HAND SIGNALS WITH VISUAL DATA

PROGRESS REPORT 2

[CSC 59866 – DD1]
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INTRODUCTION

“Hand Signals with Visual Data” is the title of our proposed project that will work to create a software to allow for gesture based controls on the end user’s computer with the aid of deep learning to help recognize the user’s hand as well as the number of fingers being held up by the user.

This report will cover the progress made by the team towards our final project. Through the course of this progress report we will also discuss the division of roles through the team, our achievements, ongoing progress, general project organization, the challenges we have faced, and our future goals.

Our project source code is being managed on GitHub and can be found at:

https://github.com/cpanican/capstone

Team Contacts

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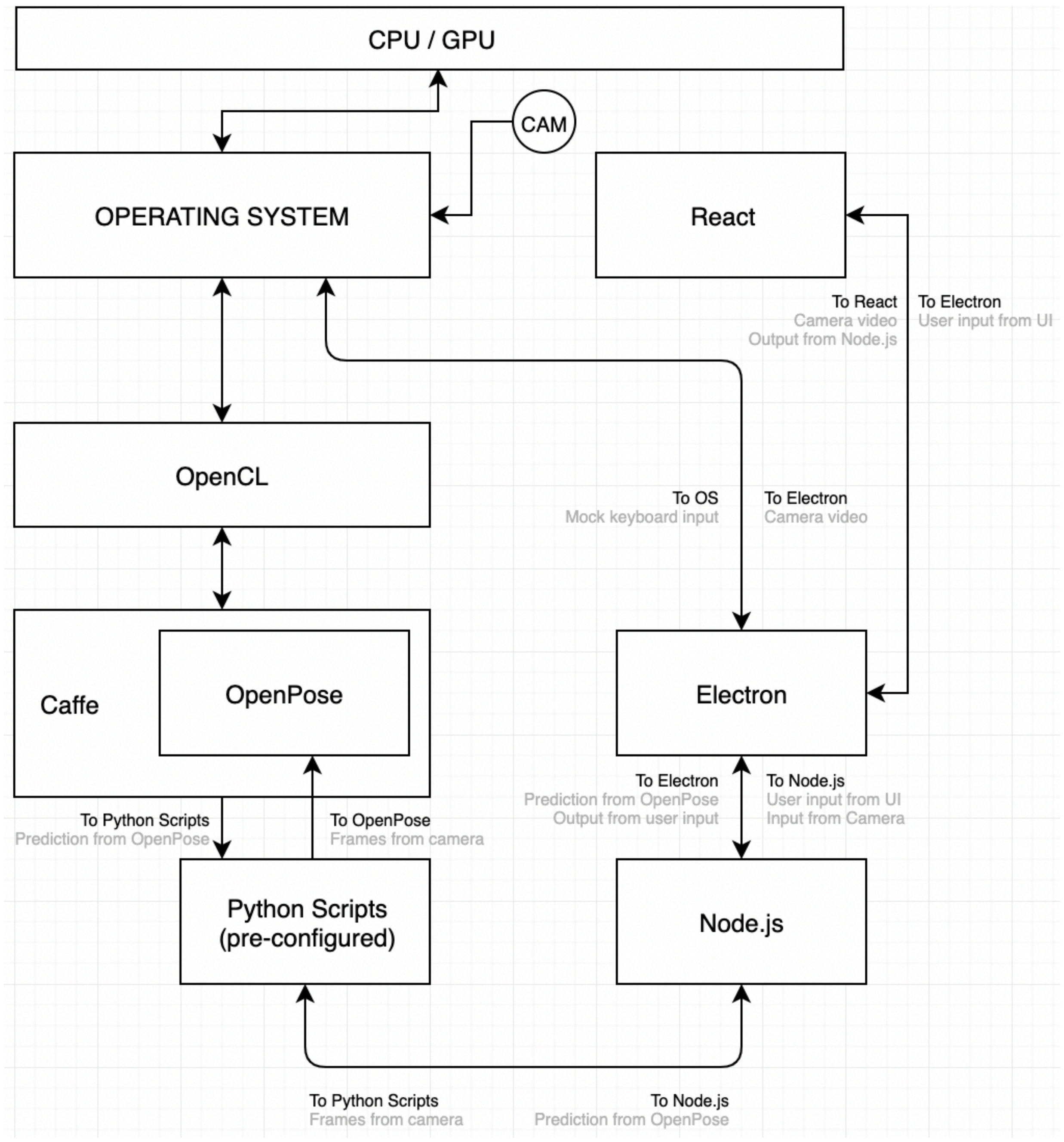
ARCHITECTURE

The diagram below presents a very basic form of our software architecture:



In the first couple of weeks of development our team has separately worked toward developing the client-side app and the machine learning model. To start off, let's take a closer look at the progress made towards our client-side app.

CLIENT-SIDE APP

As described in the architecture above, we are using a combination of Node.js along with the Electron Framework built on top of Node.js, and React library to manage our front-end DOM. In the first few weeks of development we have established code standards, based off of Airbnb's Es-Lint configurations which can be found on their GitHub JavaScript Packages.

In accordance with Electron's developer guide, our app establishes two main processes – Main and Renderer. The Main process is in charge of handling the communication between the operating system and the Renderer process. The Main process is written using Node.js but will be capable of invoking other scripts if necessary. The Renderer process manages the GUI, although it does have its own utilities structure which allows for a modular approach to communication between the Renderer and Main processes.

The communication between the Main and Renderer process is done using instances of an Inter Process Communicator (IPC) which is packaged with the Electron framework. The IPC Main is invoked in the Main process while the IPC Renderer is selectively called in the Renderer process.

