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

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A Bachelor's Thesis by Christian Peters

Motivation

- 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

- An 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

- 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 tracks)
- Hierarchical arrangement of multiple wires grouped together as wire chambers
  - Wires are used to detect particle presence
  - Particle hits wire $\rightarrow$ wire gets activated

The CLAS12 Drift Chamber

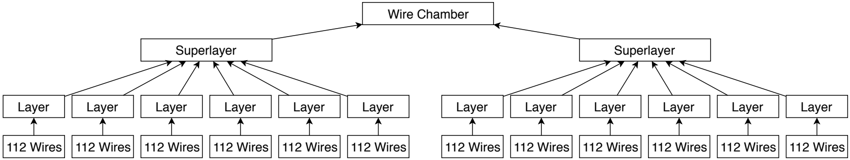
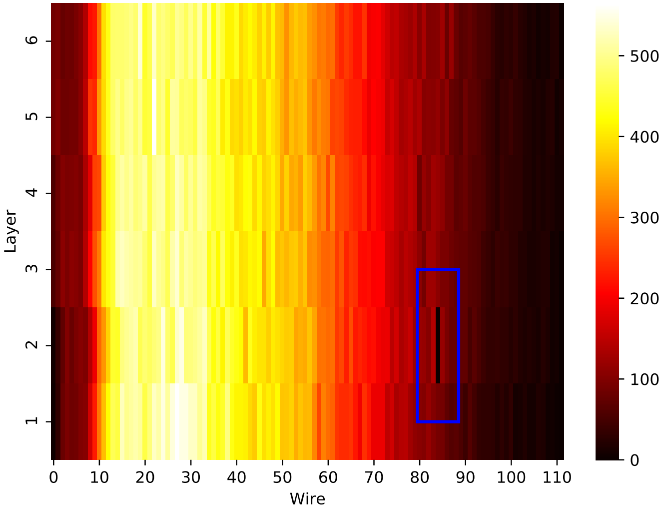


Figure: The hierarchical structure of a single wire chamber.

Drift Chamber Faults

- 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 of a superlayer can be visualized as heatmaps
  - Easier to detect faults

Dead Wire



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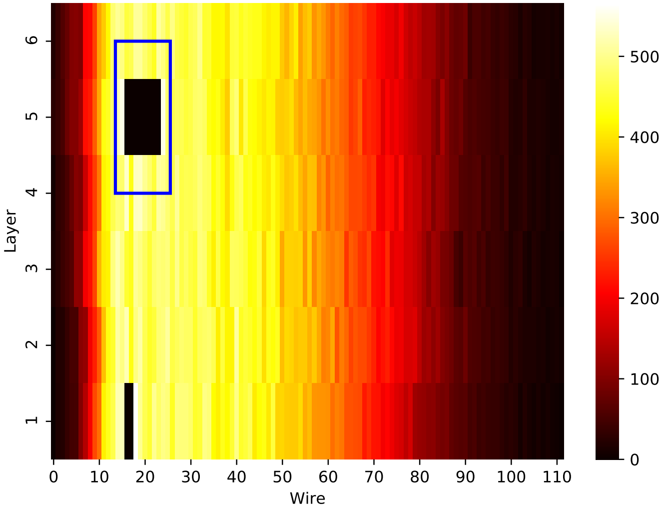
Dead Pin



