Determining Risk Level for Workers Lifting Objects

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Goals, Background

This project consists of **classifying accelerometer and gyroscope data** to **determine relative risk** of a person lifting a box off of a flat surface **using machine learning.** Data consists of **720 trials** collected by NIOSH of subjects lifting the same object from various positions.

If successful, this model could be used to **quickly identify issues when lifting** in the workplace and affordably **reduce workplace injury** without invasive exoskeleton-style sensor clusters as what currently exists.

Intellectual Merit

There is no research that currently exists investigating automatically detecting lifting risk.

Additionally, there is little to no research investigating the use of CNNs for high-feature, small datasets separating visually similar activities.

The use of convolutional neural networks for classifying accelerometer data (as opposed to video) for activities in general is relatively new in general.

Broad Impact

Back pain is the **#1 cause of workers compensation and missed days in the workplace ($13.7B annually)**

At any time, over 20% of the world suffers from it.

Current solutions to mitigating back pain involve extensive training or personal monitoring, which is expensive and doesn't scale.

An automated solution is both relatively inexpensive and reduces the feedback loop for workers to **immediate** instead of when the pain happens, at which point the reason is lost

System

Model consists of a 2D CNN to train on the input data

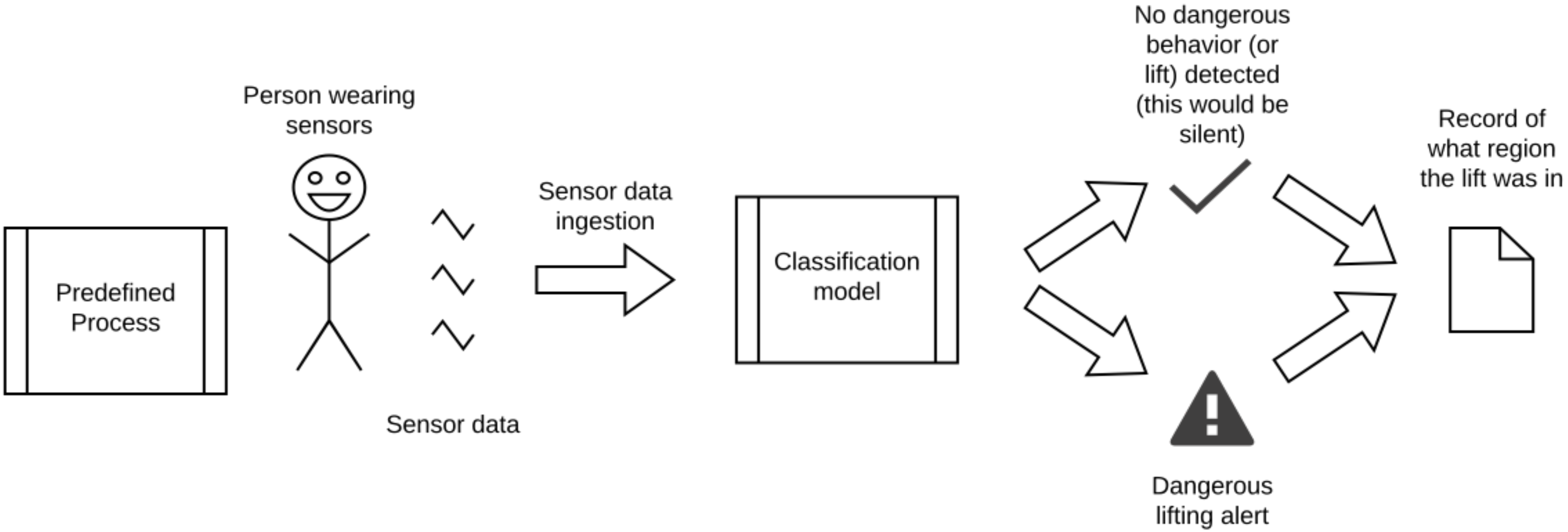
Data is preprocessed with a Butterworth filter and standardized to a mean of 0 and SD of 1 for compatibility with the model

Training occurs offline with a fast stopping procedure of 10 epochs (failure to descend the gradient for 10 epochs triggers a stop)

