Optimizing Sensor Data for Physical Activity Recognition

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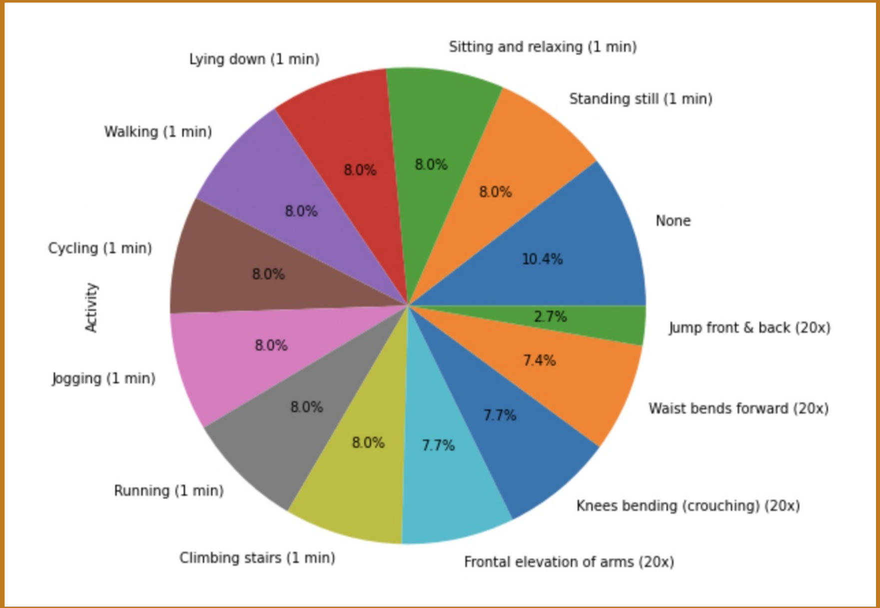


Overall Goal: The primary aim of this project is to enhance the functionality of wearable devices in recognizing and distinguishing various physical activities with greater accuracy through refined sensor data analysis. The project's success will be gauged by the precision and dependability of the activity classification models and by how meaningful and interpretable the data analysis outcomes are.

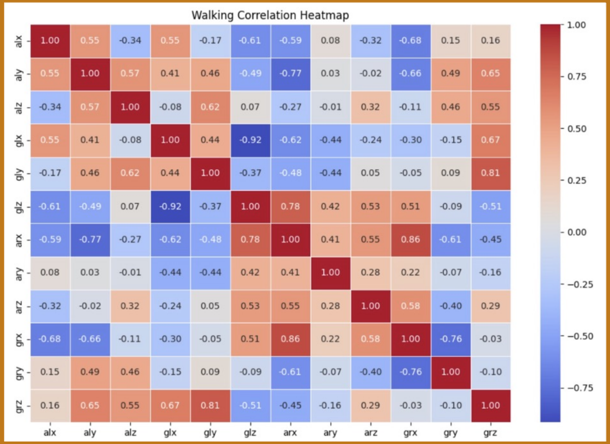
- **Activities Covered**: Running, Climbing, Walking, and Cycling.
- Acceleration from Angle Sensors
- Gyroscope from Lower Arm Sensors