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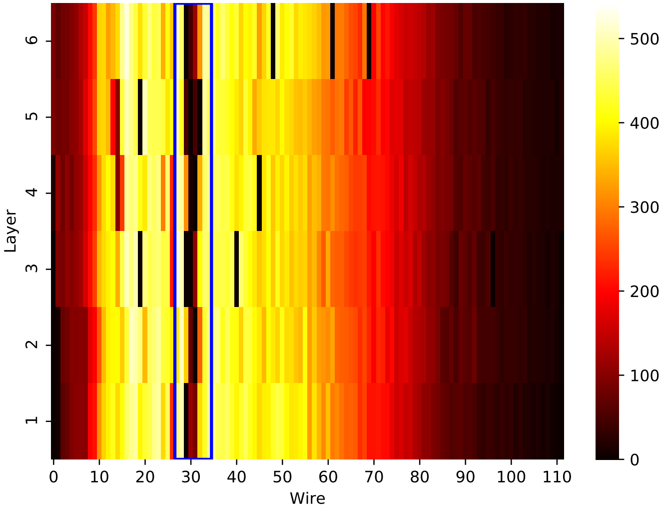
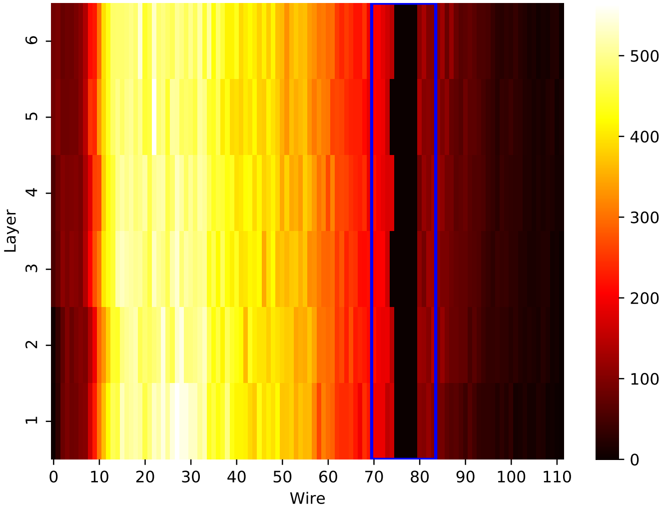
Dead Connector



Dead Fuse



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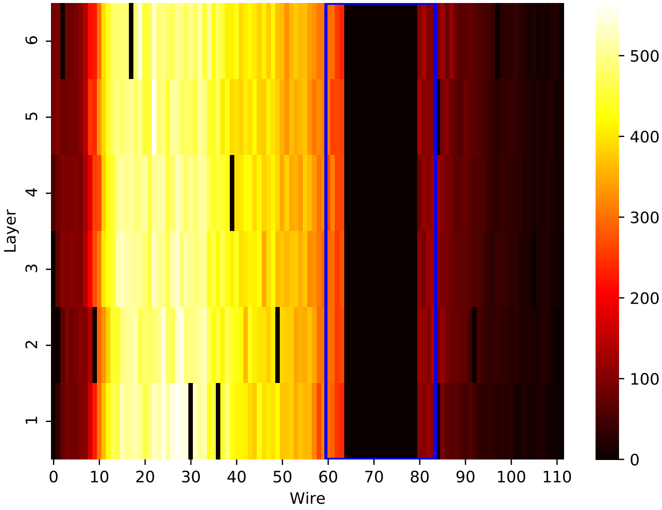
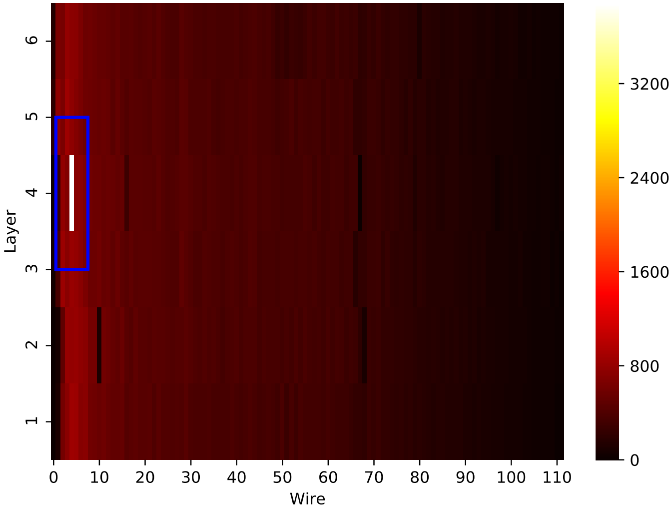
Dead Channel



Hot Wire



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Artificial Neural Networks

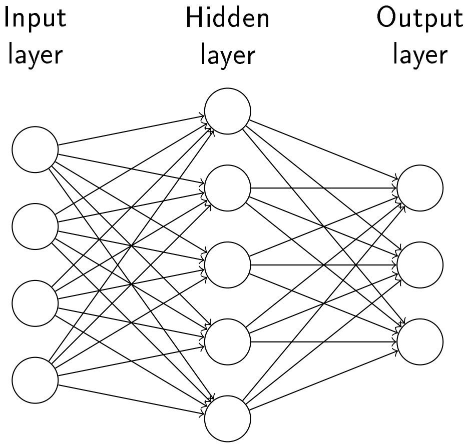


Figure: A common ANN-structure represented by a directed graph.

