Characterizing the Quality of 3D Printed Parts using Deep Learning

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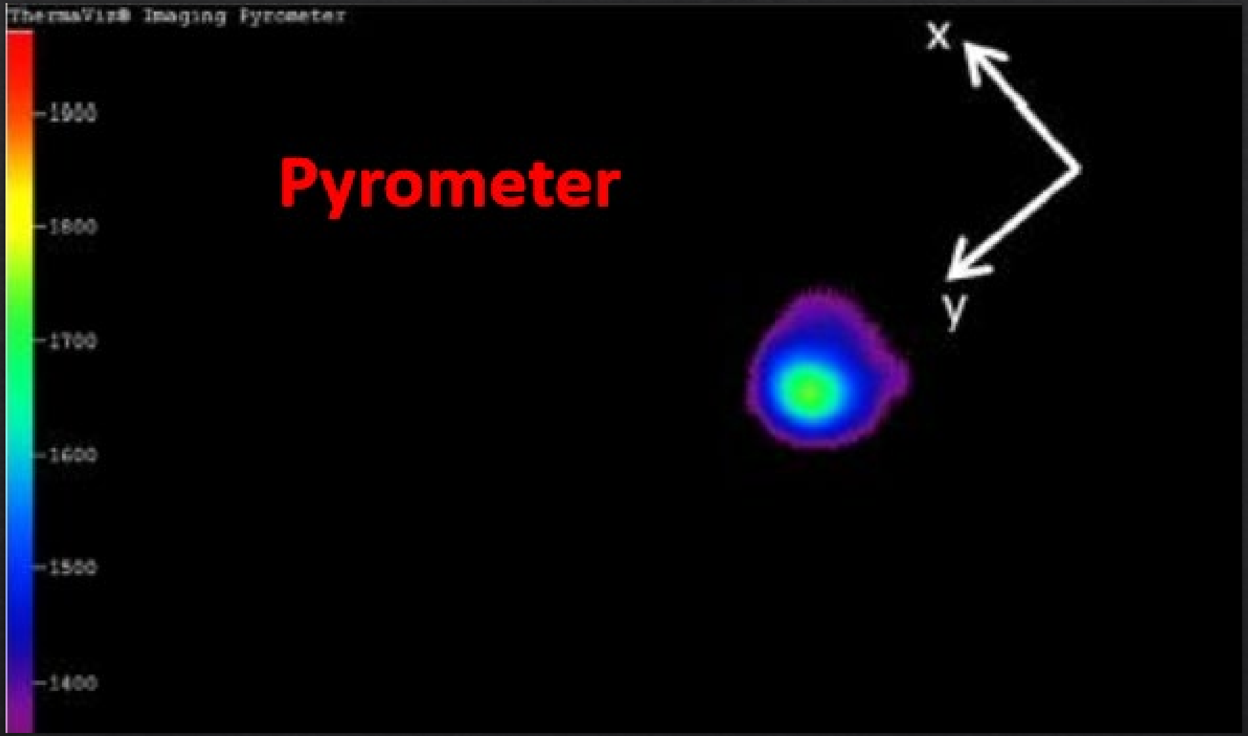
Statement of the Problem