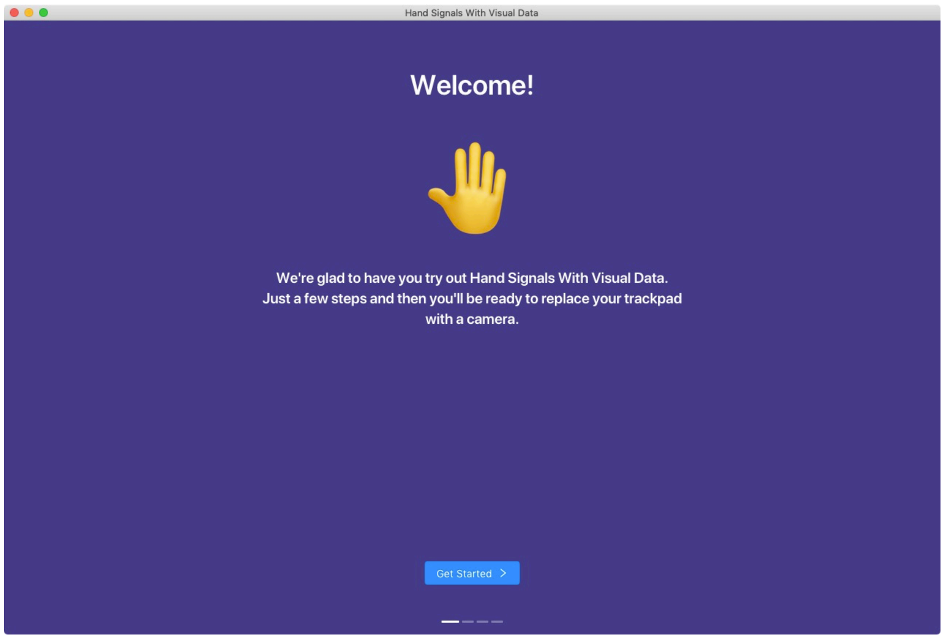
Below is an example of event listeners being registered in the Main process.

```
/*
File: app/public/electron.js
*/

  app.on('ready', () => {
  // EVENT LISTENERS
      ipcMain.on('get-window', getWindow);
      ipcMain.on('create-settings', createSettings);
      ipcMain.on('save-model', (event, arg) => {
  // …..
      createWindow();
  });
```

Here is an example of the event listener being triggered through the Renderer process.

```
/*
File: app/src/Utilities/Server.js
*/

  getDateModel = async (d) => new Promise((resolve, reject) => {
    ipc.on('save-model-done', (e, reply) => {
      resolve(true);
    });
    ipc.send('save-model', {
      url: this.__url + ENDPOINTS.DOWNLOAD_DATE.url(d),
      method: ENDPOINTS.DOWNLOAD_DATE.method,
    });
  })
```

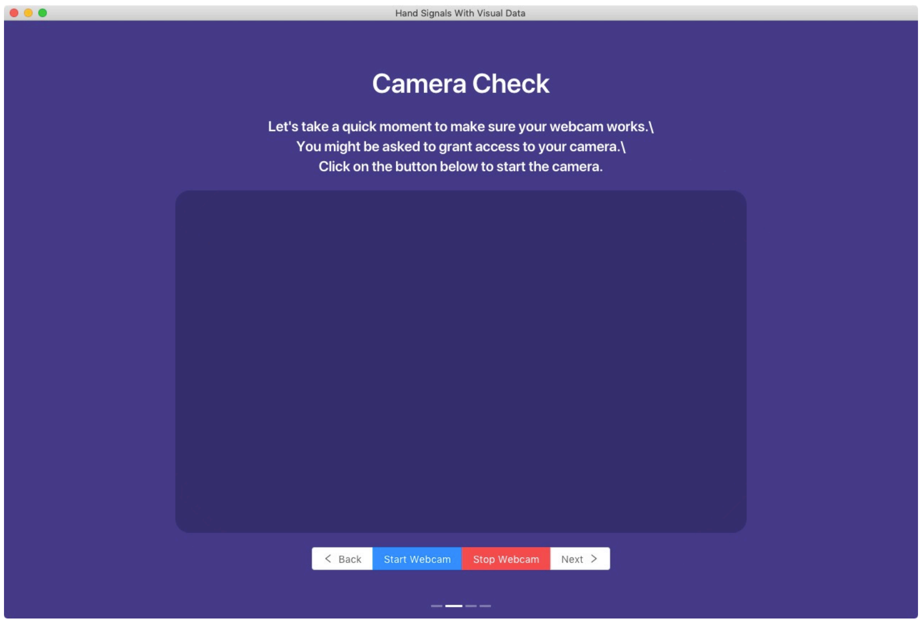
The invocation of an IPC event allows for replies from the listener in the Main process, this enables a two-way channel between the IPC Main and IPC Renderer. These IPC tunnels are responsible for downloading models and will handle simulating key presses.


Hand Signals With Visual Data

Welcome!

We're glad to have you try out Hand Signals With Visual Data.
Just a few steps and then you'll be ready to replace your trackpad
with a camera.

