Walking Activity Recognition on Smartphone data using Deep Neural Networks

made by:

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Our Motivation

The ability to recognise activities by analysing data getting from a person's device is one of the main subjects of study of the scientific areas of HAR and machine learning.

Although accurate activity recognition is challenging because human activity is complex and highly diverse.

Most of the human daily tasks can be simplified or automated.

Out main goal

The main purposes of our work is to make a model that will help to recognize user activity.

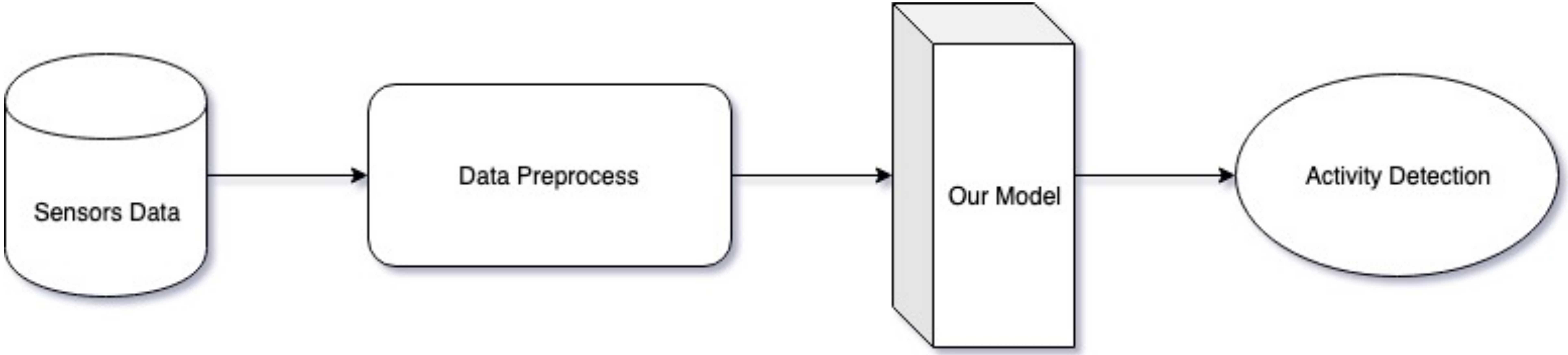
Problem setting

The problem set is to predict the activities that the persons do while walking,
This problem is framed usually as univariate or multivariate classification task.

With this project we are trying to build a proper machine learning architecture capable of fit the data and be generalizable in order to clarify activities by walking.

Our proposed solution

Our primary objective is build a deep neural architecture based on the sensor data in order to predict users activities with the highest possible accuracy.



First step

—

Collect the sensor data and make assertions about the information quality, explore the data

Second step

—

Explore and detect high-medium level action pattern, preprocess the data and arrange it.

Third step

—

Train a classifier model capable of discriminate over the low level patterns and compare with the ground truth.

Data collection

Existing data until now

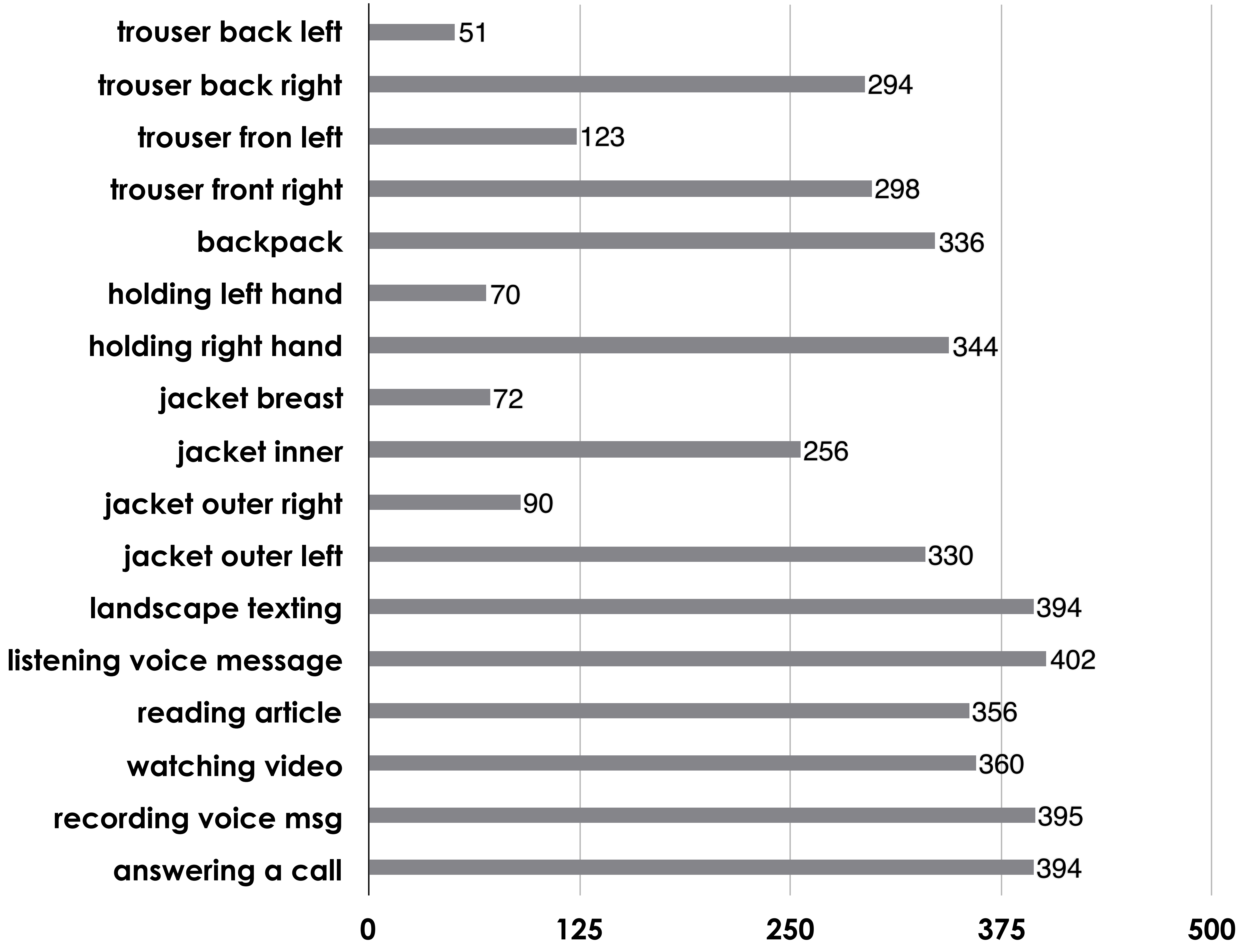
Dataset	Samples	Persons	Sensors	Associate Task	Accuracy	Number of Activities	Sampling Rate
ActiveMiles	4390726	10	A, G	deep learning approach	95.1%	7	50 – 200 Hz
WISDM v1.1	1098207	29	A	Artificial features + Dropout	85.36%	6	20 Hz
RealWorld	944,356	15	A	CNN + statistical features	98%	8	50 Hz
HMMwithPre	10663	25	A,G,M,AP	tacking Denoising Autoencoder and LightGBM	95.73%	8	100 Hz
HSBD	10349	30	A, G	tacking Denoising Autoencoder and LightGBM	98.22%	6	50 Hz
HDBD	5584	30	A, G	tacking Denoising Autoencoder and LightGBM	96.31%	6	50 Hz
HASC	-	7	A	deep recurrent neural network	95.42%	6	100 Hz

