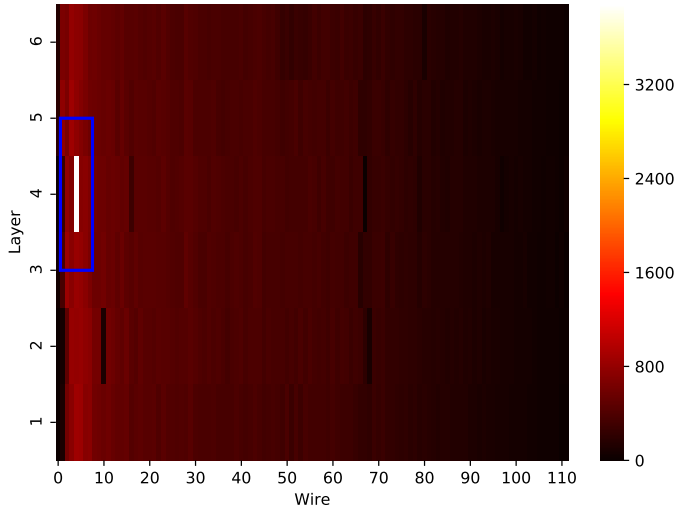
# Dead Fuse



# Dead Channel



# Hot Wire





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