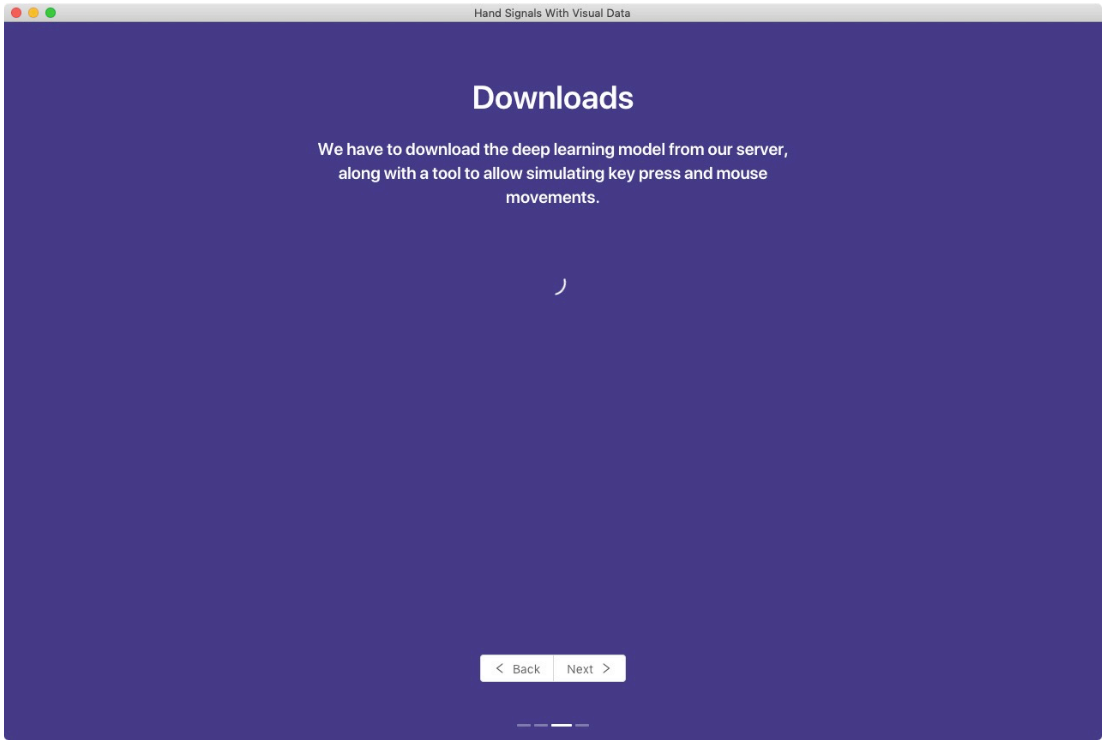
This is the welcome page of our application, it tells the user that there are a few steps that need to be completed before the user can replace their trackpad with a camera.


Hand Signals With Visual Data

Camera Check

Let's take a quick moment to make sure your webcam works.\
You might be asked to grant access to your camera.\
Click on the button below to start the camera.

First it ask user to check if their webcam is working by clicking the “start webcam” button. If the user want to stop the webcam, the “stop webcam” button does that.



Downloads

We have to download the deep learning model from our server, along with a tool to allow simulating key press and mouse movements.

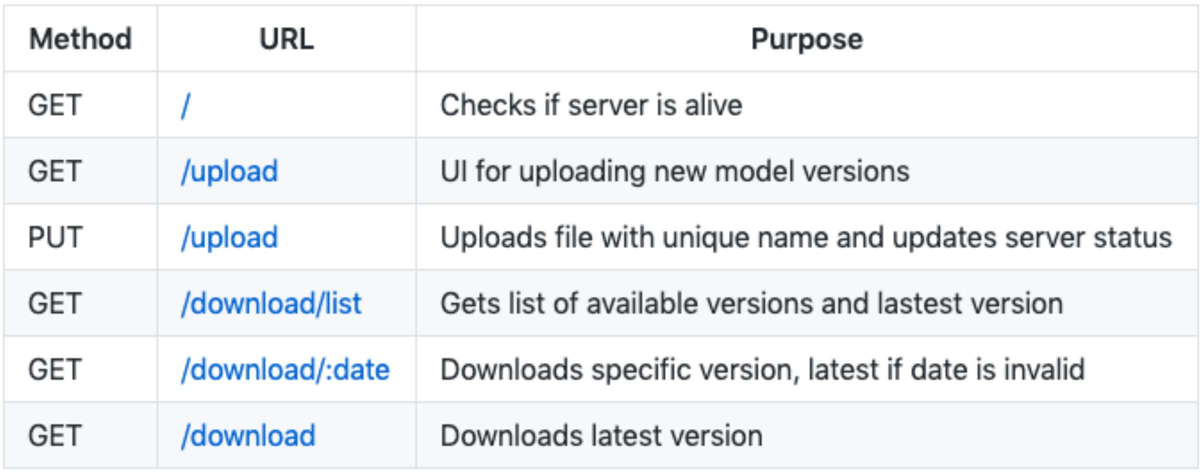
Here it tells the user that it needs to download the deep learning model from the sever to allow simulating key press and mouse movement. Since there are no models currently in our sever, the app will be constantly searching in our server to fetch the uploaded model.

SERVER

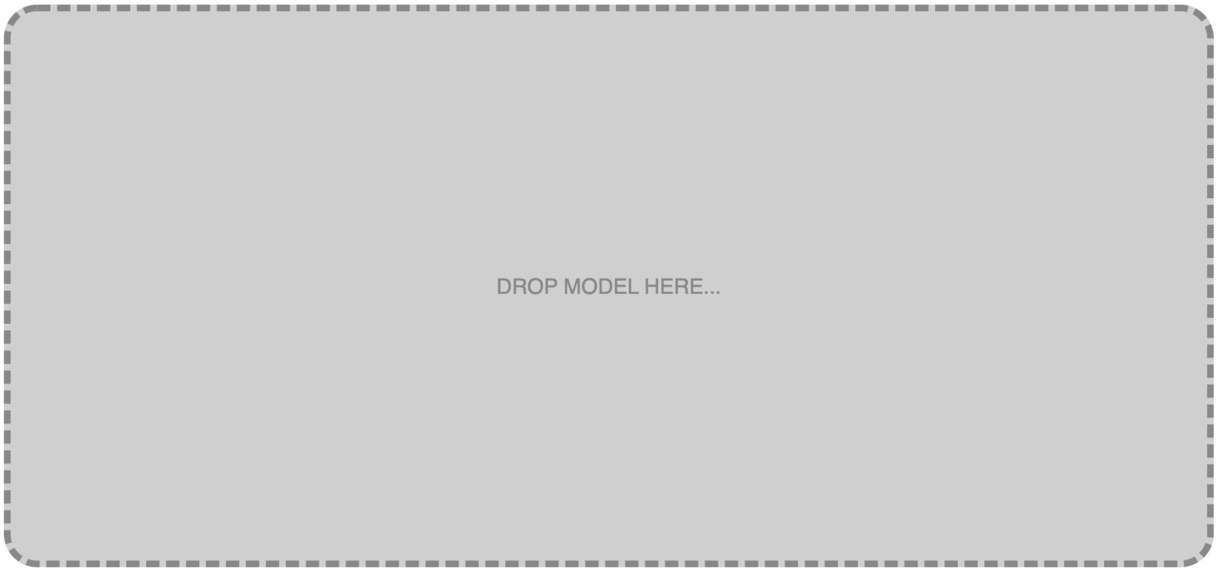
Our server is also written in Node.js – the main purpose of our server is to provide downloadable models to the client app, this allows for version control of the models and gives the user control over which version they want to use. Our server uses Express.js, a Node.js library that simplifies hosting a REST API using Node.js. The project structure for an active server is the following:

```
.server
+-- index.js                                   - server root
|   +-- uploads/                               - folder containing uploads
|   |   +-- status.json                        - maintains model version info
|   |   +-- {filename}-{datestring}.{extension} - format of saved models
```