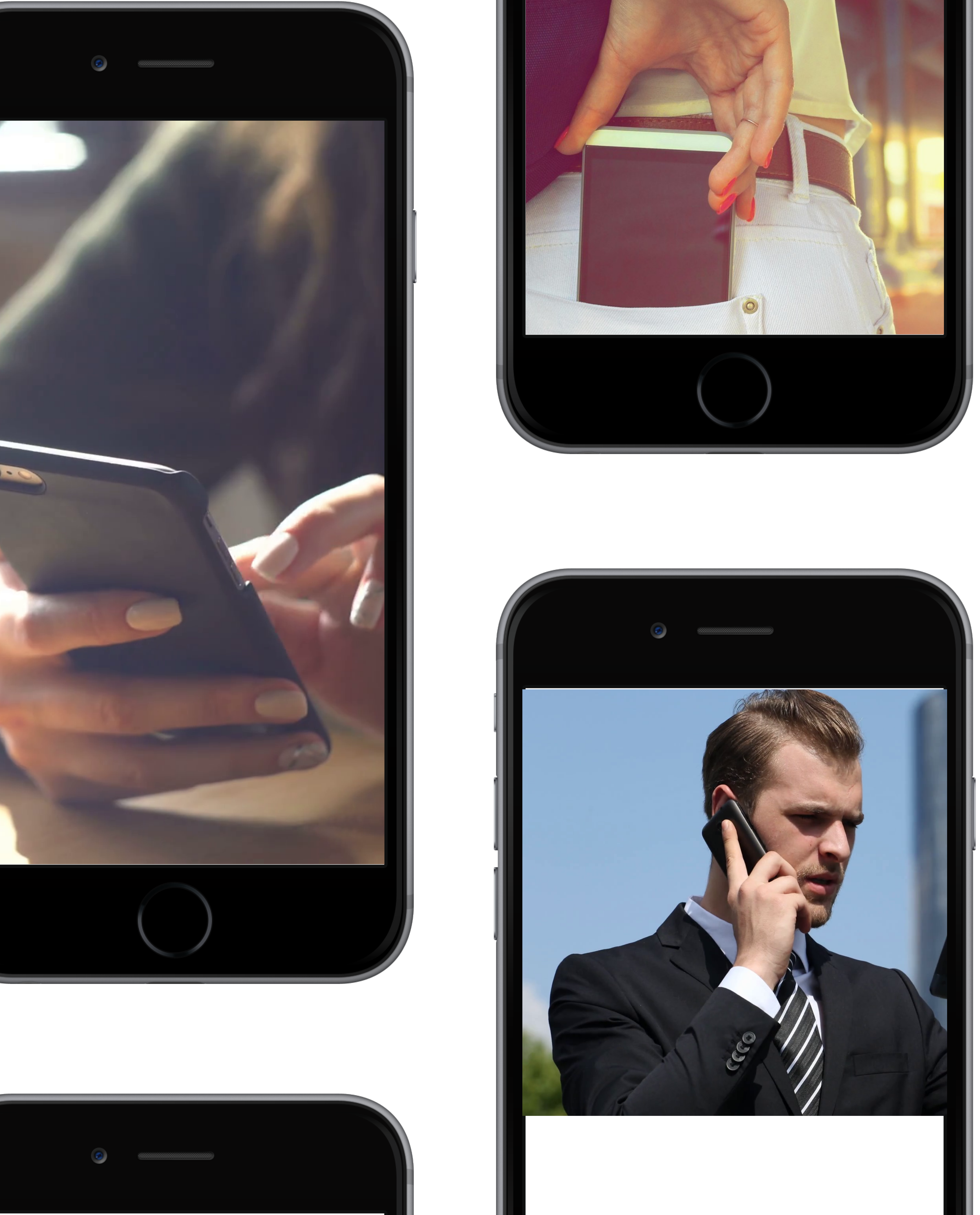
18

Totally new classes

Unique classes among 25 person that include activities
by walking with the smartphone in different positions

Position of the phone and activity





Final Activity Set up

Important Activities
Backpack
Holding in right hand
Jacket outer left
Text portrait
Text landscape
Listening voice message
Recording voice message
Reading article
Watching a video
Telephoning

Out of the18 activities these 10 activities are the most Important based on uniqueness of data.

Preprocessing

2018
Eric Klieme,Christian Tietz &Christoph Meinel

Beware of SMOMBIES: Verification of Users based on Activities while Walking

2016
Haytham Fayek

Speech Processing for Machine Learning: Filter banks, Mel-Frequency Cepstral Coefficients (MFCCs) and What's In-Between

2018
Sandeep Kumar

Human Activity Recognition on Smartphones
using Machine Learning Algorithms

2017
Mario Parreño

Smartphone Continuous Authentication Using Deep Learning Autoencoders, (authentication continuously)

2018
Xile Gaos

A Human Activity Recognition Algorithm Based on Stacking Denoising Autoencoder and LightGBM, (1D CNN, feature extraction with autoencoders to sanitize the noise in sensors)

2018
Jindong Wang

Deep Learning for Sensor-based Activity Recognition: A Survey (Compilation of models that researchers have done in order to predict the human activities)

2017
Daniele Ravì

Deep Learning for Human Activity Recognition: A Resource Efficient Implementation on Low-Power Devices (datasets:ActiveMiles, WISDM v1.1, Skoda)

2015
Ordoñez Javier

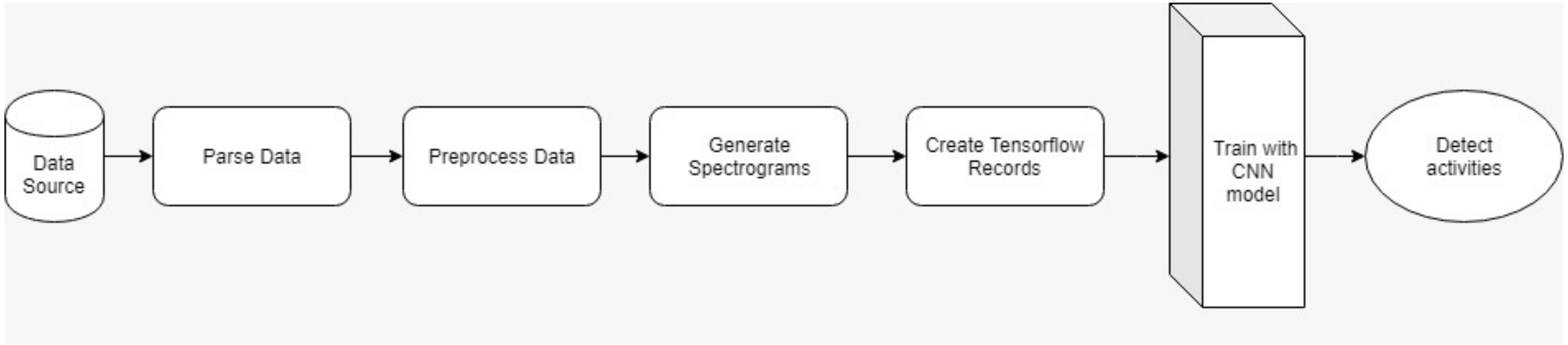
Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition, (they didn't use spectrograms)

2017
Sajanraj T Dr

Human Activity Recognition by Smartphone using Machine Learning Algorithm for Remote Monitoring. (IDLE, walking, run, step up, step down)