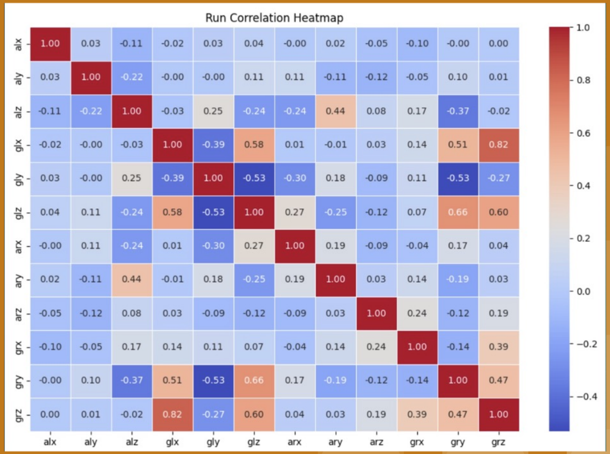
Exploratory Analysis

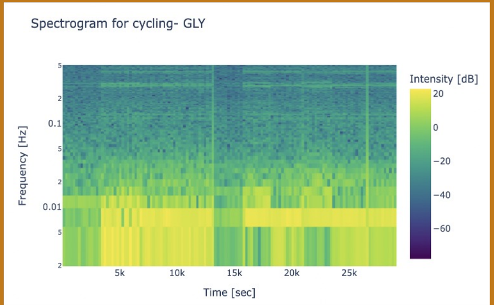
- A higher correlation between the acceleration from the right-lower-arm sensor (arx, ary, arz) and the gyro from the right-lower-arm sensor on the Z axis (grz) during walking trials

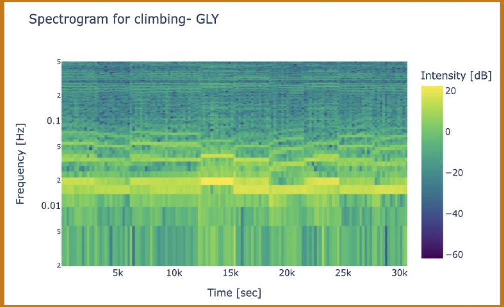
- The gyro sensor on the Z-axis measures rotational movement around the Z-axis, which aligns with the swinging motion of the arms as they rotate slightly during natural walking swings. This rotation isn't as pronounced in other activities.

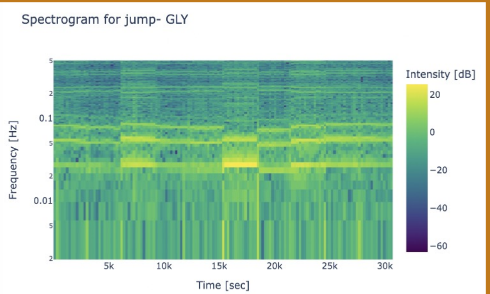
- While running does involve arm swings similar to walking, the increased intensity and speed result in a broader range of motion and different dynamics. The arms may also move more in the vertical direction as the body bounces with each step, which affects the correlation between the sensors.