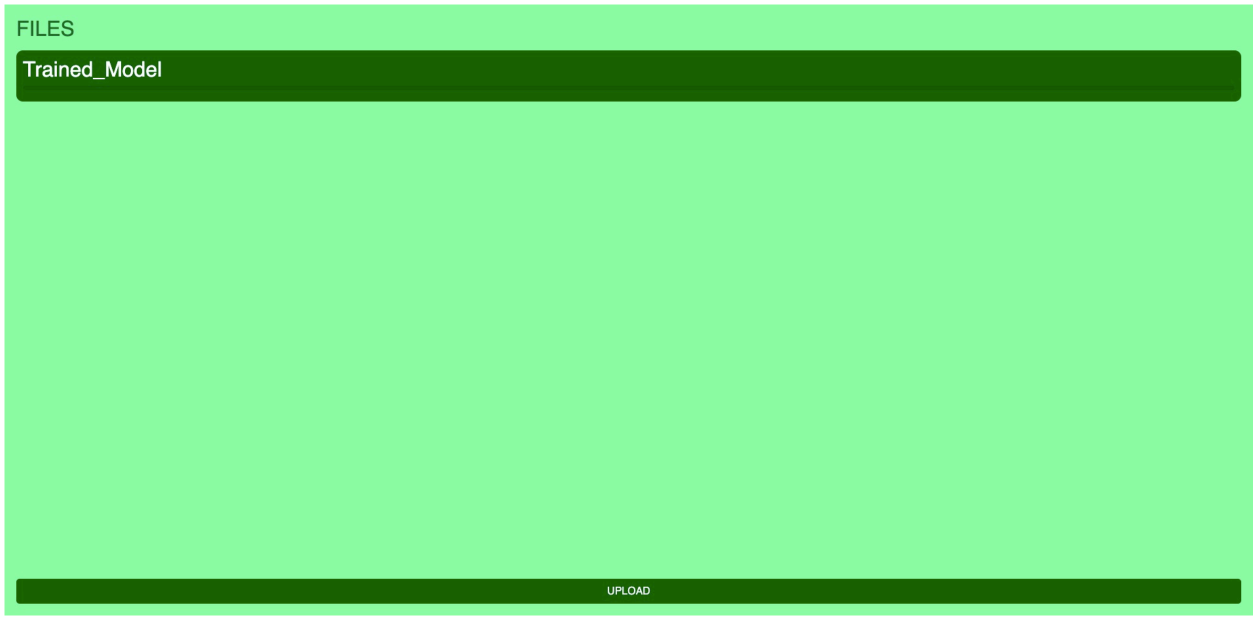
The uploads directory stores the uploaded models and handles the version listing, in order to achieve this, our REST API establishes the following endpoints:



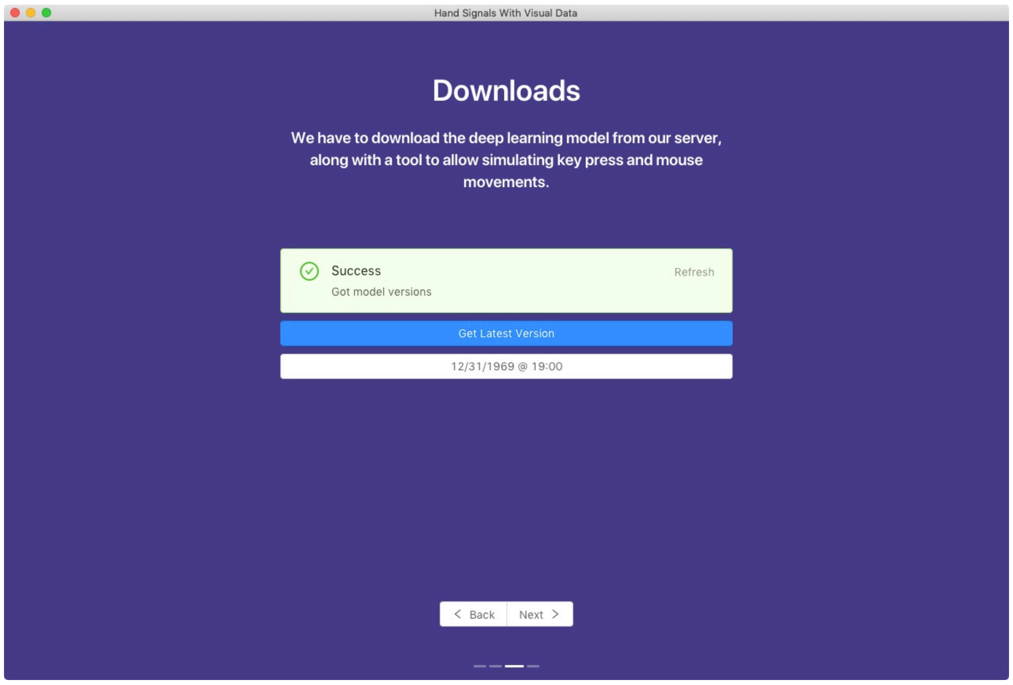
Method	URL	Purpose
GET	/	Checks if server is alive
GET	/upload	UI for uploading new model versions
PUT	/upload	Uploads file with unique name and updates server status
GET	/download/list	Gets list of available versions and lastest version
GET	/download/:date	Downloads specific version, latest if date is invalid
GET	/download	Downloads latest version