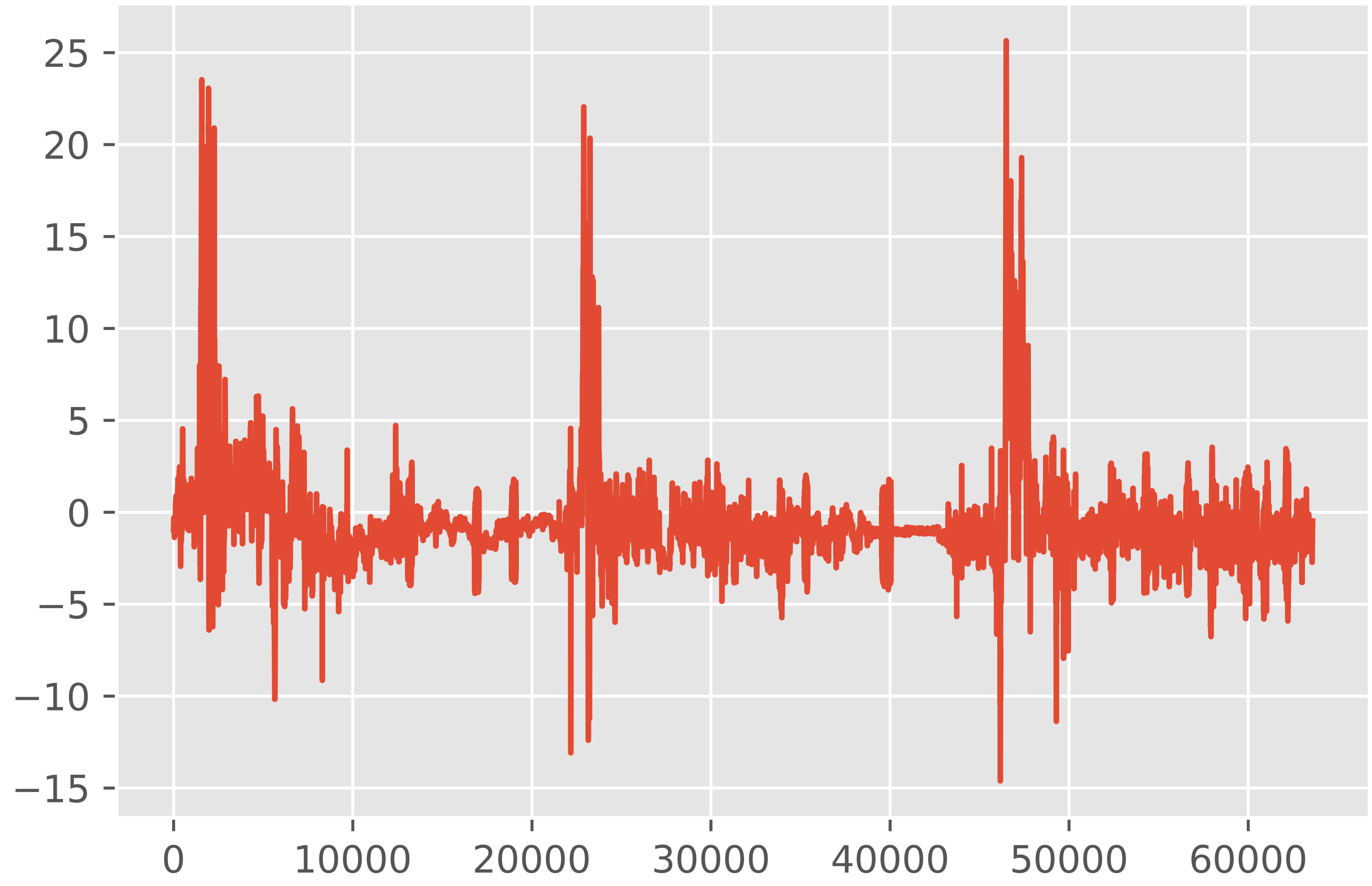
Our Machine learning pipeline

In order to achieve good and fast results we improved our ML, with input pipeline performance



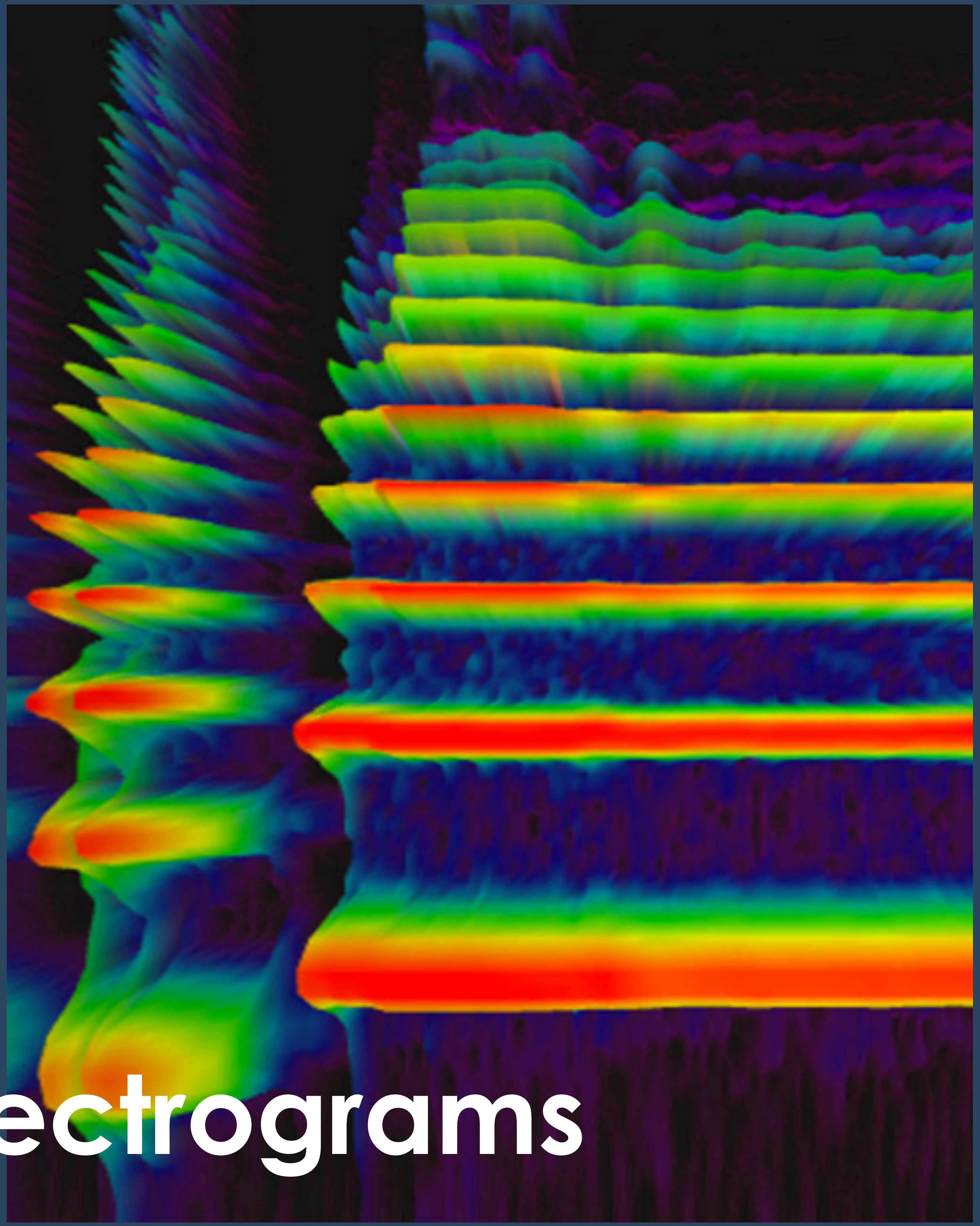
We strict the data building time series and applying the FFT transformations we generate spectrograms, build 3 channel images, generate TF Records and consume the data in a 3 layered convolutional neural network.

1st step: Time Series



We build with the information from 25 persons different time series corresponding to the activities sampled from the data recollection

Time series data was build according to the sensors dimension, in the case of the sensors selected (Accelerometer and Gyroscope), the series were created for (x,y,z) coordinate.



Spectrograms

Spectrogram is a basic tool of representation used in the analysis of signals. It is a representation of the distribution of energy of a signal in terms of the time, frequency and amplitude