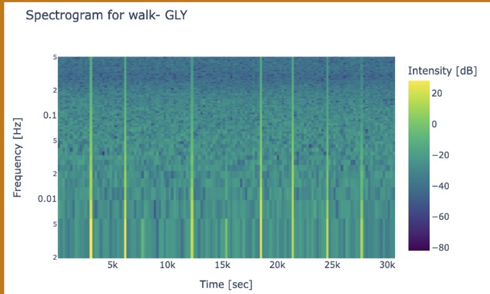


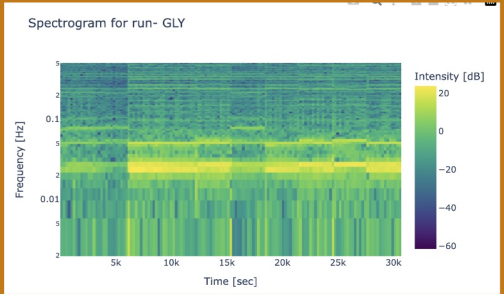




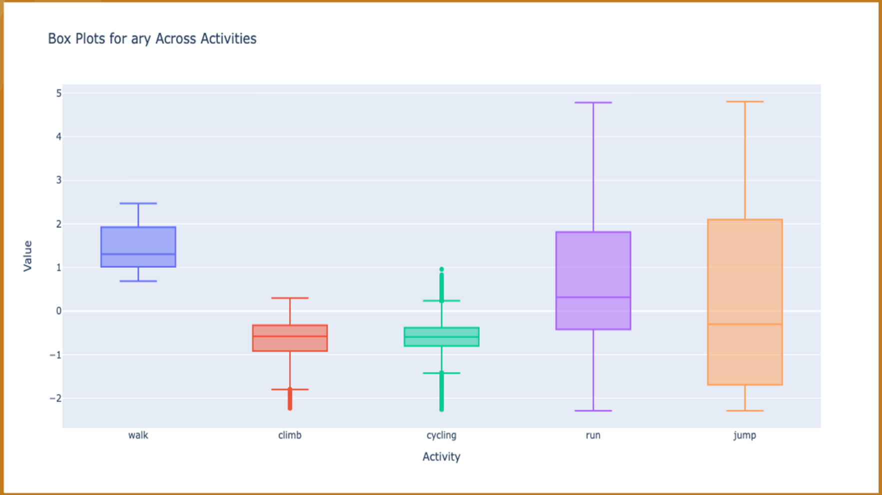


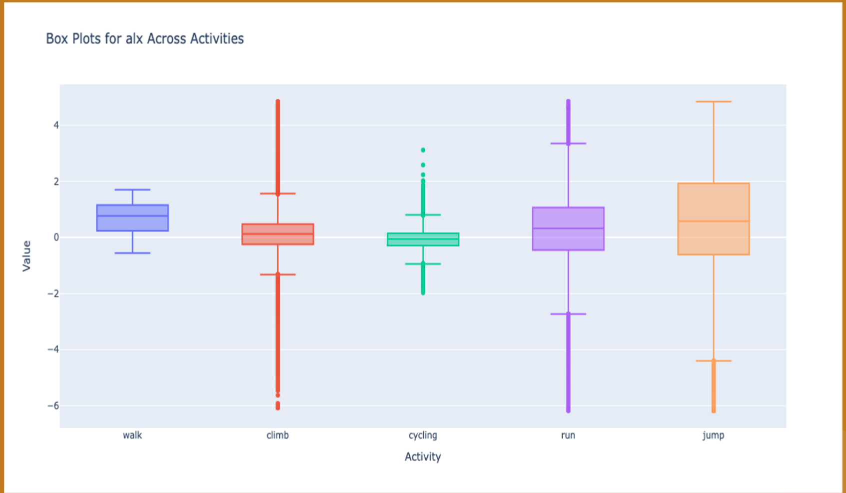






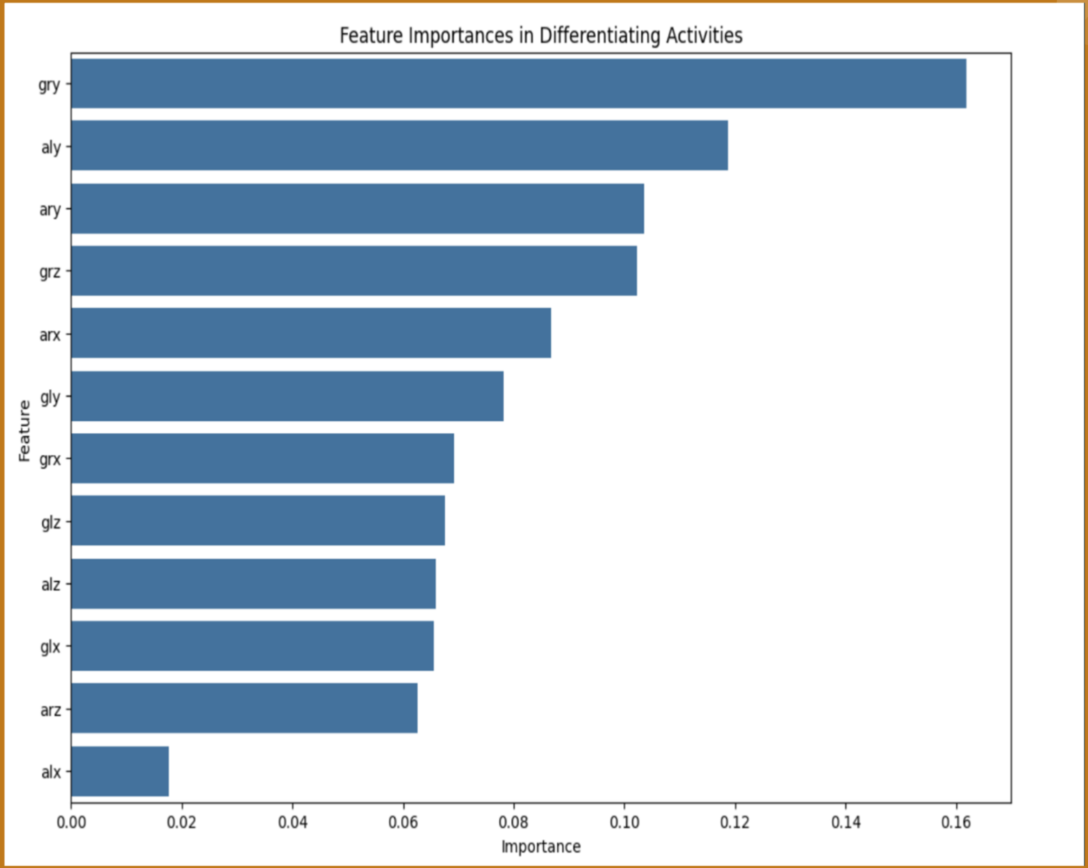
- **Y-Axis (Frequency)**: Indicates the frequencies of the rotation rates. Low frequencies might denote slower, more deliberate movements, while higher frequencies could indicate quicker, sharper movements.
- Walking might produce brief bright strikes due to the regular, but not very intense, rotations or shifts in balance associated with each step. These brief strikes are due to the natural swinging and slight rotation of the body or limb, which reset with each step.
- Longer bright strikes → prolonged rotational movements of angles
- Higher Frequency → rapid changes and oscillations in movements
- This method could be used to detect the anomalies in movement by showing unexpected spikes or patterns





- Positive ARY (Acceleration on Right Arm Sensor) → Accelerated arm forwarding movement
- Negative ARY → accelerated arm pulling back movement