The image above is our UI for uploading new models in our server, we can simply drag any files that contains our model into it. After dragging in a file that contains our model, we can then click upload and upload the model to our server as seen in the image below:



After the model is successfully uploaded to the server, we can go back to the download section of the application to see that the model is retrieved and ready to be downloaded:

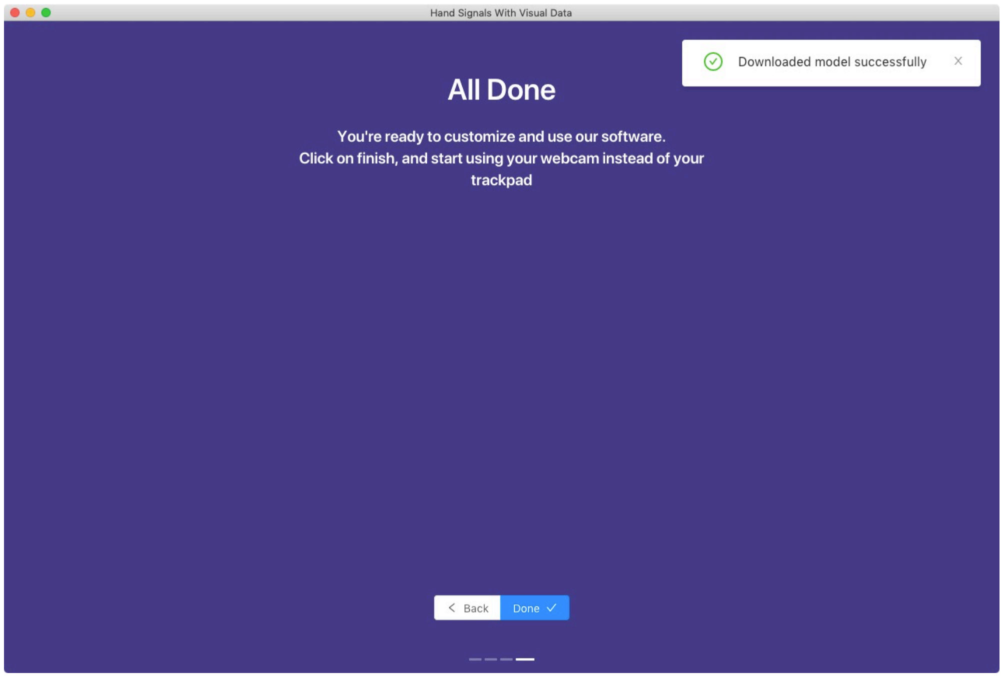

Hand Signals With Visual Data

Downloads

We have to download the deep learning model from our server, along with a tool to allow simulating key press and mouse movements.

Success
Got model versions

Simply clicking on the model that was just uploaded, will download the model and will be ready to use:


Hand Signals With Visual Data

Downloaded model successfully

All Done

You're ready to customize and use our software.
Click on finish, and start using your webcam instead of your trackpad

DEEP LEARNING

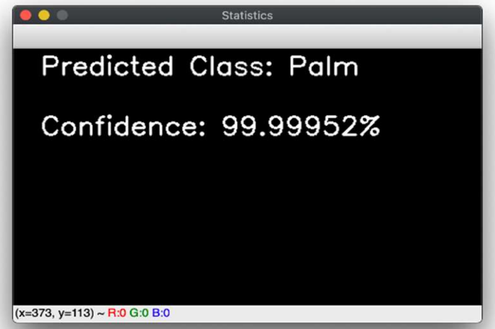
In our project, we will utilize deep learning by gathering visual data from a webcam and use that data to trigger commands in the user's machine. Our group picked CNN because of its ability to process images. Other neural networks, such as RNN, cannot excel in this task.

CNN contains fully connected layers in which each neuron in one layer is connected to all neurons in the next layers. There are 4 building blocks in making a CNN:

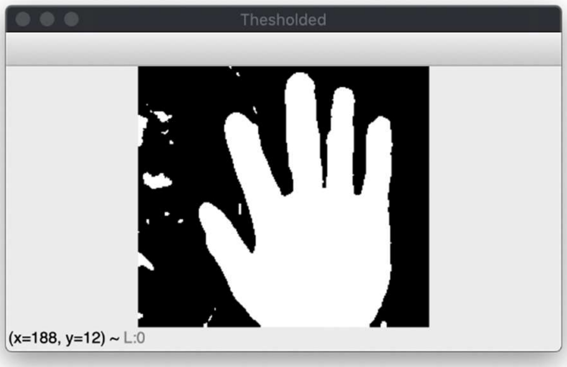
1. Convolution – receiving input signals from another layer and using filters/kernels to convolve across the input. This is where the network "learns" important filters as it runs.
2. Subsampling – also known as pooling layer. It reduces the dimensions of data with a filter size and a stride and also controls overfitting. It is usually inserted after a convolution.
3. Activation – controls how information flows from one layer to another.
4. Fully connected – connects all neurons in a layer from its previous layer to its sub-layers.