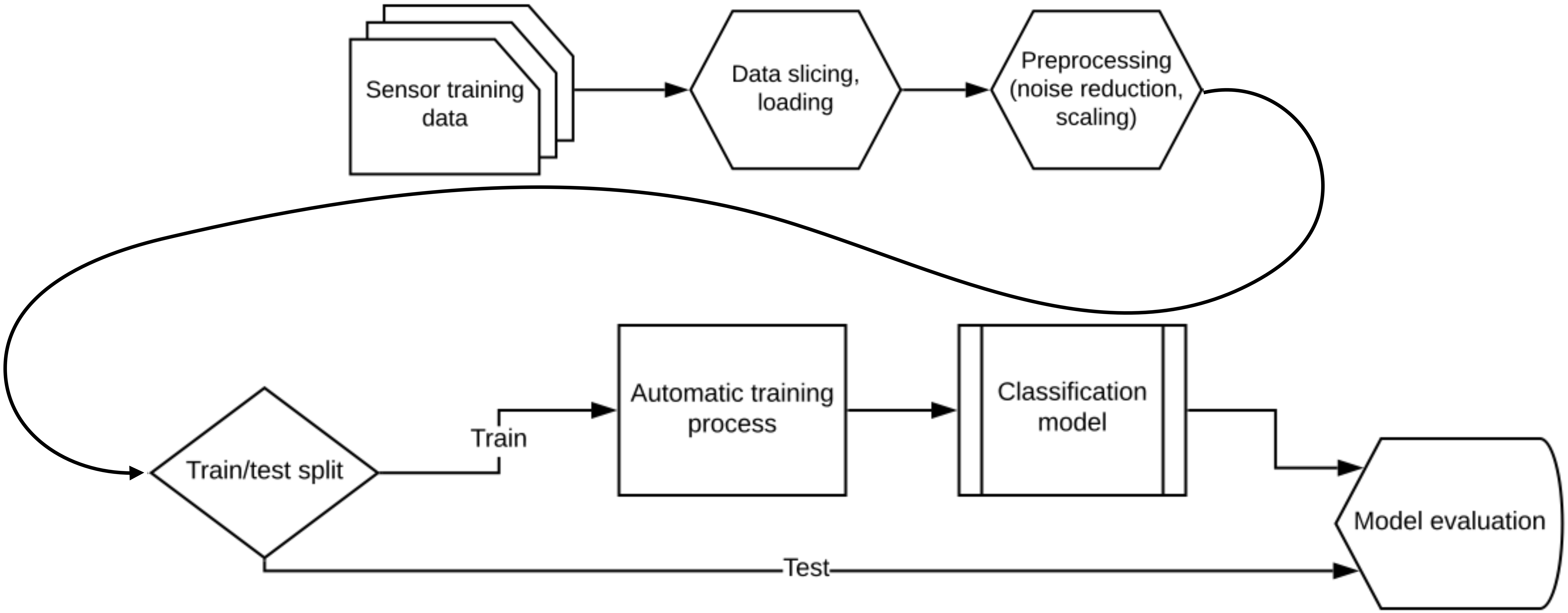
Applications would involve feeding a lift into the system and outputting the relative risk level of the lift in real-time

Model is flexible; original equipment utilized Bluetooth for communication

Design


Predefined Process
Person wearing sensors
Sensor data
Sensor data ingestion
Classification model
No dangerous behavior (or lift) detected (this would be silent)
Dangerous lifting alert
Record of what region the lift was in

Design


Sensor training data
Data slicing, loading
Preprocessing (noise reduction, scaling)
Train/test split
Train
Automatic training process
Classification model
Test
Model evaluation

Layers

Layer Type	Parameters
Input (95x95x3 matrix)	
2D convolution	32 filters, 3x3 kernel
Average pooling	2x2 cell
Dropout	25%
2D convolution	64 filters, 3x3 kernel
2D convolution	64 filters, 3x3 kernel
Average pooling	2x2 cell
Dropout	25%
2D convolution	128 filters, 3x3 kernel
2D convolution	128 filters, 3x3 kernel
Average pooling	2x2 cell
Dropout	25%
Flatten	
Fully connected	1024 units
Batch normalization	
Dropout	25%
Softmax output	

Software

Underlying libraries, general technology

Model development interface:

Keras

TensorFlow

python™

scikit learn

NVIDIA CUDA

Technology

Data collection was performed by NIOSH with inertial measurement units (IMUs), made of an accelerometer and gyroscope.

General model is based on the University of Oxford's Visual Geometry Group (VGG) CNN.

