HIKNet: A Neural Network for Detecting Head Impacts from Kinematic Data

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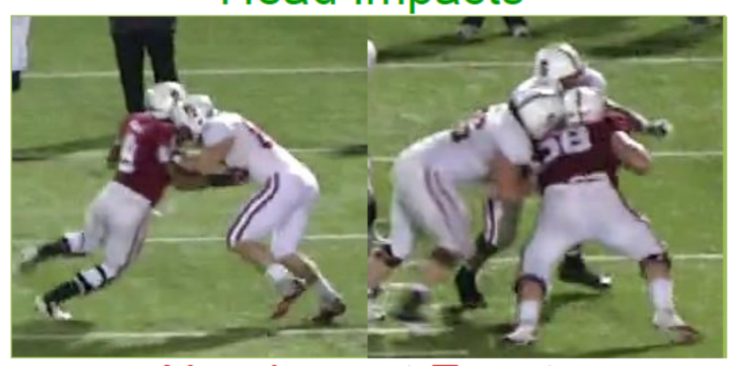
BACKGROUND and MOTIVATION

- Mild Traumatic Brain Injury (mTBI) is a serious health concern, especially in contact sports such as football, and can cause acute and long term debilitating symptoms[1,2]
- The Camarillo Lab at Stanford has developed and deployed an instrumented mouthguard that records linear acceleration and angular velocity of head impacts[3]
- Device must be able to accurately classify between real impacts or false positives (e.g. spitting, chewing, etc.) to be useful
- In previous work, sequential feature selection was used to determine the most important classifier features, and these were used to train a SVM classifier[4,5]
- We propose to use a neural net, which will automatically extract important features to distinguish between real and false impacts to a high degree of accuracy

Head Impacts



Non-impact Events

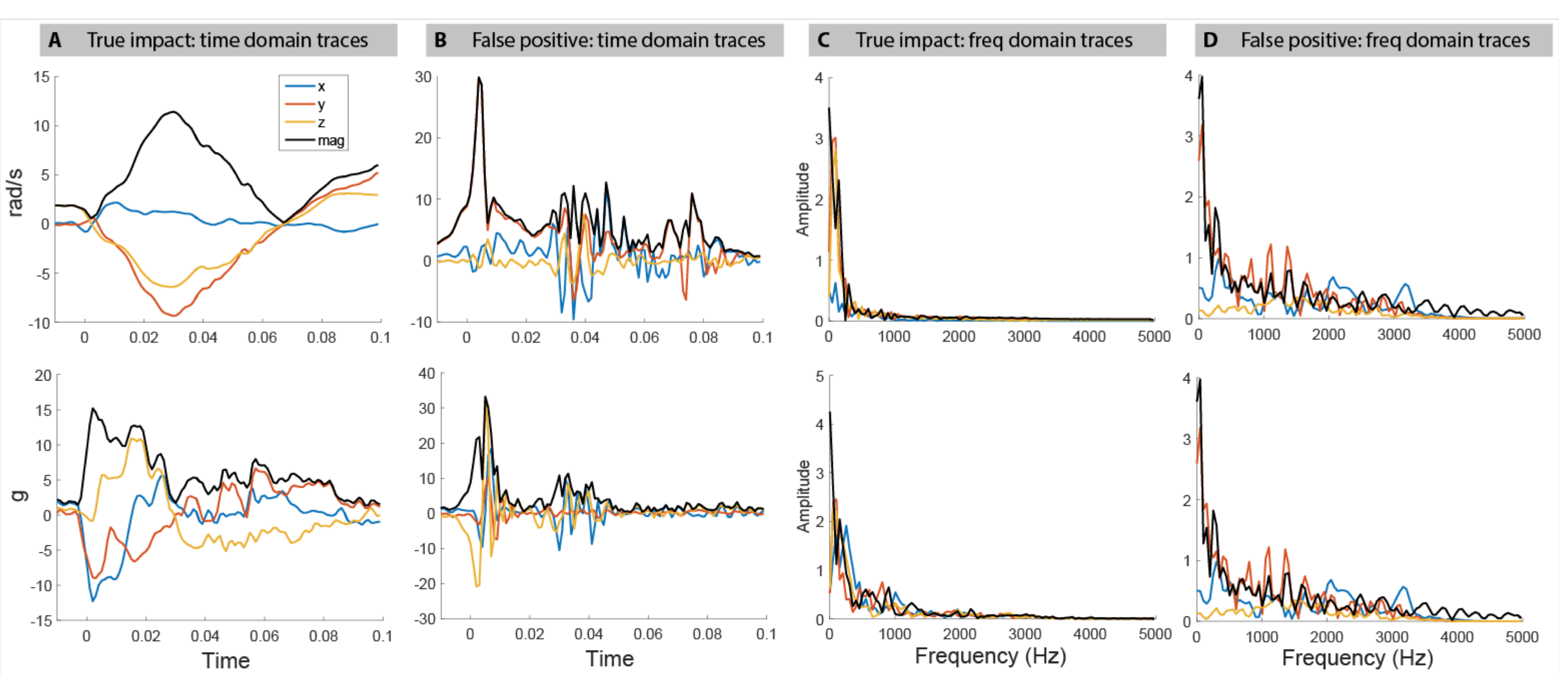
Image adapted from [4]