In the past few weeks of development, our group has made enough progress to show a functioning product. One of the accomplishment our team has made so far is that we were able to create a Convolutional Neural Network to detect different hand gestures.

The program is able to use the user's webcam as input, then it will output a predicted gesture. Shown below are screenshots of our model's prediction input and output.



```
Predicted Class: Palm

Confidence: 99.99952%
```



For our current model we are using Digit/Number classification similar to what we used in the MNIST database classification.

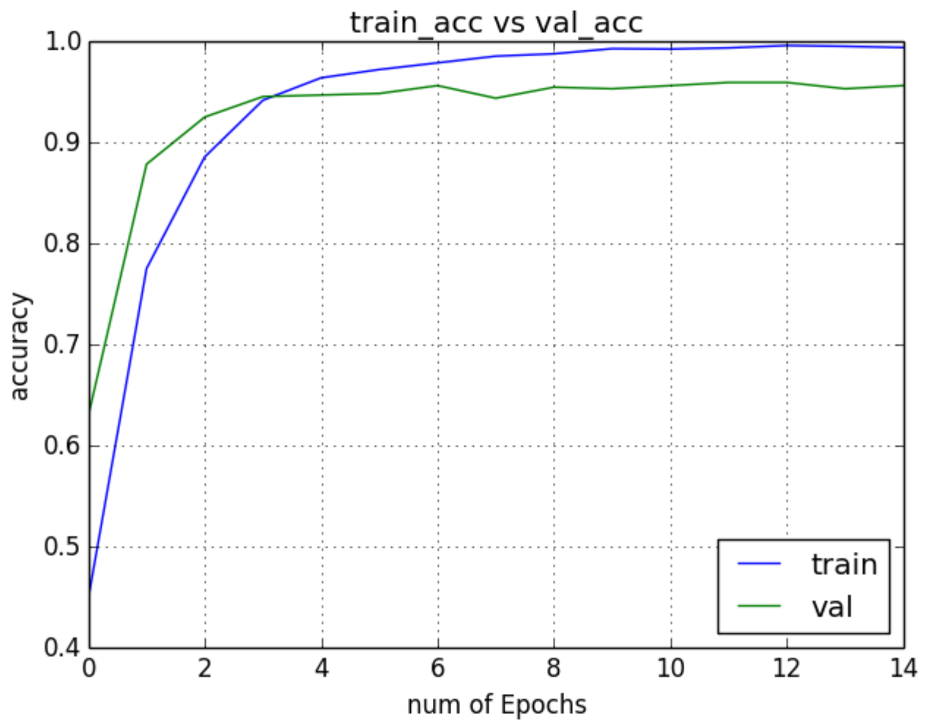
To generate our dataset, we are using a script that continuously extracts frames from a video stream, similar to what the end usage would be using a computers built-in webcam. These frames are then fed into our model trainer which is defined as:

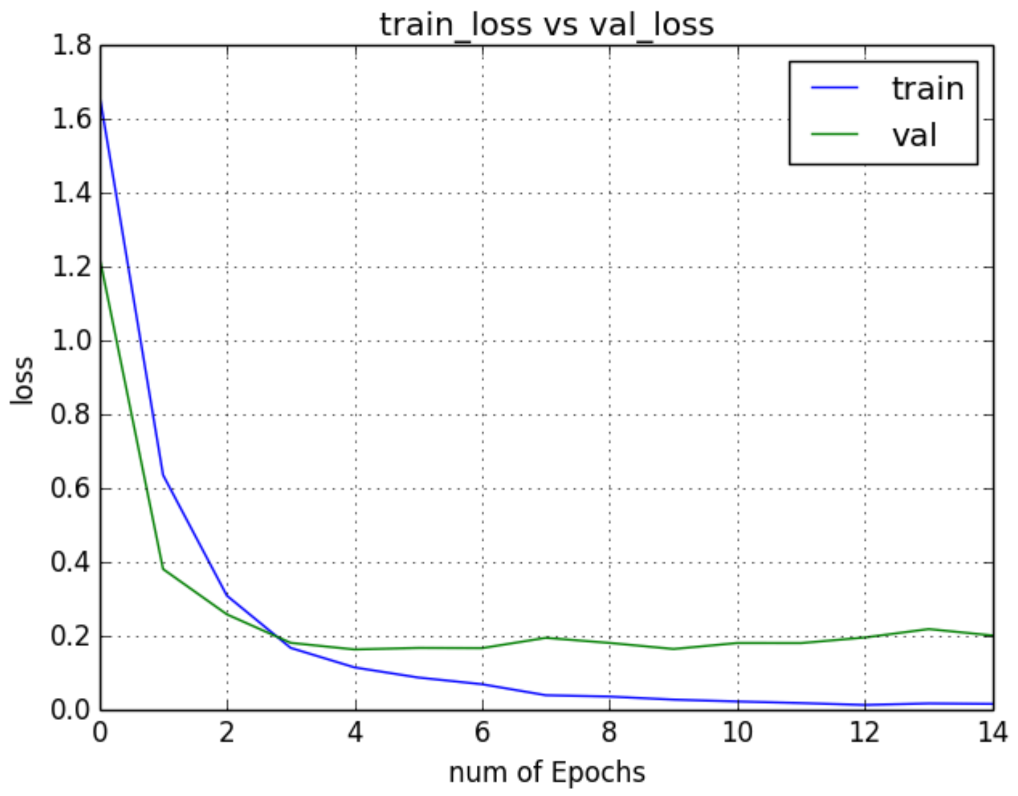
```
model = Sequential()
model.add(Conv2D(nb_filters, (nb_conv, nb_conv),
                    padding='valid',
                    input_shape=(img_channels, img_rows, img_cols)))
convout1 = Activation('relu')
model.add(convout1)
model.add(Conv2D(nb_filters, (nb_conv, nb_conv)))
convout2 = Activation('relu')
model.add(convout2)
model.add(MaxPooling2D(pool_size=(nb_pool, nb_pool)))
model.add(Dropout(0.5))

model.add(Flatten())
model.add(Dense(128))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(nb_classes))
model.add(Activation('softmax'))
```