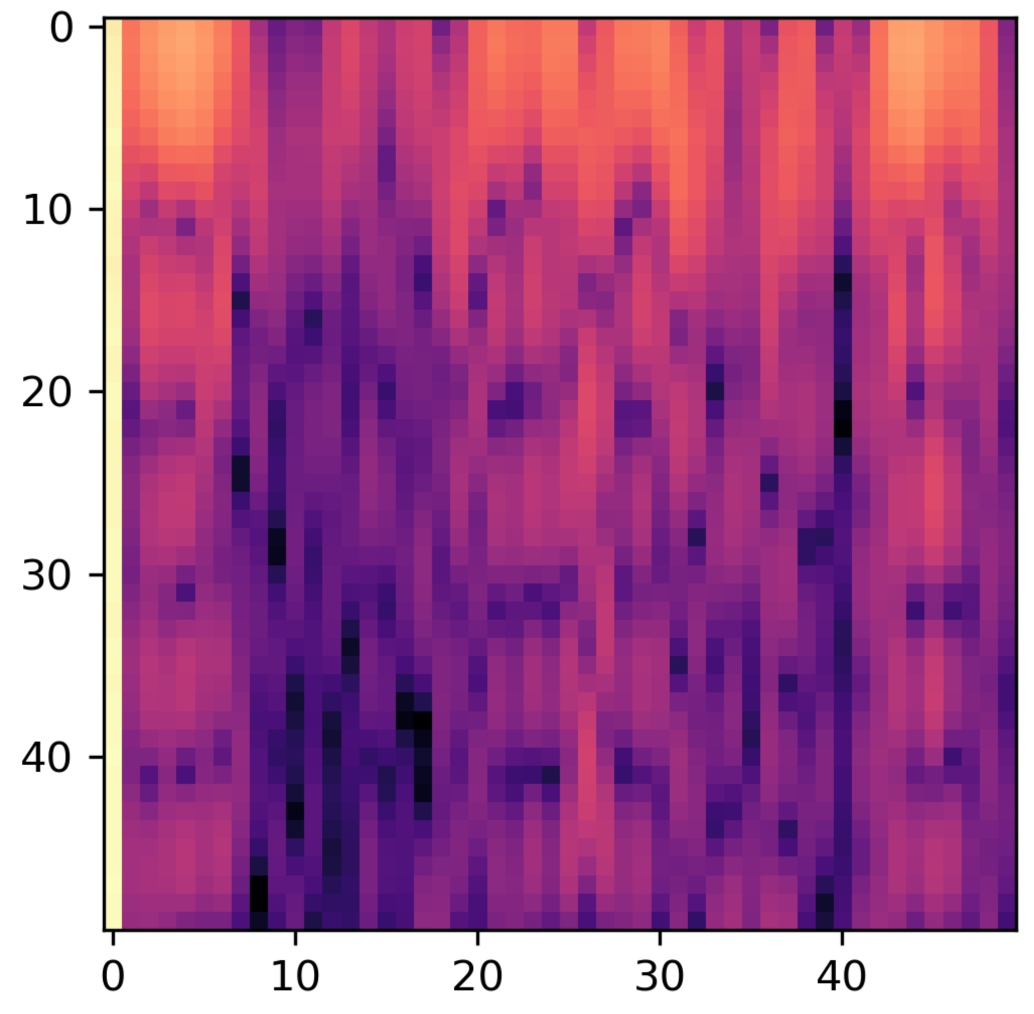
Fast Furier transformation & periodograms

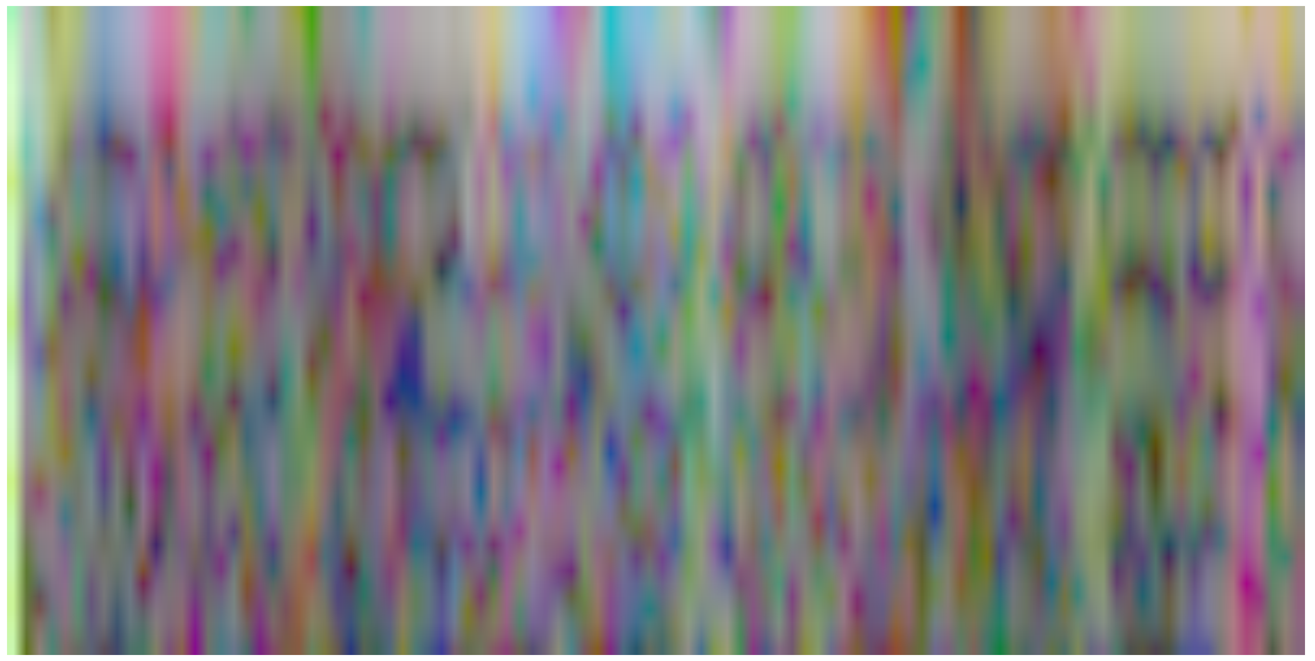
In oder to transform the signal into something different (more interpretable) we can express every signal in the form of Furier Transform, then see the perturbations in terms of frequency over the time.

$$x(t) = \int_{-\infty}^{\infty} f(x) e^{-2\pi jtx} dx$$

Using the transformation we estimate the spectral density of the signal, which is called periodogram. With the stacking of this periodograms we construct the spectrogram.

2nd step: Spectrograms



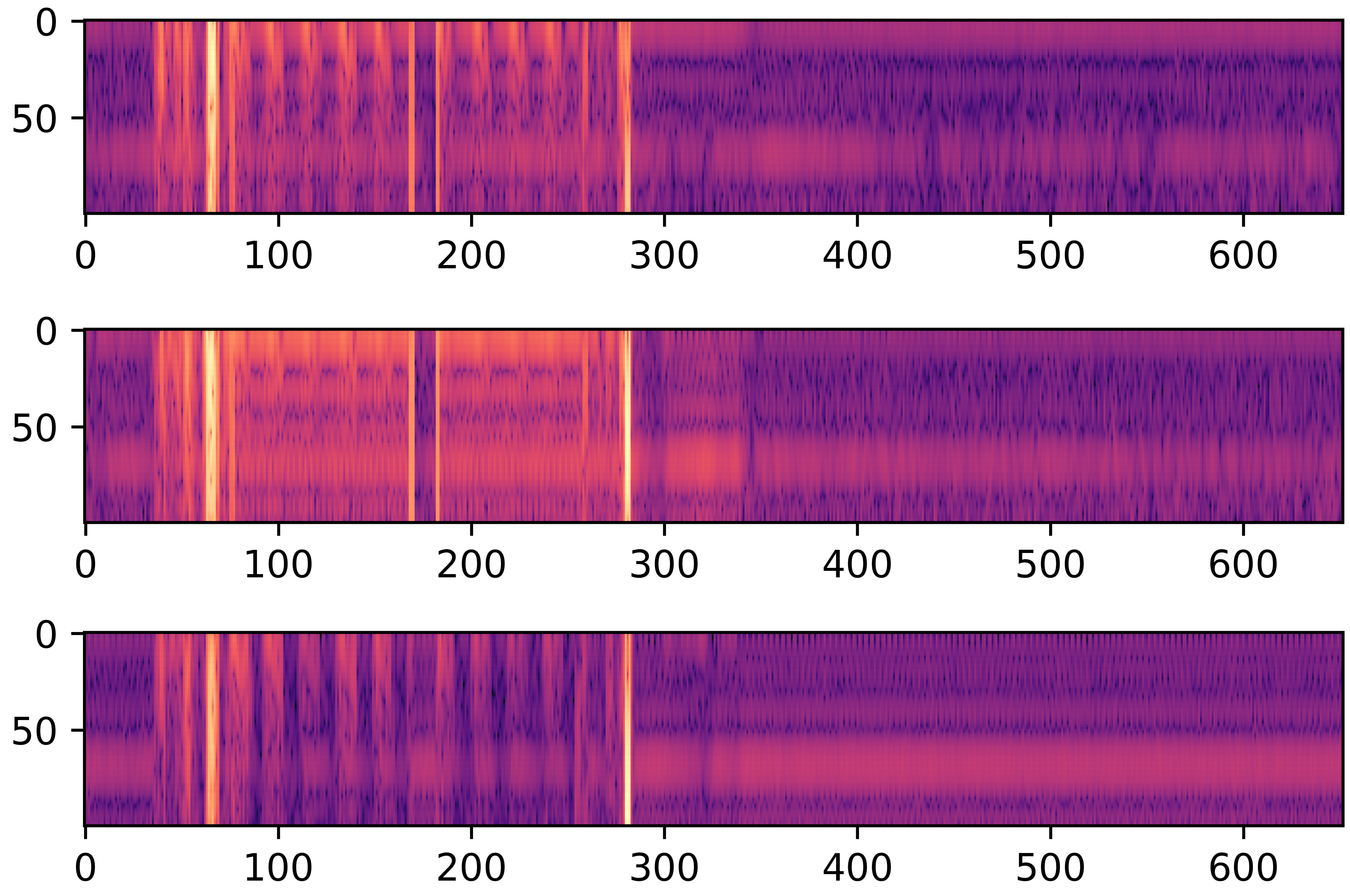


We build spectrograms based on the FFT and log banks creating a windowing among the series coordinates