Training was achievable on commodity consumer hardware (NVIDIA 960M, 4GB VRAM).

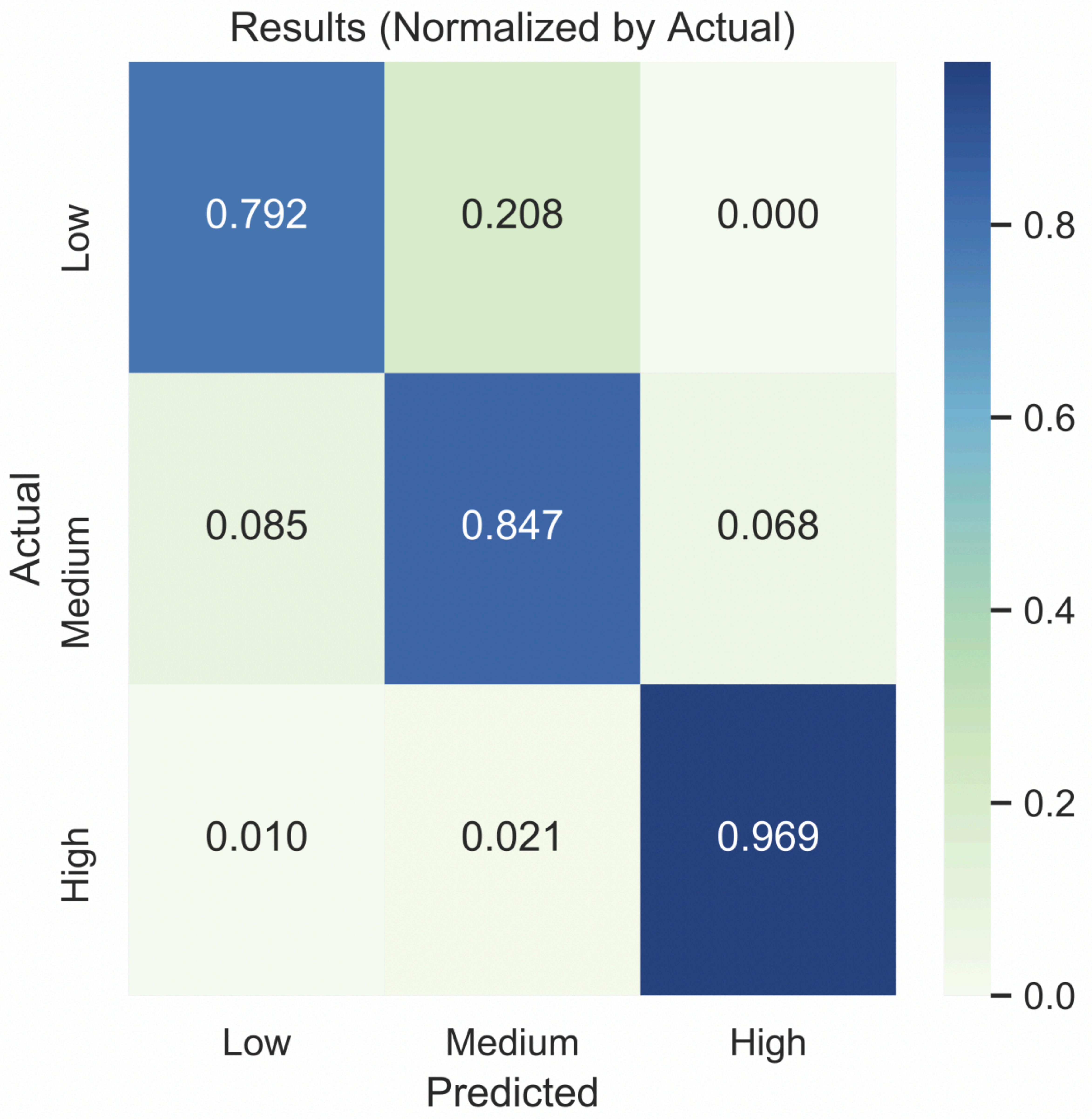
Milestones

Task	Completed?
Create and test a wide range of configurations of the model	Yes
Develop a visualization of salience mapping for CNN input data	Yes
Design a strategy to de-noise an image matrix	Yes
Develop a system to automatically correct input samples for xyz rotation error	Discarded
Document training, model, data ingestion approaches	Yes
Port data ingestion for a flexible input configuration	In Progress