Our model has following twelve layers:

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_1 (Conv2D)            (None, 32, 198, 198)      320       
_________________________________________________________________
activation_1 (Activation)    (None, 32, 198, 198)      0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 32, 196, 196)      9248      
_________________________________________________________________
activation_2 (Activation)    (None, 32, 196, 196)      0         
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 32, 98, 98)        0         
_________________________________________________________________
dropout_1 (Dropout)          (None, 32, 98, 98)        0         
_________________________________________________________________
flatten_1 (Flatten)          (None, 307328)            0         
_________________________________________________________________
dense_1 (Dense)              (None, 128)               39338112  
_________________________________________________________________
activation_3 (Activation)    (None, 128)               0         
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_2 (Dense)              (None, 5)                 645       
_________________________________________________________________
activation_4 (Activation)    (None, 5)                 0         
=================================================================
```

On training our model for fifteen epochs, we were able to achieve the following accuracy and loss:


train_acc vs val_acc
accuracy
num of Epochs
train
val
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0
2
4
6
8
10
12
14

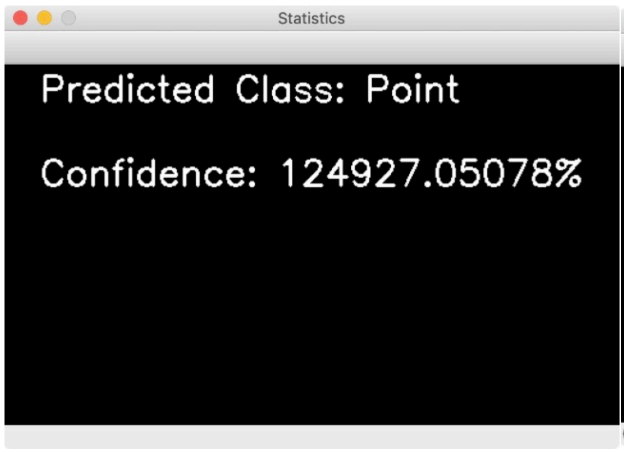

train_loss vs val_loss
loss
num of Epochs
train
val
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0
2
4
6
8
10
12
14

CNN is good in detecting edges and that's why it's useful for image classification kind of problems. In order to understand how the neural net is understanding the different gesture input it's possible to visualize the layer feature map contents.

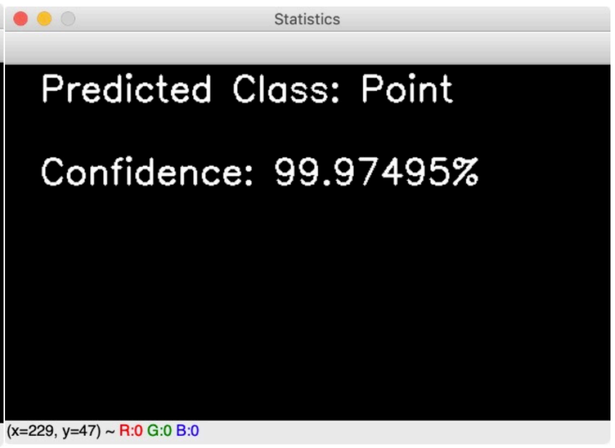
Using Keras we can visualize the layers:

```
layer = model.layers[layerIndex]

get_activations = K.function([model.layers[0].input, K.learning_phase()],
[layer.output,])
activations = get_activations([input_image, 0])[0]
output_image = activations
```

A bug we first ran into, but has since been fixed was when we were generating and training a new gesture, the accuracy/confidence of that gesture was over 100%. The two images below shows what it was before the bug fix and after the bug fix:



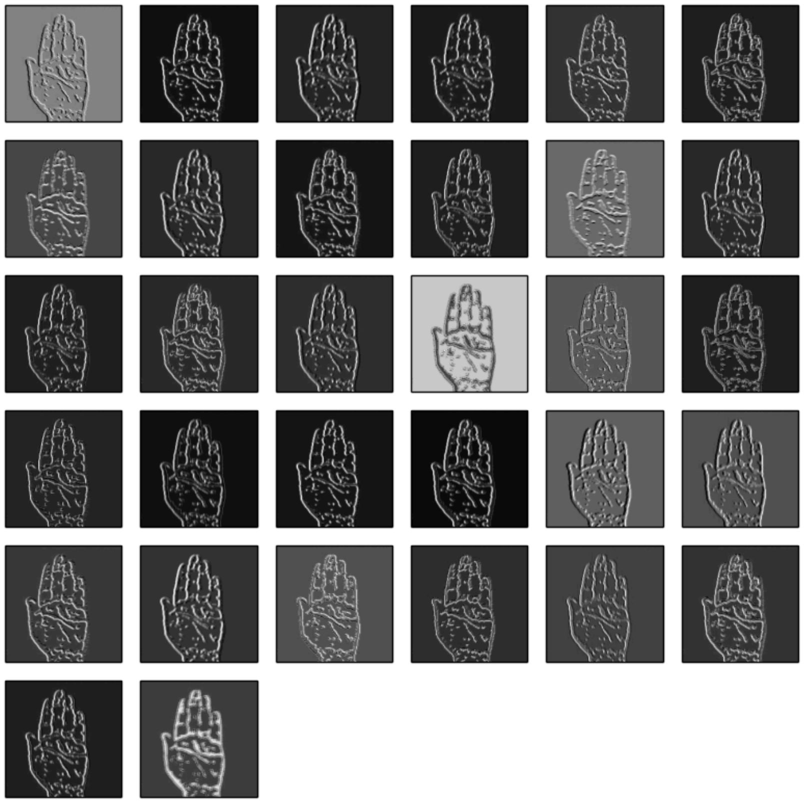
```
Predicted Class: Point