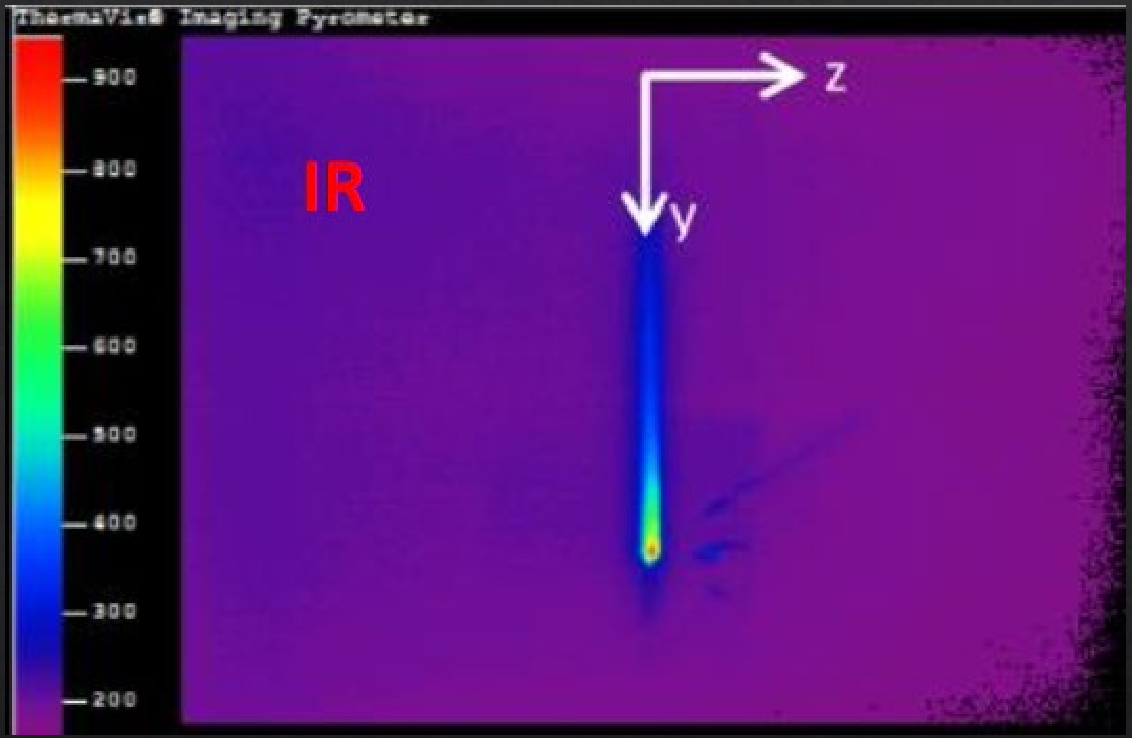
- During the additive manufacturing process, there is a risk of **defects** arising in printed parts
  - **Porosity** – the presence of void space inside the part body; weakens the part
- We would like to **detect** defects such as these before printing is finished, so we can dynamically correct them

The Data

- An Optomex LENS 750 system was equipped with a pyrometer aimed at the melt pool, and an infrared camera in the print chamber
- The system printed a thin wall out of Ti-6Al-4V
- The pyrometer and IR camera feeds were captured as pixel value matrices at each time step

Examples


ThermaVis® Imaging Pyrometer
1900
1800
1700
1600
1500
1400
Pyrometer
x
y


ThermaVis® Imaging Pyrometer
900
800
700
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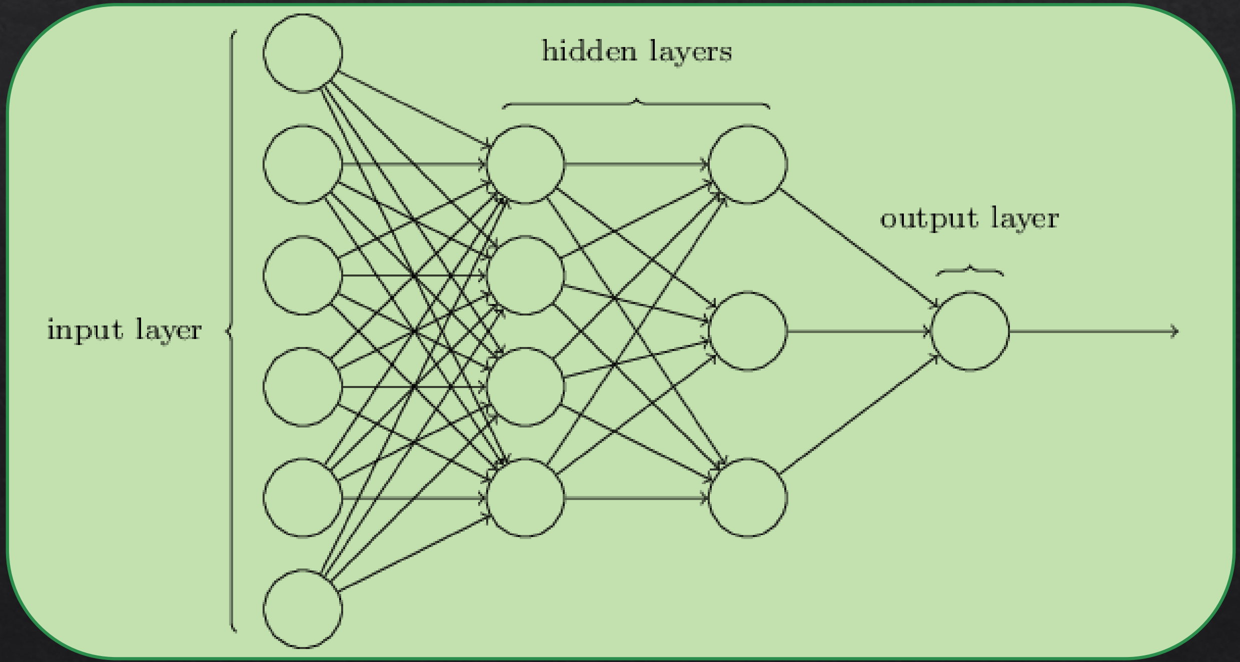
400
300
200
IR
z
y