- The difference in left and right movement of angles is not significant


Feature Importances in Differentiating Activities
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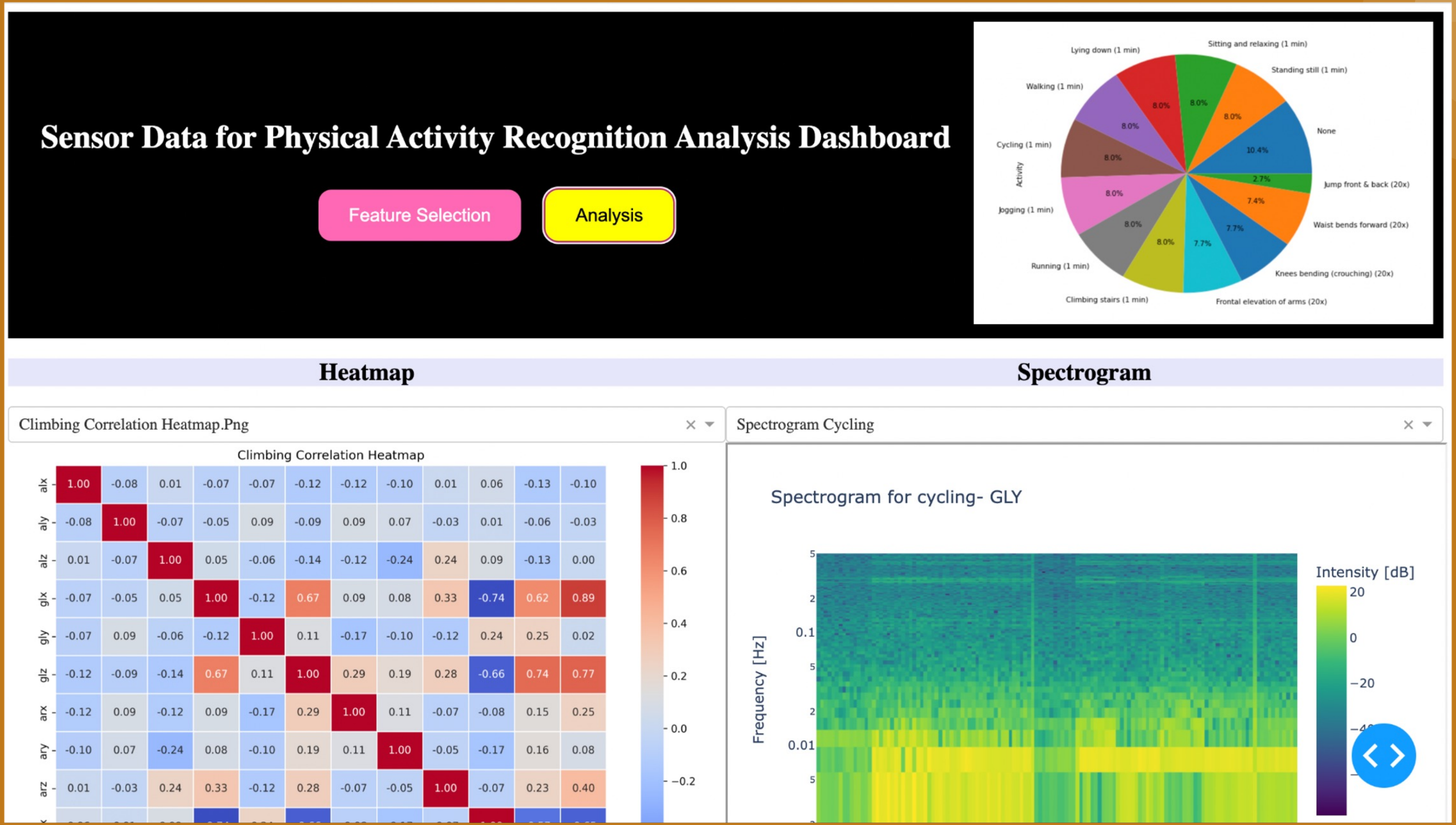
Importance

Interactive Dashboard Application



Machine learning models:

- We used a total of 4 models to get an understanding of the activities and able to predict it accurately.
- The 4 models are as follows:
- KNN
- Logistic Regression
- Random forest classifier
- CNN with LSTM

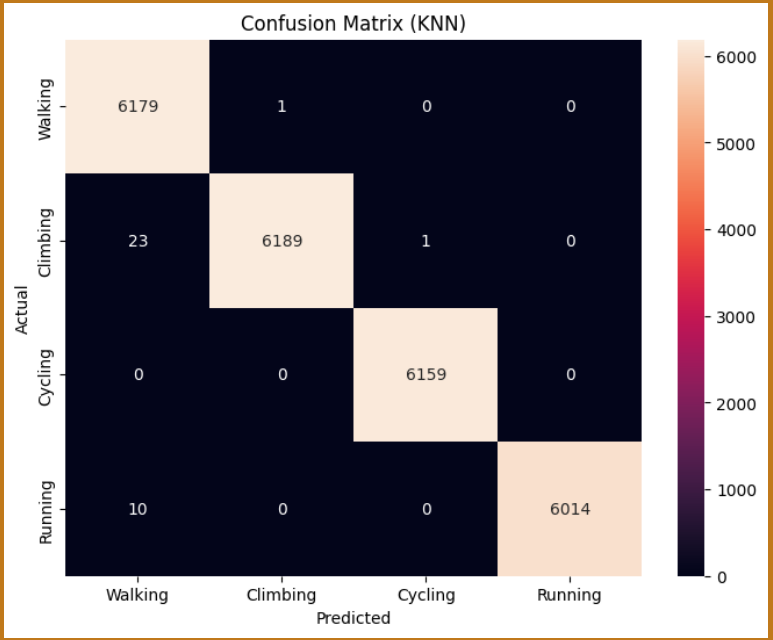
- We tried to use SVM but unable to train the data as it was taking a lot of time.
- Once we got the training data, we used standard scaler to scale but the results were not that accurate when we test it with data that is not scaled.
- But if we do not use scaling, we can feed the raw data which increases the prediction accuracy.
- Its basically boils down to the type of model you are trying to create.
- To have better accuracy we did not use scaling for CNN+LSTM model.