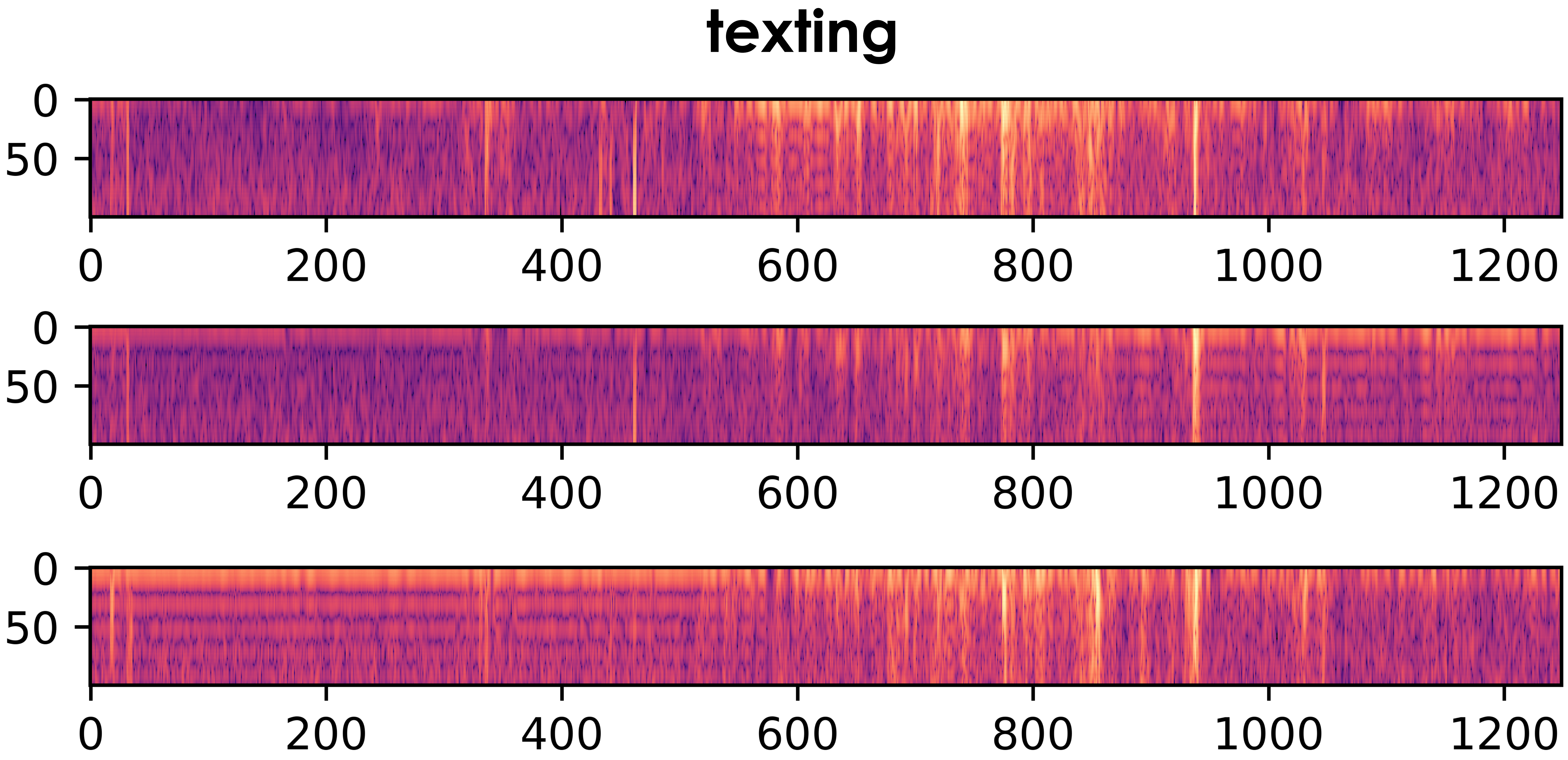
First image is a spectrogram of 50x50 from one window in the x coordinate of texting activity, the second spectrogram was done with the double length this time 100x50, for 3 coordinates (x,y,z) at one window, this spectrograms were the ones that we used at training

Accelerometer

listening voice message



Accelerometer



HOW TO MAKE MAGIC POSSIBLE

Image recognition.

Convolutional Neural Networks

Convolution layers
Extract inputs of the feature volume.

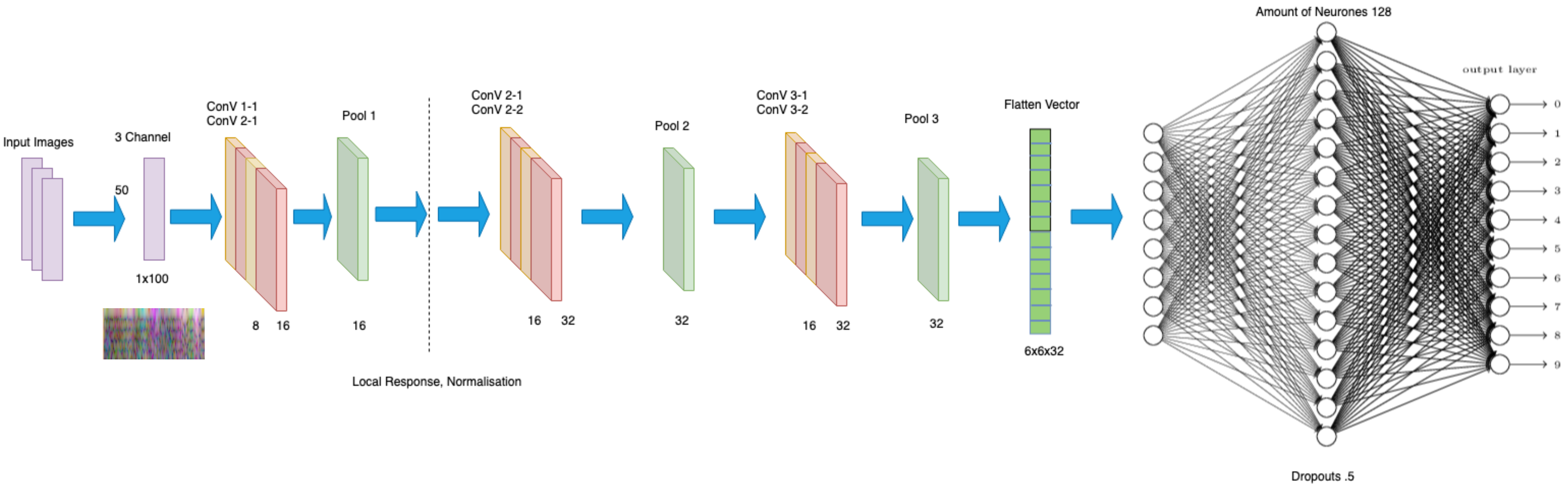
Fully connected layers
Connect every neuron in every layer.

Input image
Decomposition in pixels fed into the network or 1D vectors (Sequential data).

Polling layers
Reduce information with non-linear downsampling (Filtering).

Classification/Regression
Desired target, (Probability).