My Approach

- Use a **neural network**: layered graph representing a series of operations converting input data (pixels) to output data (class)
  - Neural networks need to **learn**: given labeled training data, compute error at each step and auto-update weights and edges



My Approach

- Combine two types of neural network:
  - **Convolutional**: Consolidates spatial data into “features”
  - **Recurrent**: Input is given in an ordered sequence
- Because there are two distinct types of data, **make two neural nets** – PyroNet and IRNet – and compare their outputs

PyroNet - Overview

- Input: Critical region of a pyrometer capture (a 69x120 .csv file)
- PyroNet is **not recurrent** because there is minimal time dependency between successive pyrometer images
- Testing accuracy is **very high** – reliably 94%

PyroNet - Data Preprocessing

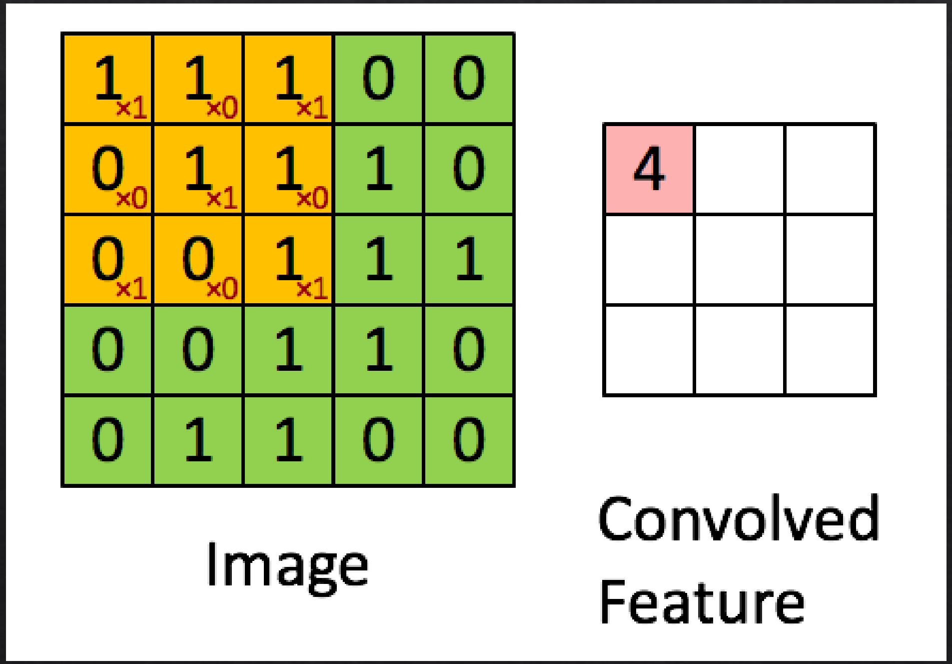
- Read .csv files into matrices, pair them with class
- Dataset: 1,492 successes, 71 failures…?
  - Success/Failure Ratio: **21:1**
- Because the dataset does not have a lot of failures, the neural net **cannot train effectively**
- We also **cannot get new data**…
  - …because the system is in **Mississippi**.