Current results achieved:

`Overall accuracy: 90.6%`

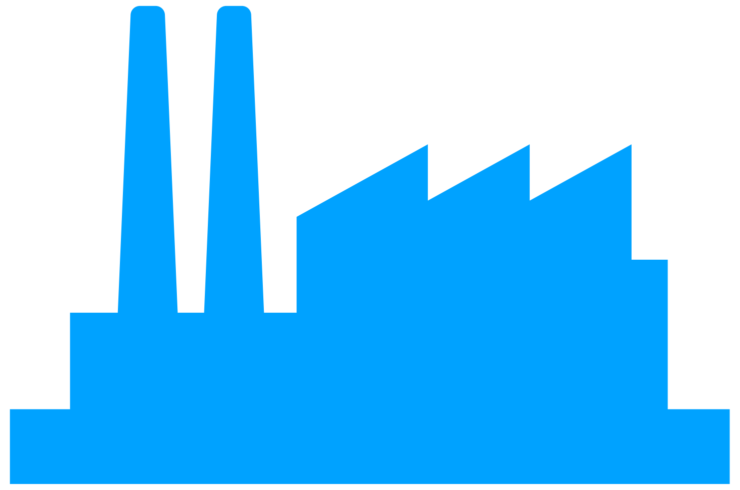
R_K `statistic: 0.839`


Results (Normalized by Actual)
Actual
Low
Medium
High
0.792
0.208
0.000
0.085
0.847
0.068
0.010
0.021
0.969
0.8
0.6
0.4
0.2
0.0
Low
Medium
High
Predicted

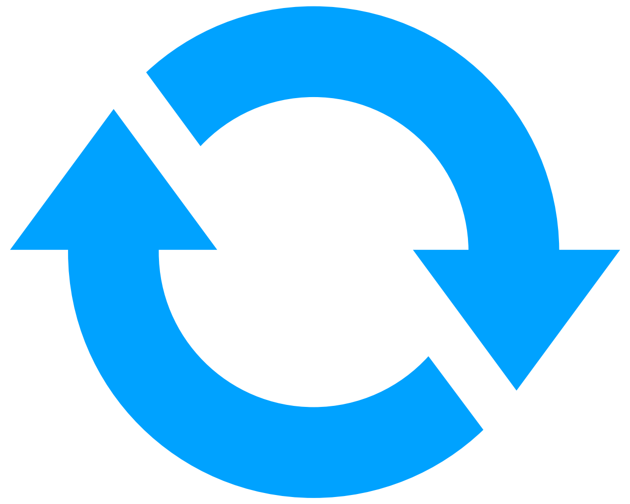
Expo Demo

- Display the speed of the classifier - show it classifying a test trial live
- Sample of the hardware involved
- Description, diagrams of the end model and data collection process

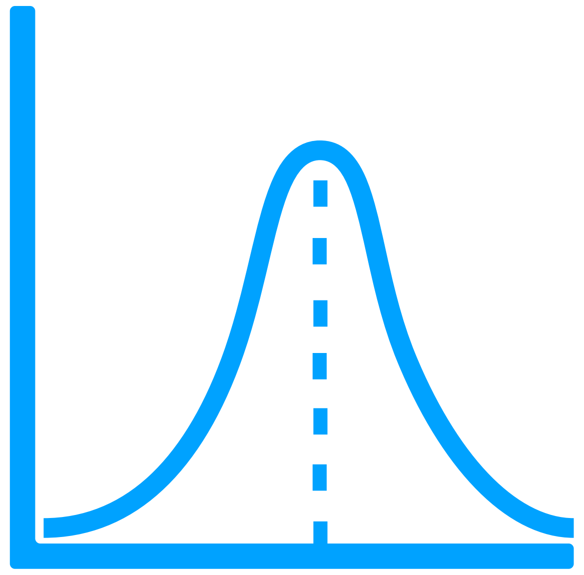
Challenges



Local maximums in model development — easy to keep tuning something that will never work



Determining whether the model was truly working (reproducibility)



Preprocessing the data

Solutions

Reducing local maximums in model development required significant additional research and frequent radical alterations to the model — solved mostly with time

Reproducibility and proving the model was solved by using static splits when testing models against each other and adding regularization to the model to force it to be simpler

Standardization and Butterworth filtering was the least invasive method of preprocessing the data — solved mostly with research

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