Modeling Artificial Neurons

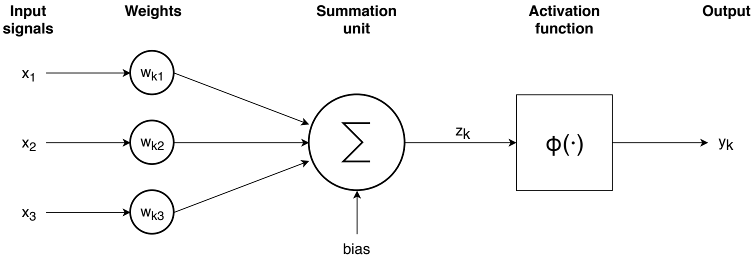


Figure: The components of a single artificial neuron k.

Activation Functions

- Determine the "activity"-level of a neuron based on the summed and weighted inputs
- Non-Linear
  - Enables the network to model complex relations
  - Multiple linear functions collapse into just a single linear function

Sigmoid Activation Function

$$\phi(z) = \frac{1}{1 + e^{-\theta \cdot z}} \tag{1}$$

- Transforms an input into a range between 0 and 1
- θ adjusts the sensitivity with respect to the input
- Reduces the impact of outliers
- Often used in the early days
  - Biological inspiration, can also be interpreted as a "firing-rate"

Sigmoid Activation Function

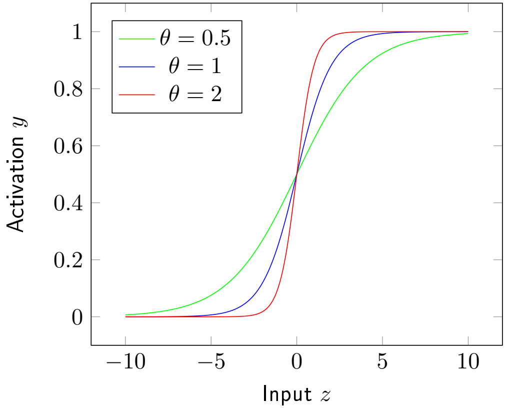


Figure: The sigmoid activation function plotted for different values of θ.

Problems with the Sigmoid Activation Function

- We sometimes want to keep big values
  - Small values tend to fade out in deep networks (many hidden layers)
- "Saturates" for very big or negative inputs, i.e. does not change much when the input changes
  - This leads to training problems as we shall see later

ReLU Activation Function

$$\phi(z) = \max(0, z) \tag{2}$$

- Remedies the problems of the sigmoid function
- Cuts away negative values $\rightarrow$ sparsity among the neuron activations
  - Promotes simpler representations
- Actually more biologically inspired than the sigmoid
- Very easy to compute

ReLU Activation Function

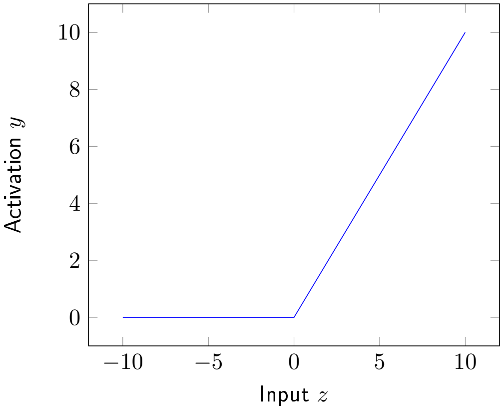


Figure: The ReLU activation function.

Softmax Activation Function

$$\phi(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \quad (3)$$

- Usually applied to the output neurons
- Outputs can be interpreted as probabilities
  - Useful in classification, every possible class gets a probability
- Using the exponential function before normalization amplifies bigger signals and attenuates weaker ones
  - Helpful in training
- Interpretation of the z_i: Unnormalized log-probabilities

Neural Networks as Classifiers

> We successfully established a mathematical model of neural networks

> How can we train them to perform classification tasks?

  > Remember, we want to classify what kinds of faults are in a superlayer within the drift chamber

> To do this, let's first take a look at classification in general

Classification

- The data consists of attributes as well as class labels
- Goal: Predict the class label by only looking at the attributes
- First step: Training
  - The classification algorithm (classifier) is presented with many training examples
  - For every new example, the classifier adjusts its parameters to improve its classification ability
  - This is done to build a predictive model
- Second step: Testing
  - Some new testing examples are presented to the classifier that it did not see during training
  - These examples are used to determine, if the classifier learned any useful concepts from the training data, i.e. to *generalize*