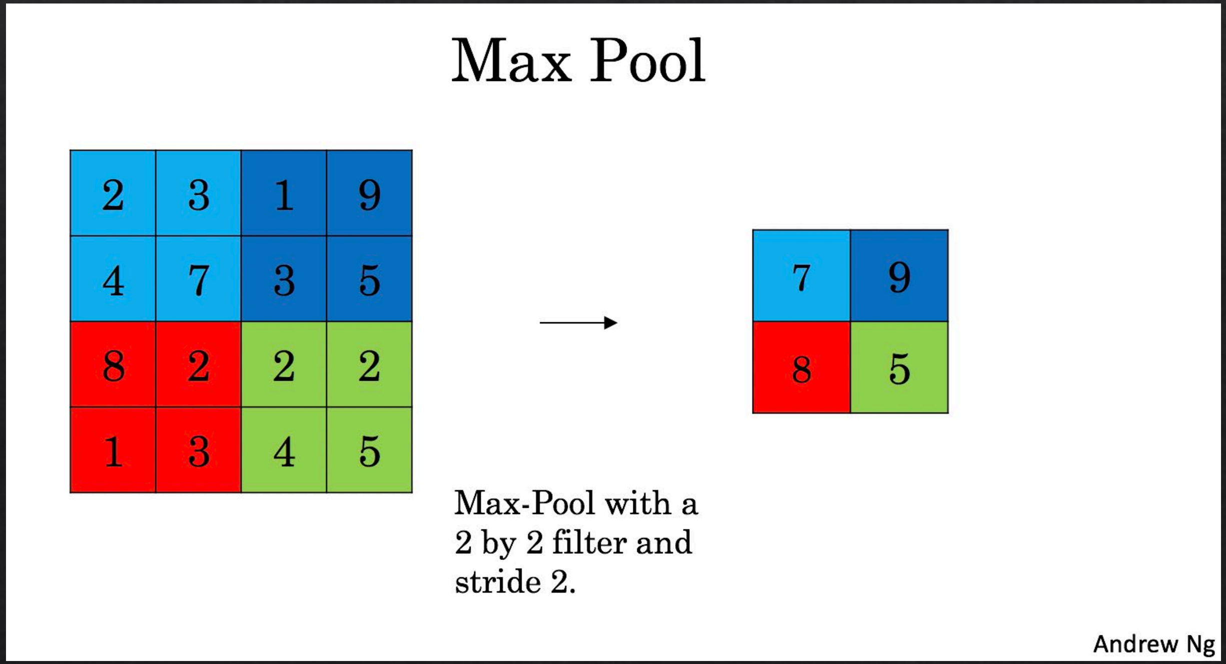
PyroNet - Data Preprocessing

- Solution: create **artificial failures** using a process called **data augmentation**
  - Take the existing images of failures and **slightly transform them** – now we have more failures!
- Dataset: 1,492 successes, 71 failures, **700 augmented failures**
  - Ratio: **2:1**

Terminology

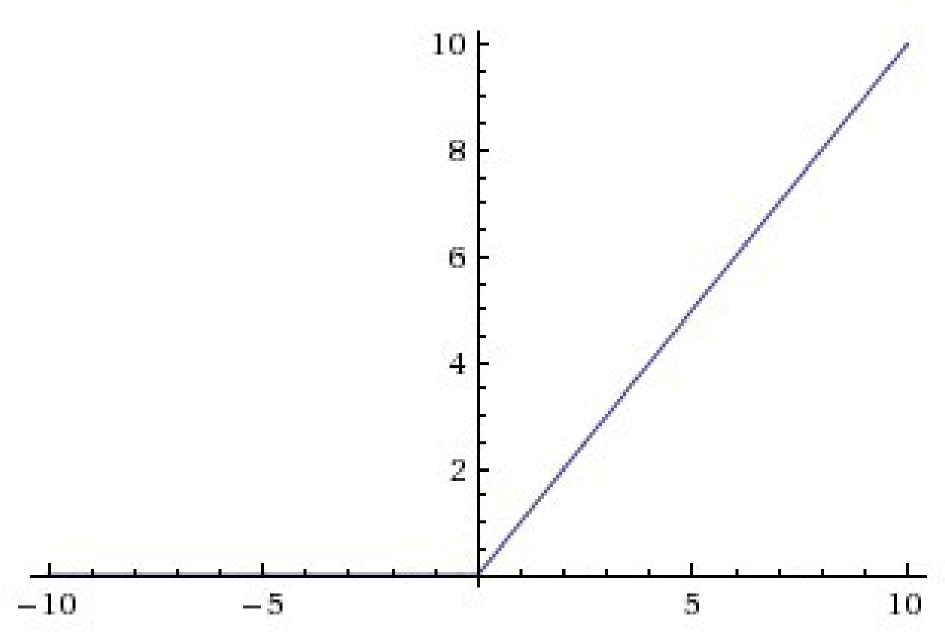
- **Conv2D**: Layer that applies a 2D convolution to the image
- **MaxPool2D**: Layer that reduces the size of its input by representing a whole area by the maximum value in that area