1. DATASET

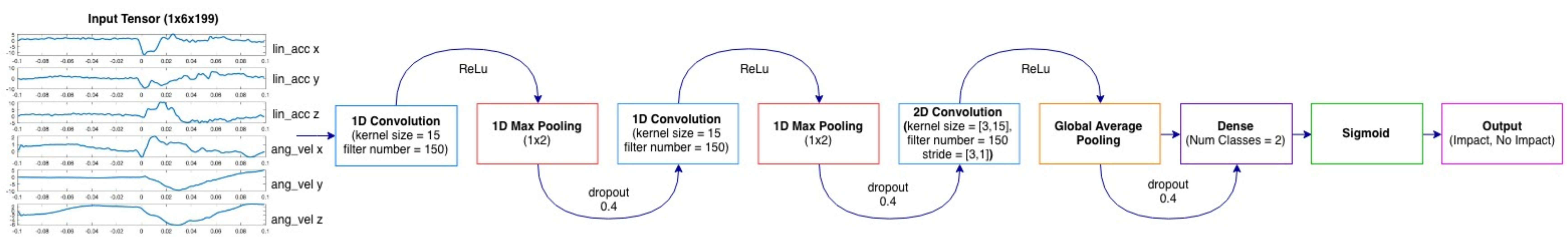
Stanford Instrumented Mouthguard

- 527 examples of 6 time traces (linear acceleration and angular velocity in x, y, z axes) each of length 199
- 264 real impacts and 263 false impacts
- Each impact has 100ms of data sampled at 1000 Hz
- Dataset was randomly split 70%/30% into a training and evaluation set
- Generally, true impacts have lower frequencies content (20-30 Hz), whereas false impacts are comprised of higher frequency content

A representative example of a real and false impact:

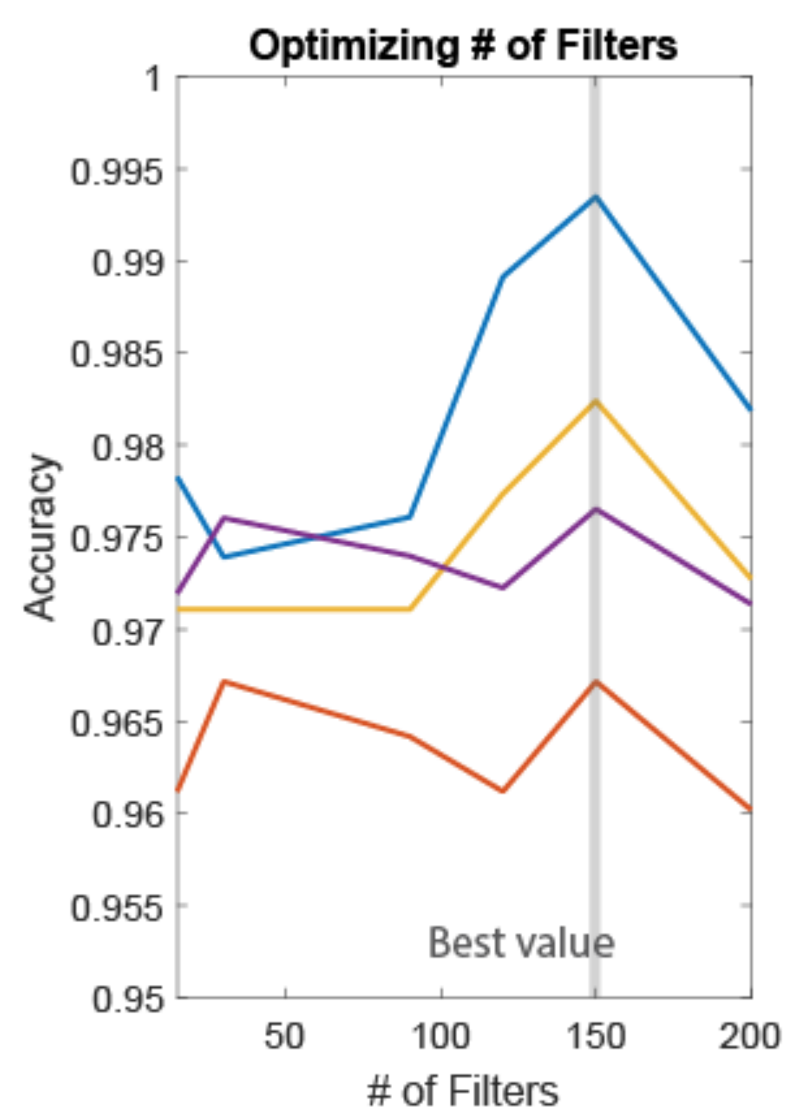


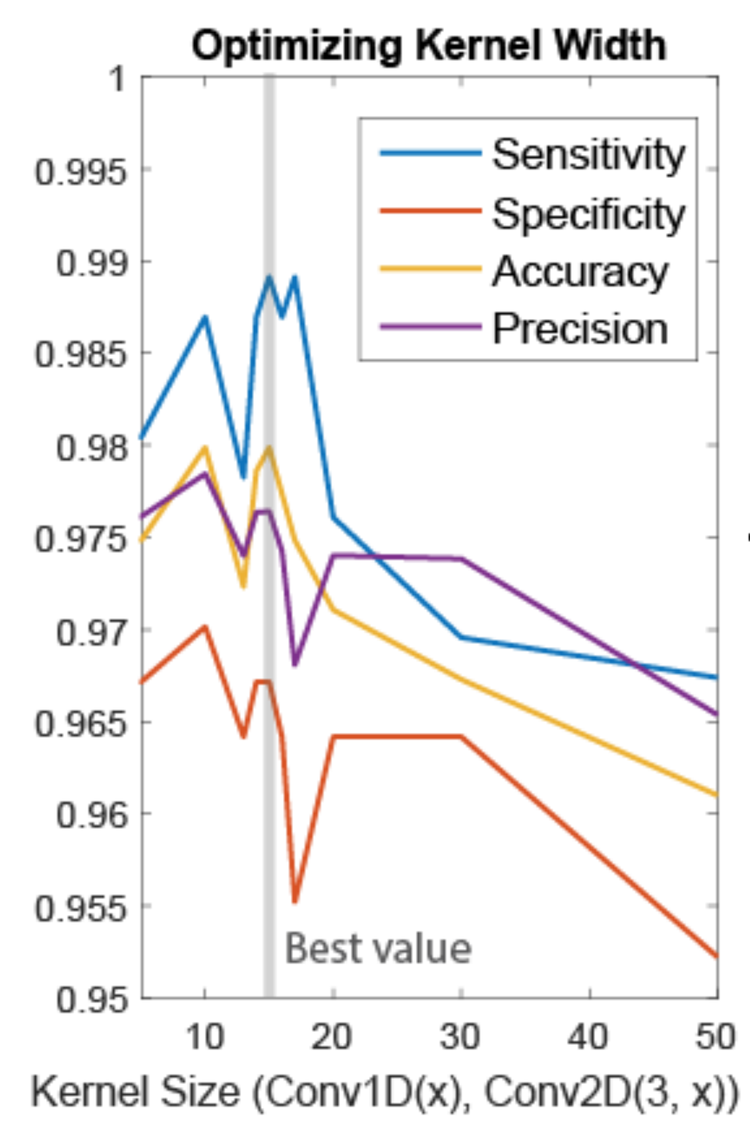
2. NEURAL NETWORK ARCHITECTURE

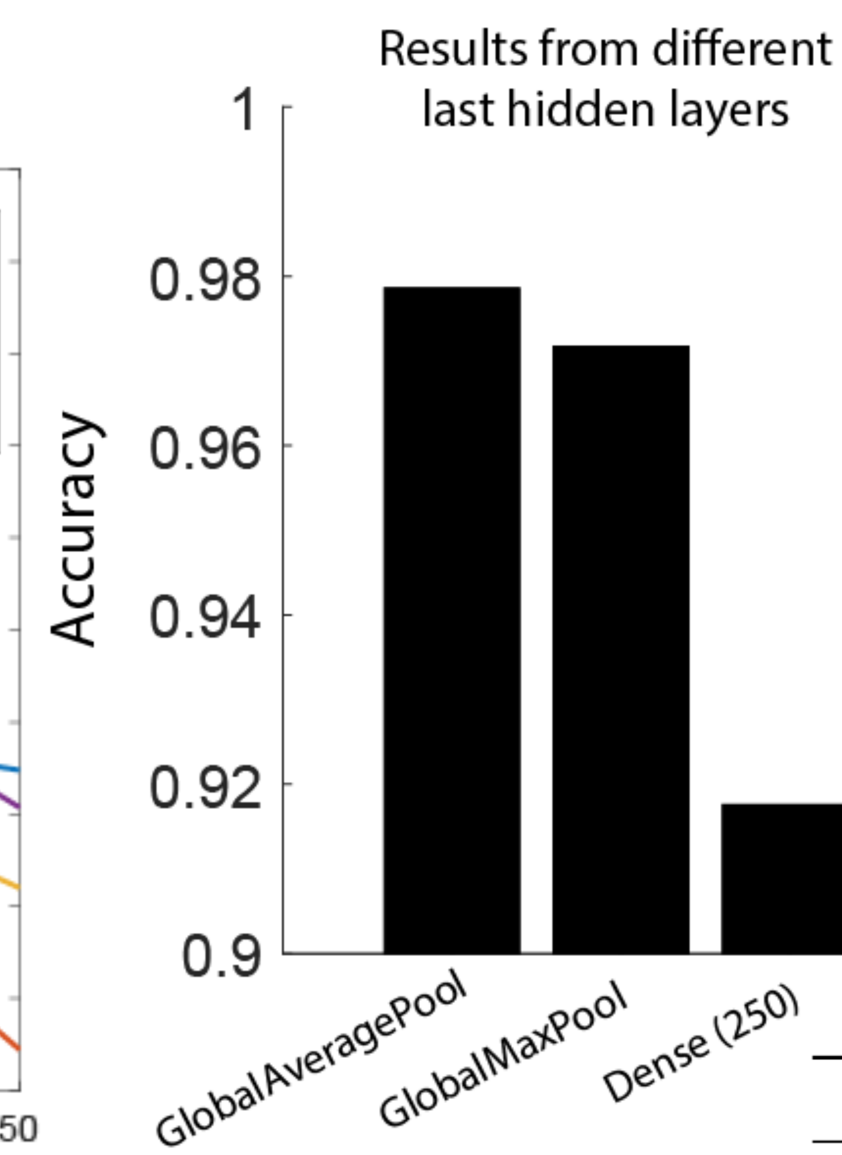


- Used Keras and Tensorflow in Python to create a deep convolutional neural network
- Baseline architecture modeled off of PerceptionNet[6] and ConvNet[7], two CNN's used for Human Activity Recognition from time series data
- The 1D convolutional layers "extract" features and feed into a late 2D convolution which classifies the data into impact and no impact
- The 2D convolution is late in the architecture to prevent overfitting

3. RESULTS and DISCUSSION







- Tested a number of architectures (e.g. U-Net) but found the PerceptionNet architecture to have highest accuracy on evaluation set
- Tuned our Net using a "greedy" optimization scheme for number of 1D conv layers, number of 2D conv layers, and type of final layer
- Parameter sweep to find optimal filter size, kernel width, and dropout thresholds
- Optimal dropout threshold 0.4, kernel width of 15, and filter size of 150
- Low parameter neural network worked surprisingly well and out performed other more complex architectures as well as existing SVM classifier

Final HIKNet Performance Metrics:

	Accuracy	Precision	Specificity	Sensitivity
HIKNet	98.2%	97.6%	96.7%	99.3%
SVM [4,5]	93.7%	92.3%	92.8%	94.6%

FUTURE WORK

- Develop a neural network that classifies between multiple classes such as head impacts, body impacts, and no impact.
- Apply neural net to a larger mouthguard dataset as more data is collected
- Analyze positive head impacts and classify them as resulting in concussion vs. no concussion (KOCNet)

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