### Iteration 3 (DL methods)

### **Problem Statement:**

To find the actions of the JCB arm, i.e; (idle, dig, swing, dump)

## Method 1

# CNN-with-regression (doesnt work as expected)

- Model: 5-layerd 2d-cnn with a mean square error loss over logits. Each layer has a 2d convolution layer with relu activation followed by 2d max-pooling.
- Output: vector of length 6, each pair represent the location of one of the three joint points. (3\*2)
- > **Trained:** >=1000 epochs
- Dataset: Train data: 40 frames, manually labelled all three points on each image Test data: 20 frames (unable to create large dataset)

#### Cons:

- x Loss was not able to converge to an acceptable range.
- ✓ Faster training time

**Note:** The plan was to use these joint points and train a time-series based RNN network. Since due to lack of enough training data, the loss was not able to converge.

### Method 2.1

## 3D-CNN v1 (works, but slow)

- ➤ <u>Model:</u> 6-layerd 3d-cnn with a cross entropy loss over softmax-logits. Each layer has a 3d convolution layer (3 frames 3 filters) with relu activation followed by 3d max-pooling.
- > Output: one-hot vector of actions
- > **Trained:** 12 epochs with k-fold training
- Dataset: Train data: used first 1:40 sec for training (approx 200 frames)
  Test data: tested the model on remaining part of the video

#### Cons:

- x High training time
- x More no. of epochs needed
- ✔ Higher accuracy

#### Method 2.2

### 3D-CNN v2 (Final working model!)

- Model: 6-layerd 3d-cnn with a cross entropy loss over softmax-logits. Each layer has a 3d convolution layer (2 frames 1 filters) with relu activation followed by 3d max-pooling.
- Output: one-hot vector of actions

- > **Trained:** 12 epochs with k-fold training
- Dataset: Train data: used first 1:40 sec for training (approx 200 frames)
  Test data: tested the model on remaining part of the video

**Pros:** (when compared to previous model - v1)

- ✔ Relative drop in training time
- ✓ Less no.of training epochs needed
- ✓ Faster processing rate during testing
- ✓ Near to higher accuracy

#### **Results:**

output video link: <a href="https://www.youtube.com/watch?v=ZFAAfcEaXpM">https://www.youtube.com/watch?v=ZFAAfcEaXpM</a> (Please play at fullscreen HD resolution, or the labels might not be visible.) (Actions being detected are – idle, digging, swing, dumping)

#### Note:

Also tested on a similar video from youtube, **without any additional training**, and it was able to detect digging and swings, for most of the time. (If trained, will perform better.) <a href="https://www.youtube.com/watch?v=cPDQ7AMzt2k">output video link</a>: <a href="https://www.youtube.com/watch?v=cPDQ7AMzt2k">https://www.youtube.com/watch?v=cPDQ7AMzt2k</a>

### **Processing time:**

Video frame rate is 24 frames per sec. The model process 12 frames at atime. On my machine (i5, 8GB RAM, NO GPU) it takes approx 1.5 sec to process 12 frames. On google colab (12GB GPU Memory) it takes approx 0.01 sec to process 12 frames.

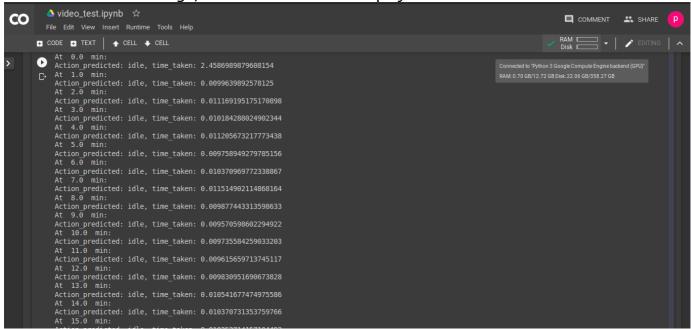
# Screenshots of runtime in Google colab

Training phase in colab:

```
COO ■ CONNECT → CELL →
```

Testing phase in colab: (takes around 0.01 sec to process 12 frames)

Note: Also in the image, the GPU allocation is displayed



### **Further improvements:**

- To create a generalized model, so that given any new video with different point-of-view / environment setting our algorithm must be able to detect the actions, with minimal amount of training.
- Conversion of fish-eye camera view to a flat image using intrinsic and extrinsic camera parameters for viewieng angles.

### Few ideas for scope of improvement:

unet(segmentation) + cnn encoder (feature extraction) + rnn (time series prediction)