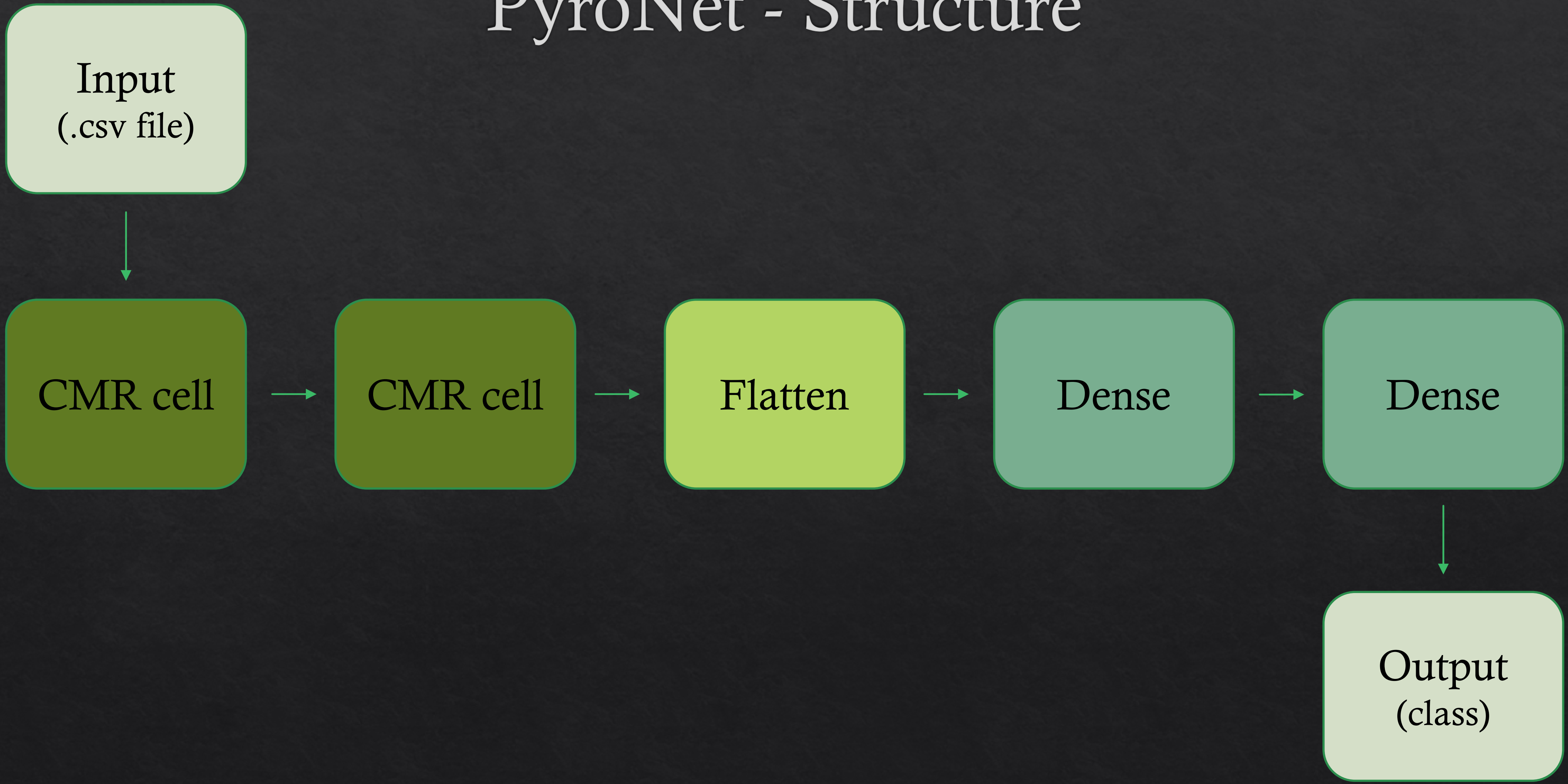


Terminology

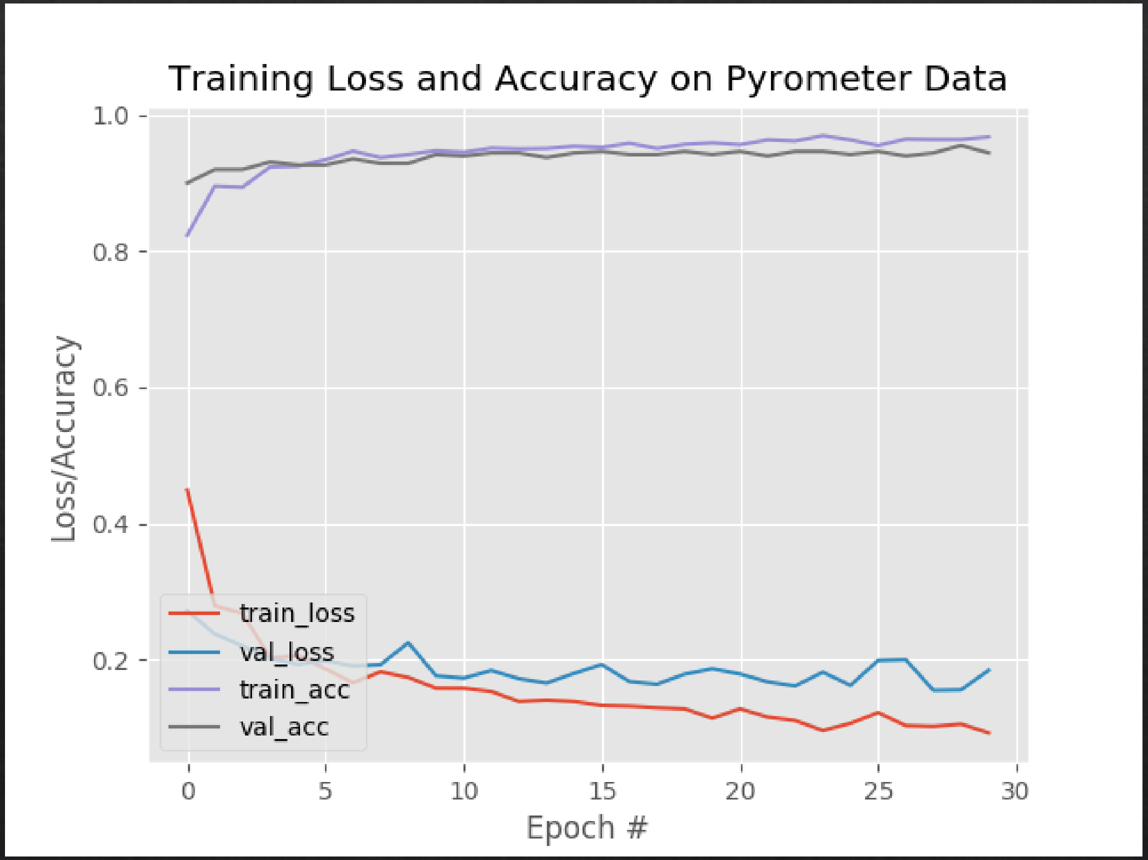
- **ReLU**: **Re**ctified **L**inear **U**nit – maps any negative values to 0, making the entire network nonlinear
- **CMR cell**: Conv2D → MaxPool2D → ReLU, in order



PyroNet - Structure



PyroNet - Metrics



Confusion Matrix (453 samples)		
	Actual Non-Pore	Actual Pore