<u>Small</u> sense v7



We created a full architecture that we named v7, it is a smaller subset of layers based on VGG16, in this case the network was fed with 3 channel spectrograms, and it was composed by 3 convolutional layers with 3 pooling reductions and 3 final convolutional layers.

We added regularization in the first layer (local response normalization), and last fully connected layers with dropouts between 0.5-0.7 including batch normalization.

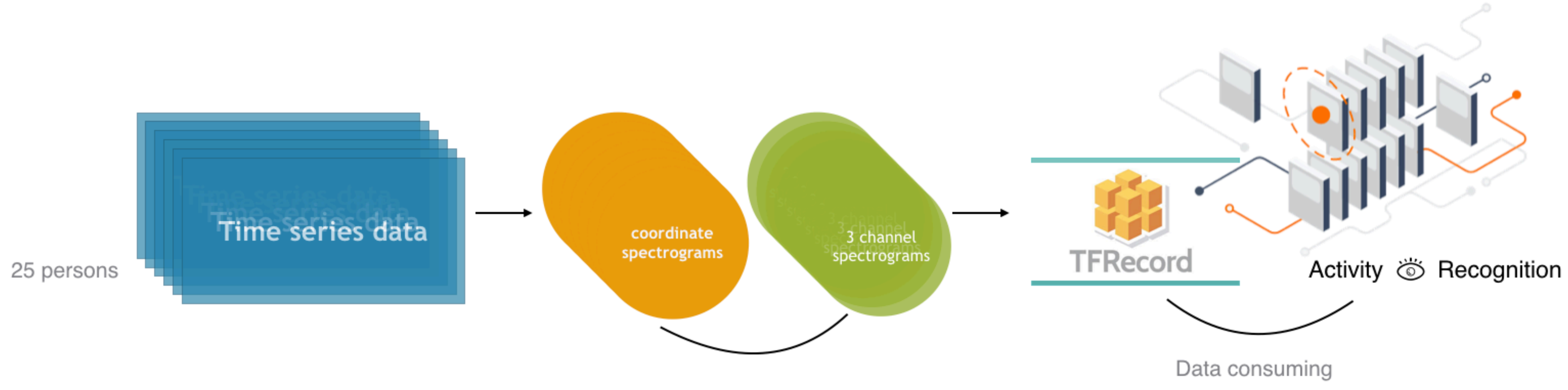
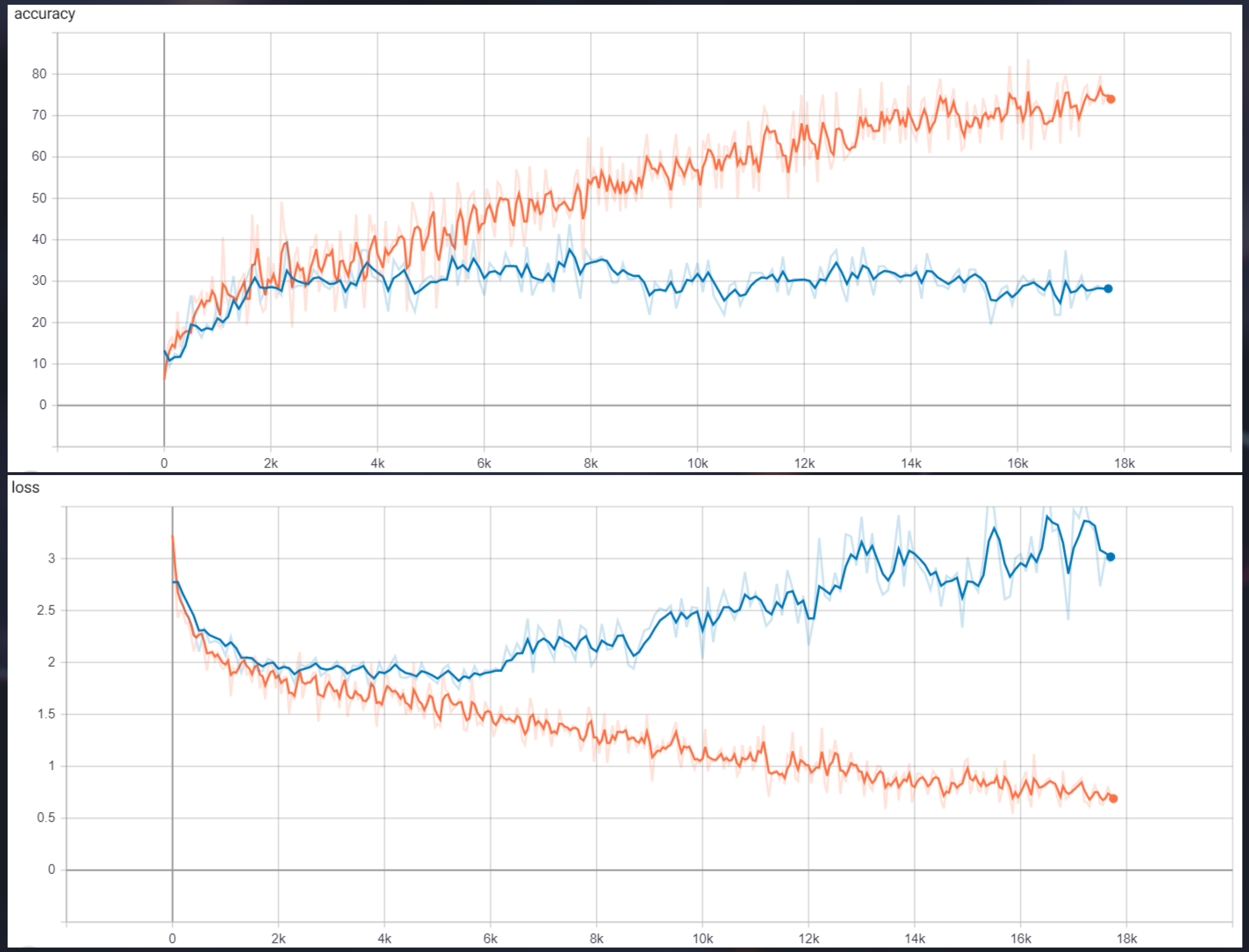
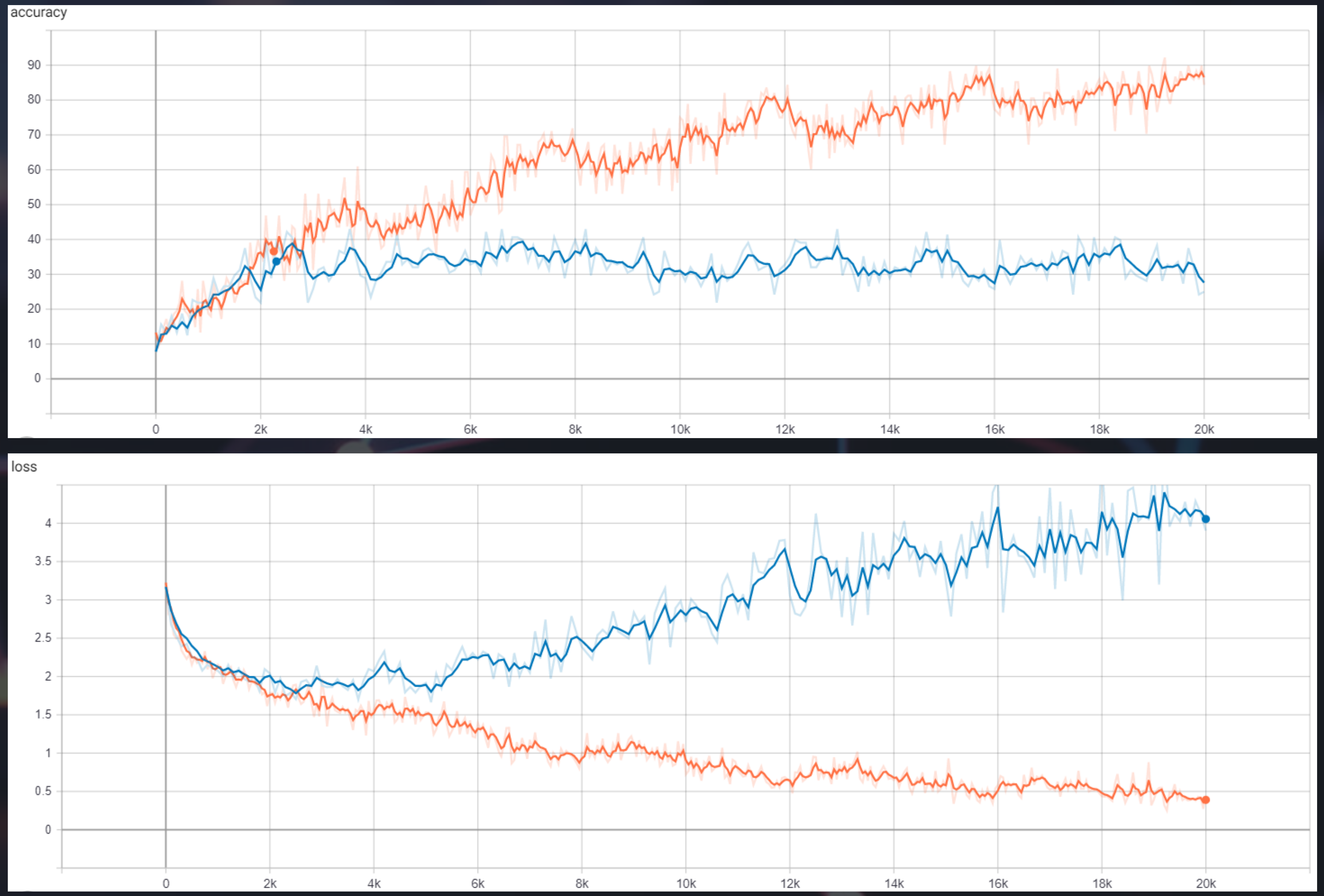