Evaluating a Classifier

> The results of the testing phase are entered into a *confusion matrix:*

	Class Positive (Predicted)	**Class Negative (Predicted)**
Class Positive (Actual)	True Positives (TP)	False Negatives (FN)
Class Negative (Actual)	False Positives (FP)	True Negatives (TN)

> This matrix is used to compute evaluation metrics like accuracy

Training the Network

> Which parameters can be adjusted during training?
>
> > The weights and biases store the network's knowledge and need to be tuned to improve performance
>
> > Other parameters like number of layers or activation function are set in advance (hyperparameters)

> How to adjust the weights and biases?
>
> > Measure the error on a batch of training examples
>
> > Minimize the error by taking a step of *gradient descent* ($\nabla error$)
>
> > Repeat this for a number of passes through the training data (one pass = one epoch)

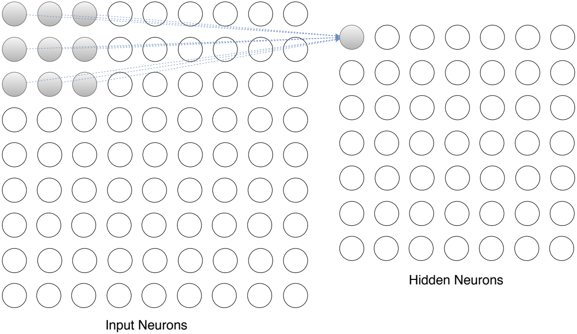
> After training, test the network on new examples
>
> > Compute evaluation metrics
>
> > Was it able to *generalize*?

Convolutional Neural Networks

- Simple ANNs work well for moderate amounts of attributes
  - Problems arise when amount of inputs grows
  - Number of parameters (weights and biases) "explodes"
  - Requires huge amounts of space and nearly impossible to train
- Sometimes, the input has a specific structure
  - E.g. images are arranged in grids of pixels (fault heatmaps are similar)
  - Every pixel has a *local* relevance
  - No need to connect every neuron to every input
- Use that structure to create simpler models that are easier to train

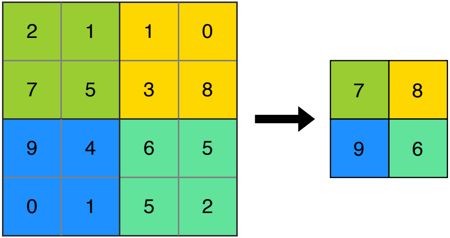
Convolution Layers

- Arrange the neurons in a grid, just like the input
- Every neuron “watches” a specific area, the *local receptive field*
  - Weights are shared → less parameters
- Works just like a sliding window (similar to a *convolution*)
- Multiple convolutions are performed → stack of hidden grids



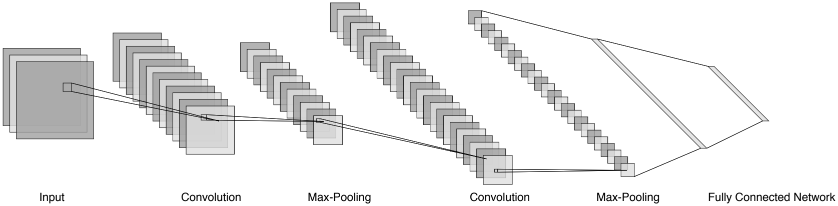
Pooling Layers

- Reduce the input's complexity by downsampling
  - Every neuron just remembers the maximum of its local receptive field
- Forget about the exact location of a feature
  - Leads to *spatial invariance*



The Convolutional Architecture

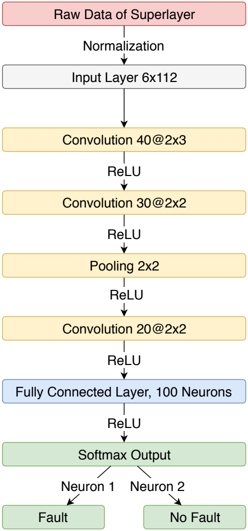
- Stack multiple convolution and pooling layers
  - These are used to extract relevant features
- Use a fully connected layer in the end to perform classification
- The network is also trained via *gradient descent*
  - Weights and biases are updated in each step to minimize classification error