Predicted Non-Pore	297	2
Predicted Pore	23	131

IRNet - Overview

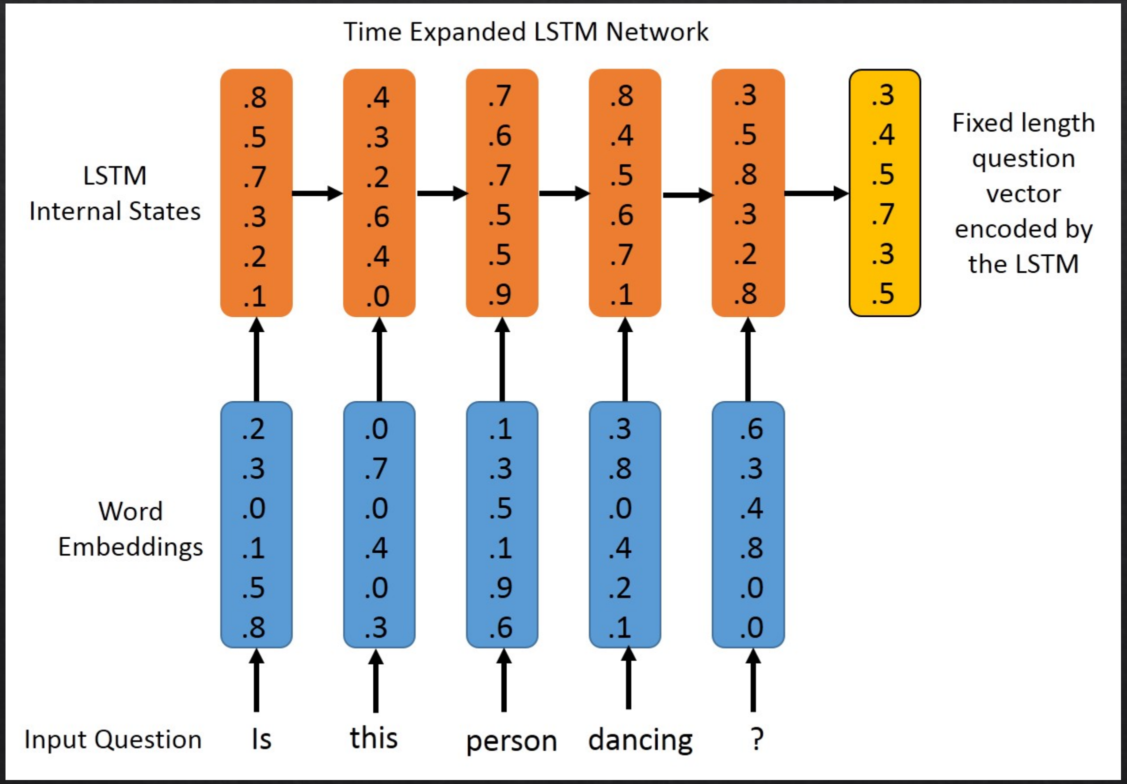
- Input: 3 subsequent frames of critical region of an IR capture (a 30x120 .csv file)
- IRNet **is recurrent** because there is spatial information that is changing with time
- Testing accuracy is roughly 90% - looking to optimize further