Image recognition.

Training Results





10 class experiment

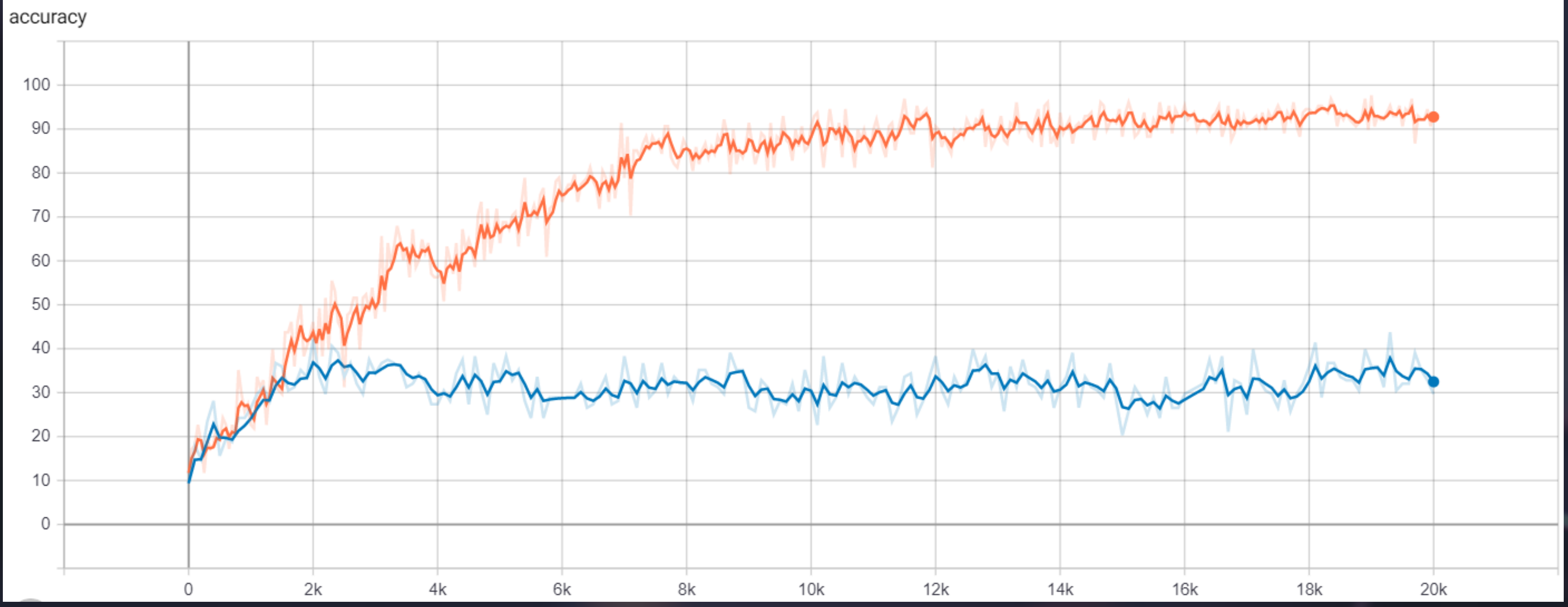
In this occasion we encountered 80% accuracy in training and around 28% in validation with normalization

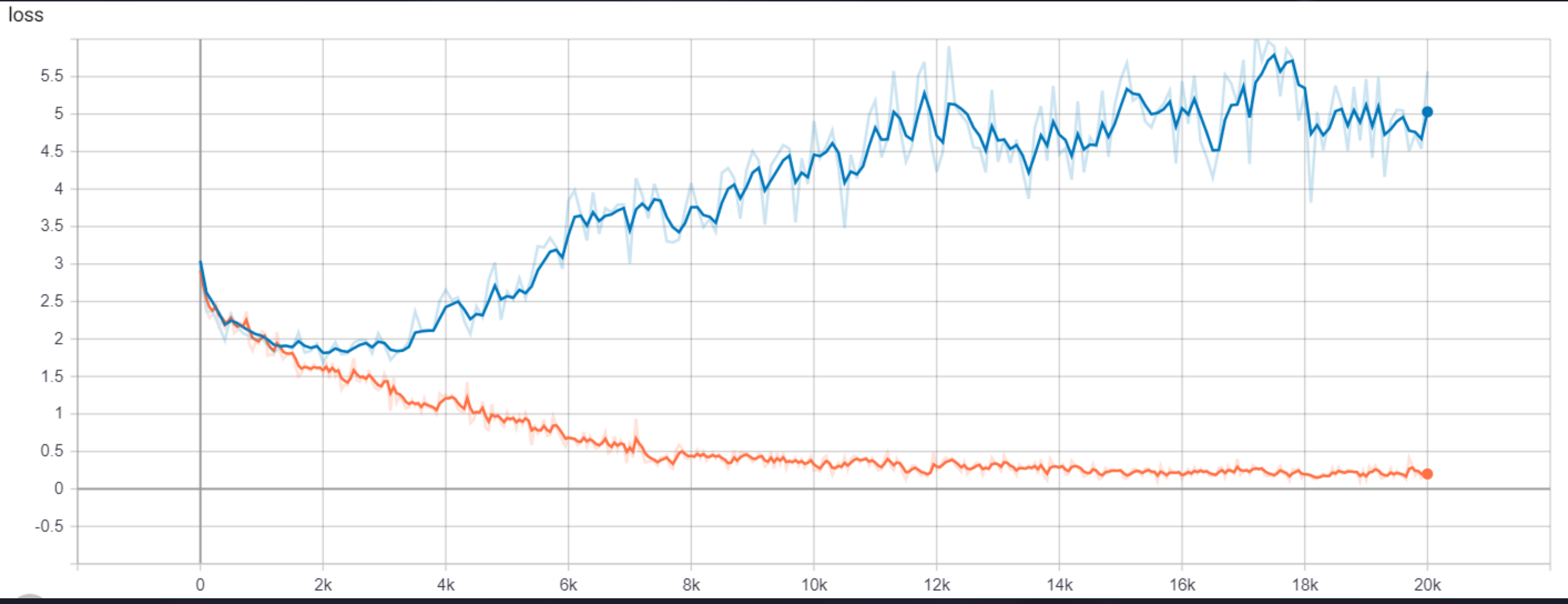
10 class experiment

around 90% in training accuracy and 31% in validation set without normalization

Image recognition.