Confidence: 124927.05078%
```



```
Predicted Class: Point

Confidence: 99.97495%
```

The image on the left shows that the gesture "point" had a confidence of over 100%, which is incorrect, the image on the right shows the fixed version and now it shows the correct confidence value for the gesture.

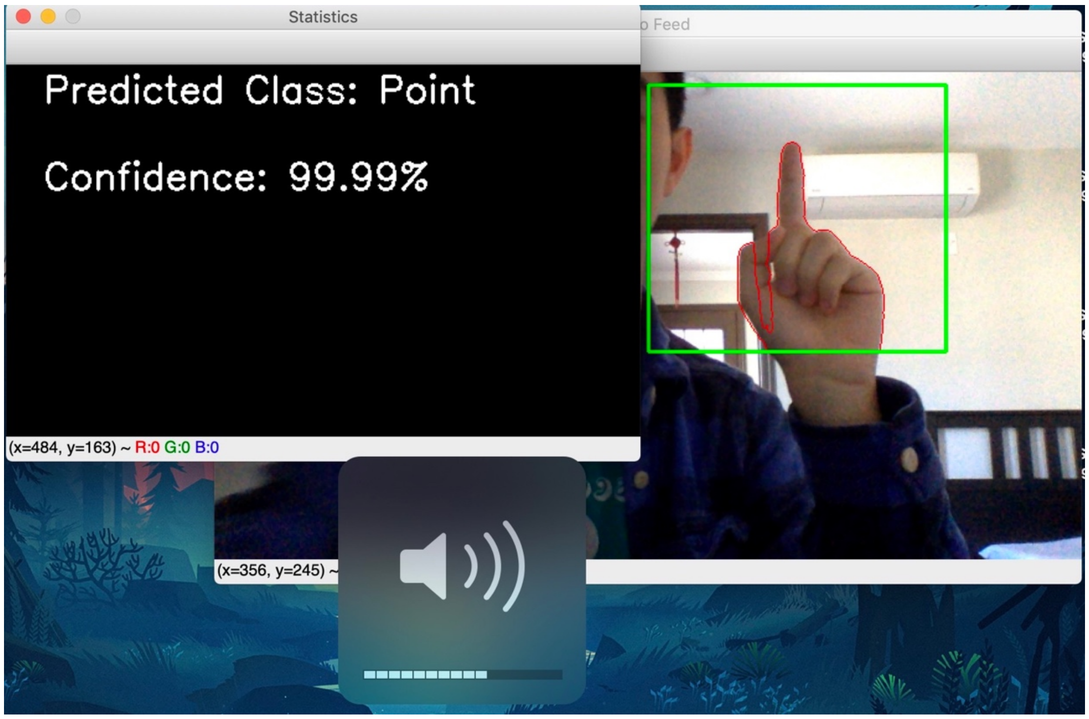
Here are the visualizations generated for the palm gesture:



Another accomplishment our team has made so far is that we are able to now map our hand gestures to the keyboard key-related actions using cliclick.

```
/*
File: ml/ContinuousGesturePredictor.py
*/
  commandDictonary = {
  // EVENT LISTENERS
      “Palm”: “play-pause”,
      “Fist”: “”,
      “Point”: “volume-up”,
      “Swing”: “mute”
  }
  parser = actionParser(commandDictonary)
  parser.doCommand(className[predictedClass])
```

in the code above, you can see that gesture “Palm” is mapped to the “play-pause” action on the keyboard, “Fist” is not mapped to anything at the moment, “Point” is mapped to the “volume-up” action and “Swing” is mapped to the “mute” action.



The image above shows a demonstration of an example of the “Point” gesture that will increase the volume on your computer every time the “Point” gesture is captured by your webcam.

CONCLUSION

Challenges

Our team is aware of the fair amount of hurdles we are currently facing in our road ahead. One major issue that we are trying to resolve is having a more optimized model in our program. There will be some overlaps between different classes because we have to account to multiple variables when collecting the data. Users might have different kinds of hardware or permissions that may block us from gathering images. Other notable challenge is moving gestures. Right now, our program can only detect static images but our main goal is to detect movements as well.

Future Goals

Our team plans to tackle the following to-do's after accomplishing our current tasks. We believe that after finishing this list, then we will have minimum viable product:

1. Better gesture detection with camera
    a. Motion detection
    b. Background elimination
2. Easy to use and intuitive interface
3. Documentation

REFERENCES

Deng, L.; Yu, D. (2014).
"Deep Learning: Methods and Applications" (PDF).
Foundations and Trends in Signal Processing.
https://www.microsoft....DeepLearning-NowPublishing-Vol7-SIG-039.pdf

OpenPose
https://github.com/CMU-Perceptual-Computing-Lab/openpose

Handtrack.js
https://github.com/victordibia/handtrack.js/
Library for prototyping real-time hand detection

Gesture Recognition
https://github.com/asingh33/CNNGestureRecognizer
https://github.com/avidLearnerInProgress/hand-gesture-recognition \
Projects with examples for gestures recognition

TensorFlow Examples
https://github.com/tensorflow/examples
General examples from TensorFlow on gesture classification and object recognition

Kaggle Dataset
https://www.kaggle.com/.../hand-gesture-recognition-database-with-cnn/
Database is composed by 10 different hand-gestures

Project Repository
https://github.com/cpanican/capstone
GitHub repository containing the source code for our project