IRNet - Data Preprocessing

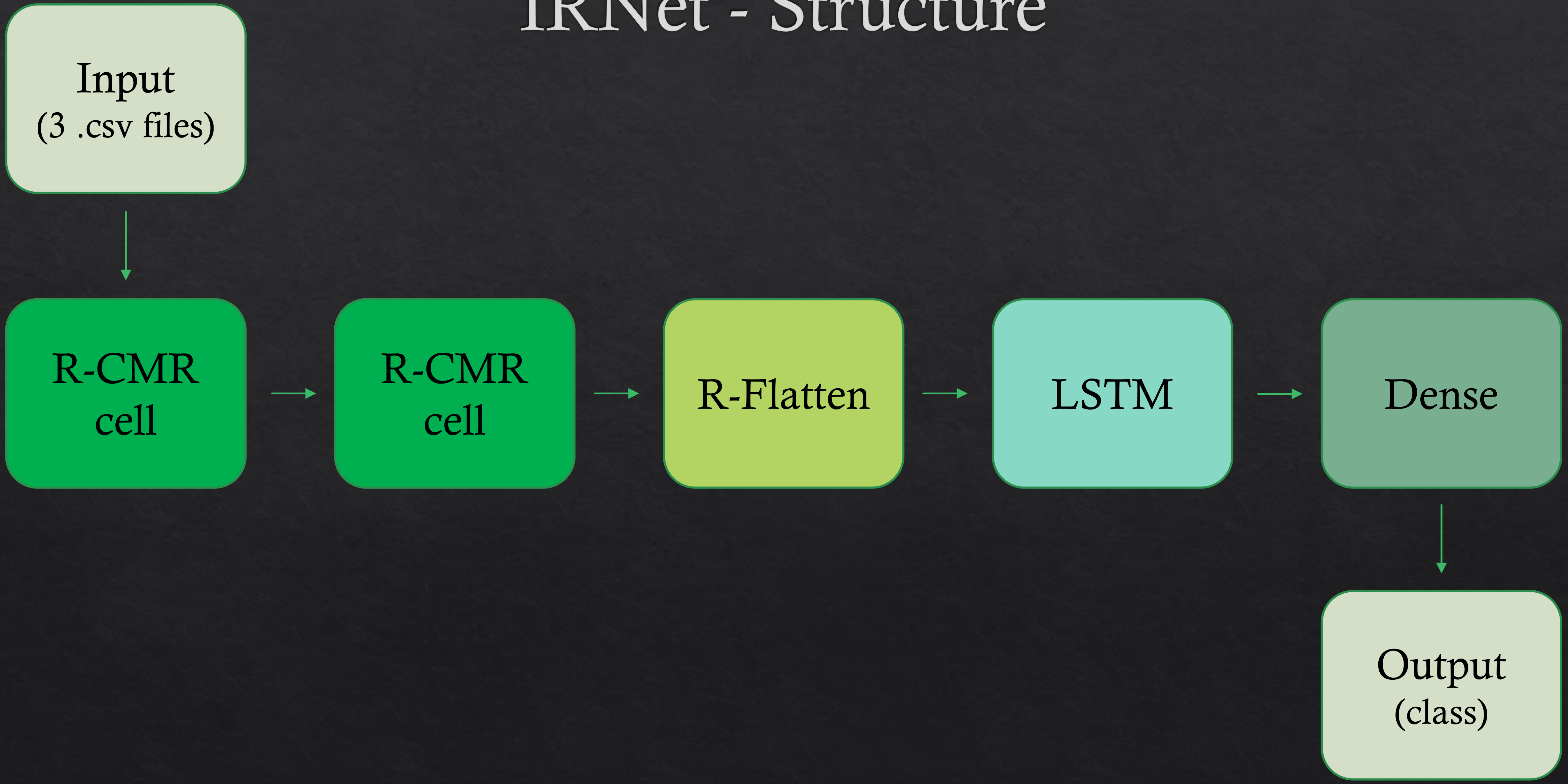
- Read .csv files into sequences of matrices, pair them with class
- Dataset: 5,392 successes, 285 failures, **3,300 augmented failures**
    - Success/Failure Ratio: **3:2**