Implementing the Fault Detector

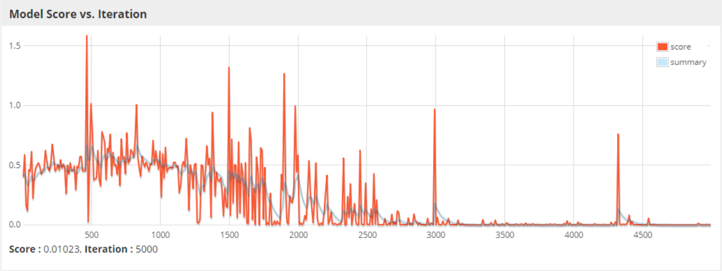
- Build a convolutional neural network in DL4J
  - Easy to monitor training and compute evaluation metrics
  - Fast due to C++ backend engine
- First, data has to be normalized
  - Activation levels can vary across superlayers
  - We only care about the distinct fault patterns
  - Scale wire activations from 0 to 1
- Many architectures and parameters were tried
  - Network too shallow $\rightarrow$ unable to learn complex faults (e.g. two dead wires next to each other)
  - Multiple faults per superlayer are possible $\rightarrow$ multiple networks were trained, each specializing in a single fault

Final Network Architecture



Training the Fault Detector

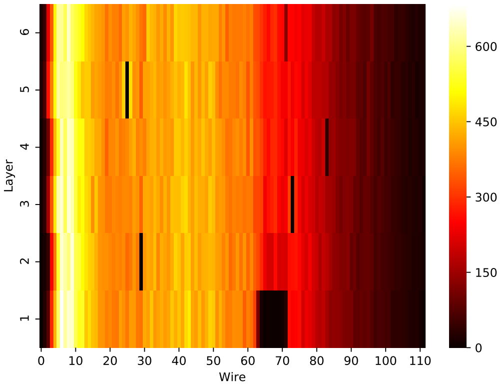
- Used Michaels simulation suite
  - Based on real world background signals
  - Randomly inserts fault combinations and generates class labels accordingly
- Each classifier was trained on 100,000 examples
- Testing was done using 10,000 new examples from the simulator
  - Accuracy > 97%



Real Data Validation

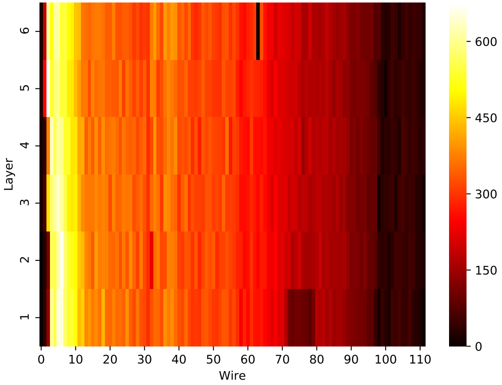
- Need to show that the detector not only works on simulated data
  - Did it extract some general concepts?
- Tested the system on some real world examples to show its strengths and weaknesses

Pin Fault and Dead Wires



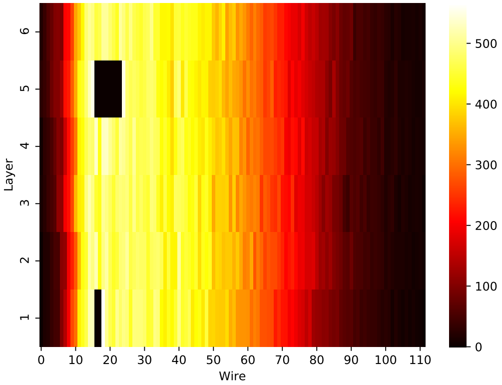
- Faults display a sharp contrast → classifier works well
  - Dead pin and dead wire classifier both report 100% fault
  - The other classifiers don't detect their fault with 99% certainty

Blurred Dead Pin Fault



> Blurred fault → classifier struggles
> - Classifier reports 99% no fault for the pin
> - We believe that more real data can solve this

Two Dead Wires



> Classifier detects two dead wires next to each other
  > Reports 93.29% certainty for the wires and 100% for the pin

Conclusion

> Convolutional Neural Networks work well for fault detection
> Blurred fault problem will be solved in the future
  > Will use real world blurred faults during training
  > After all, a deep learning system can only be as good as the data it was trained on
> Next step: fault localization
  > Need to know, where exactly a fault is located
  > State-of-the-art: YOLOv3, a CNN specialized in object localization
  > Use the present system as a pre-stage classifier
> Excited to see, how the system will perform on the hundreds of petabytes of real CLAS12 drift chamber data