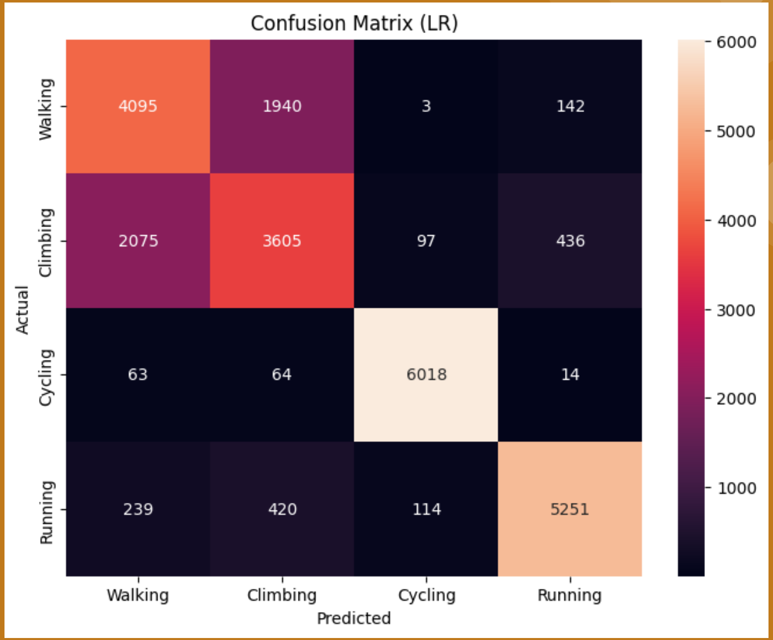
Machine learning models:

Model Name	Accuracy	Precision	Recall	F1-score	Time (in seconds)
KNN	0.99	0.98	0.9	0.9	144.27
Logistic Regression	0.77	0.76	0.79	0.77	8.36
Random Forest Classifier	0.99	0.99	0.99	0.99	18.77

Note: Logistic regression showed the least accuracy for the activity recognition

Correlation matrix samples:





LSTM model with CNN:

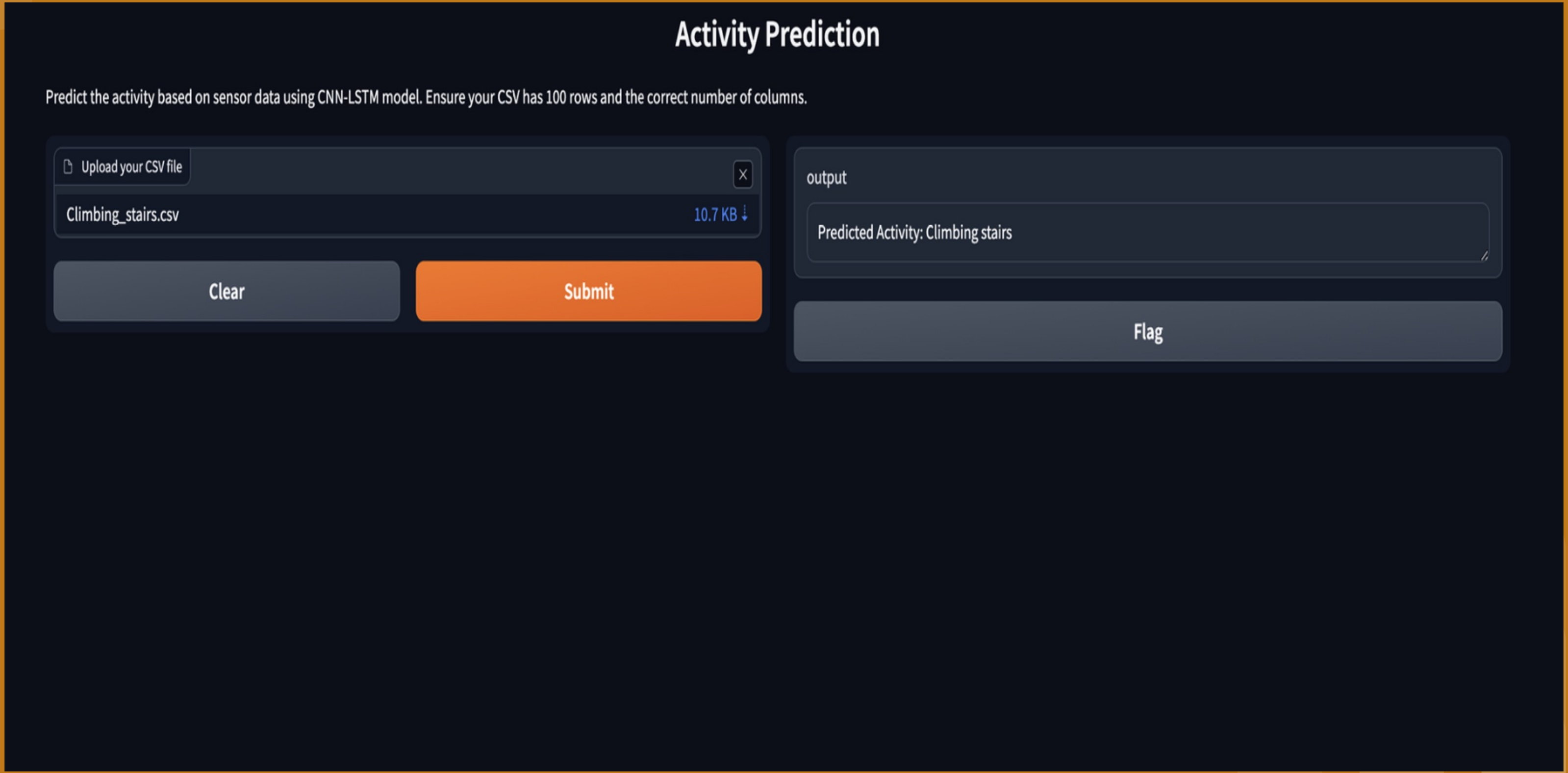
- The model uses CNN with LSTM.
- The time taken to train the data is 584 seconds
- Model has an accuracy of 99%

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 98, 64)	2,368
max_pooling1d (MaxPooling1D)	(None, 49, 64)	0
dropout (Dropout)	(None, 49, 64)	0
conv1d_1 (Conv1D)	(None, 47, 128)	24,704
max_pooling1d_1 (MaxPooling1D)	(None, 23, 128)	0
dropout_1 (Dropout)	(None, 23, 128)	0
time_distributed (TimeDistributed)	(None, 23, 128)	0
lstm (LSTM)	(None, 23, 100)	91,600
dropout_2 (Dropout)	(None, 23, 100)	0
lstm_1 (LSTM)	(None, 100)	80,400
dropout_3 (Dropout)	(None, 100)	0
dense (Dense)	(None, 50)	5,050
dense_1 (Dense)	(None, 4)	204

Total params: 204,326 (798.15 KB)
Trainable params: 204,326 (798.15 KB)
Non-trainable params: 0 (0.00 B)

Model Application



Thank You