Terminology

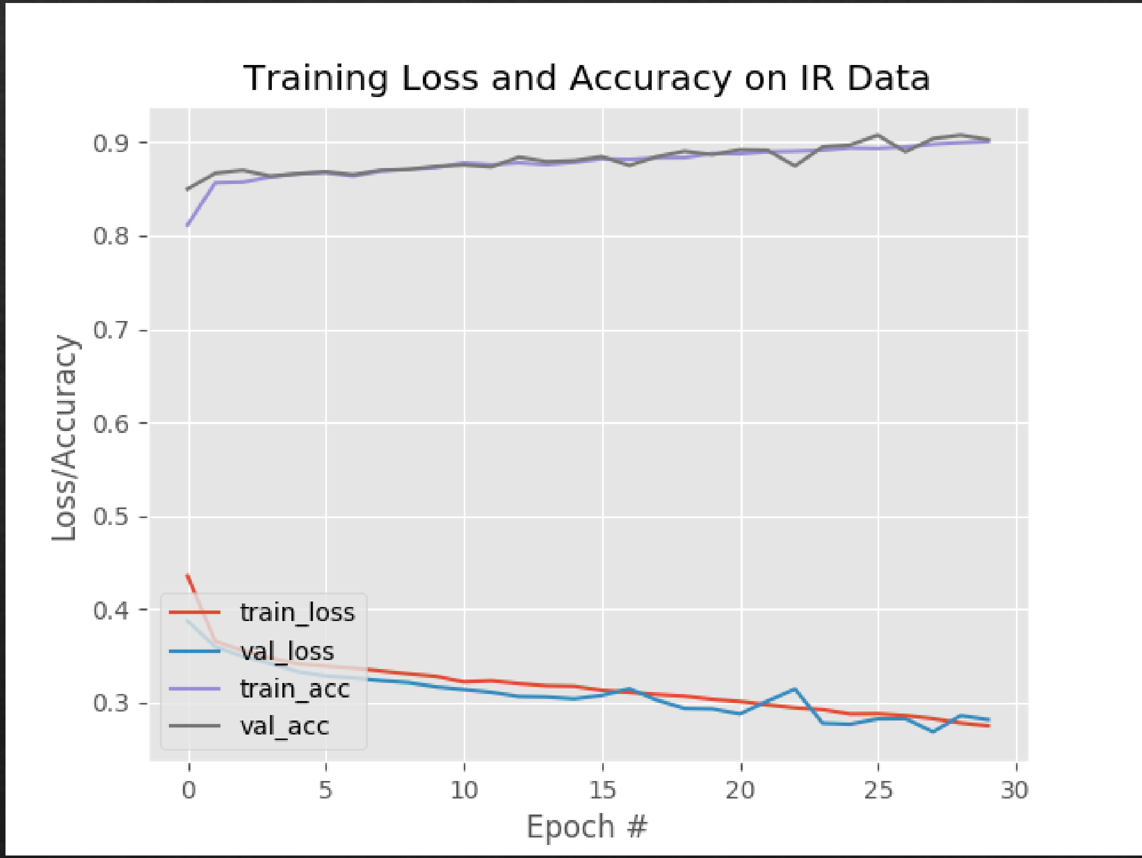
- **LSTM**: **L**ong **S**hort-**T**erm **M**emory – layer that maintains information across a sequence of inputs for use in calculation
- **R-CMR cell**: A CMR cell that processes a sequence of inputs to produce a sequence of outputs



IRNet - Structure



IRNet - Metrics



Confusion Matrix (1911 samples)		
	Actual Non-Pore	Actual Pore
Predicted Non-Pore	1021	57
Predicted Pore	129	704

Potential

- The neural nets have the ability to **quickly recognize patterns that could form pores**
  - Pursue **increased accuracy**
  - Test neural net on **other structures** besides the thin wall
  - Expand neural net to **predict more types of defects**

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