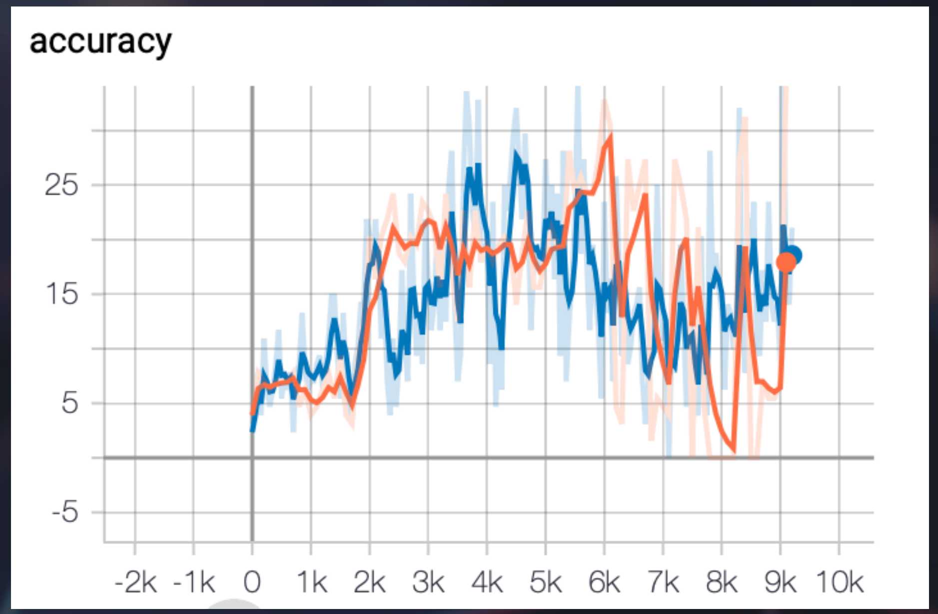
Training Results

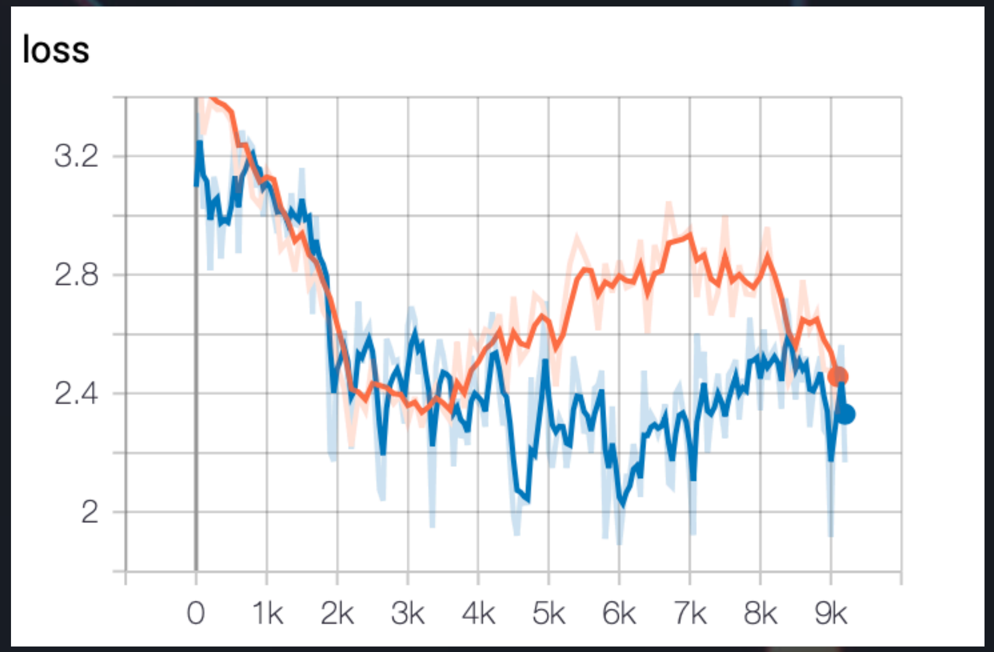




10 class experiment

In this occasion we encountered 92% accuracy in training and around 31% in validation without normalization and 0.7 dropout



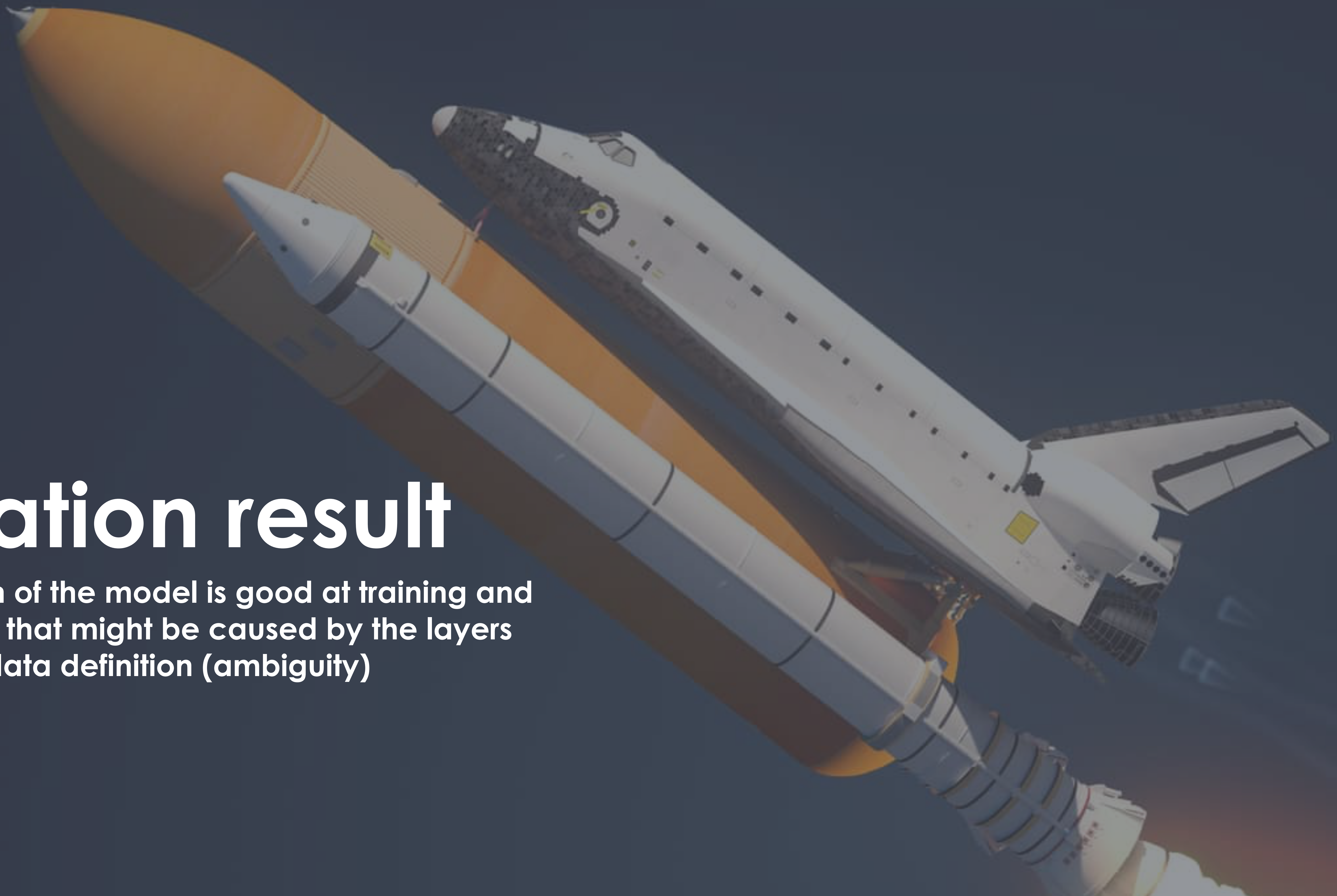


18 class experiment

Worst performance until today, 1 channel images for accelerometer and gyroscope

Generalization result

The generalization of the model is good at training and bad at test, things that might be caused by the layers regularization or data definition (ambiguity)



How to improve

01 Try new architectures variating the regularizations and optimizer

02 Drop labels and tune models adding data

03 Change the definition of the data, working with pure time series models

04 Add the temporal component to the definition of the architecture CNN-RNN

05 Experiment with expensive architectures (Bad for deployment)

Questions and Suggestions

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