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Artificial Neural Networks

- Class of machine learning algorithms
  - Loosely inspired by biological nervous systems
- Collection of artificial neurons that are connected with each other
  - Enables them to exchange signals along their connections
  - Can be represented by a directed graph
- Usually arranged in layers
  - *Input Layer* collects input signals and passes them on
  - *Hidden Layers* apply transformations to incoming signals and pass the outcomes further into the network
  - *Output Layer* applies a final transformation representing the networks' result
- Goal: Convert input into meaningful output by applying multiple transformations

Components of the neural model

- A set of weighted inputs
  - Each input originating from neuron j and traveling into neuron k is first multiplied by a weight w_{kj}
- A summation unit
  - All the weighted inputs are summed and a constant value, the *bias*, is added to yield the result z_k
- An activation function
  - Applies a non-linear transformation $\phi(\cdot)$ to the output of the summation unit
  - This result, called y_k, is propagated further into the network alongside the connections

The Role of the Bias Value

- The bias is added as a constant to the sum of the weighted inputs in the summation unit
- Acts like a threshold that has to be overcome
  - Negative bias: Positive weighted inputs needed for the neuron to become active
  - Positive bias: Negative weighted inputs needed to stop the neuron from being active

The Role of the Bias Value

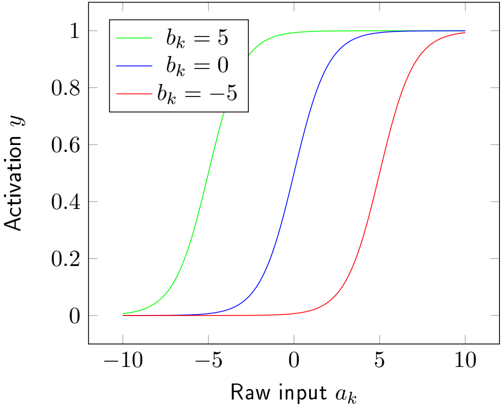

Figure: The sigmoid activation function plotted for different bias values.

Evaluation Metrics

- **Accuracy:**
  - Percentage of testing examples that were classified correctly

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

- **Precision:**
  - Percentage of correctly classified examples among all examples classified as positive

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

Evaluation Metrics

- **Recall:**
  - What percentage of positive examples was classified correctly?

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

- **F1 Score:**
  - Harmonic mean of precision and recall

$$\text{F1 Score} = \frac{2 * Precision * Recall}{Precision + Recall} \tag{7}$$

Dead Wire Classifier

- Accuracy: 97.61%
- Precision: 99.96%
- Recall: 95.65%
- F-Measure: 97.76%

	Dead Wire (Predicted)	**No Dead Wire (Predicted)**
Dead Wire (Actual)	5212	237
No Dead Wire (Actual)	2	4549

Table: Confusion matrix of the dead wire classifier.

Dead Pin Classifier

- Accuracy: 99.95%
- Precision: 99.92%
- Recall: 99.98%
- F-Measure: 99.95%

	Dead Pin (Predicted)	**No Dead Pin (Predicted)**
Dead Pin (Actual)	4739	1
No Dead Pin (Actual)	4	5256

Table: Confusion matrix of the dead pin classifier.

Dead Connector Classifier

- Accuracy: 98.77%
- Precision: 99.23%
- Recall: 95.69%
- F-Measure: 97.43%

	Dead Connector (Predicted)	**No Dead Connector (Predicted)**
Dead Connector (Actual)	2334	105
No Dead Connector (Actual)	18	7543

Table: Confusion matrix of the dead connector classifier.

Dead Fuse Classifier

- Accuracy: 98.95%
- Precision: 97.32%
- Recall: 98.20%
- F-Measure: 97.76%

	Dead Fuse (Predicted)	No Dead Fuse (Predicted)
Dead Fuse (Actual)	2288	42
No Dead Fuse (Actual)	63	7607

Table: Confusion matrix of the dead fuse classifier.

Dead Channel Classifier

> Accuracy: 99.11%
> Precision: 98.84%
> Recall: 98.64%
> F-Measure: 98.74%

	Dead Channel (Predicted)	**No Dead Channel (Predicted)**
Dead Channel (Actual)	3493	48
No Dead Channel (Actual)	41	6418

Table: Confusion matrix of the dead channel classifier.

Hot Wire Classifier

- Accuracy: 100.00%
- Precision: 100.00%
- Recall: 100.00%
- F-Measure: 100.00%

	Hot Wire (Predicted)	No Hot Wire (Predicted)
Hot Wire (Actual)	5532	0
No Hot Wire (Actual)	0	4468

Table: Confusion matrix of the hot wire classifier.