Detecting Blood Alcohol Level using Smartphone

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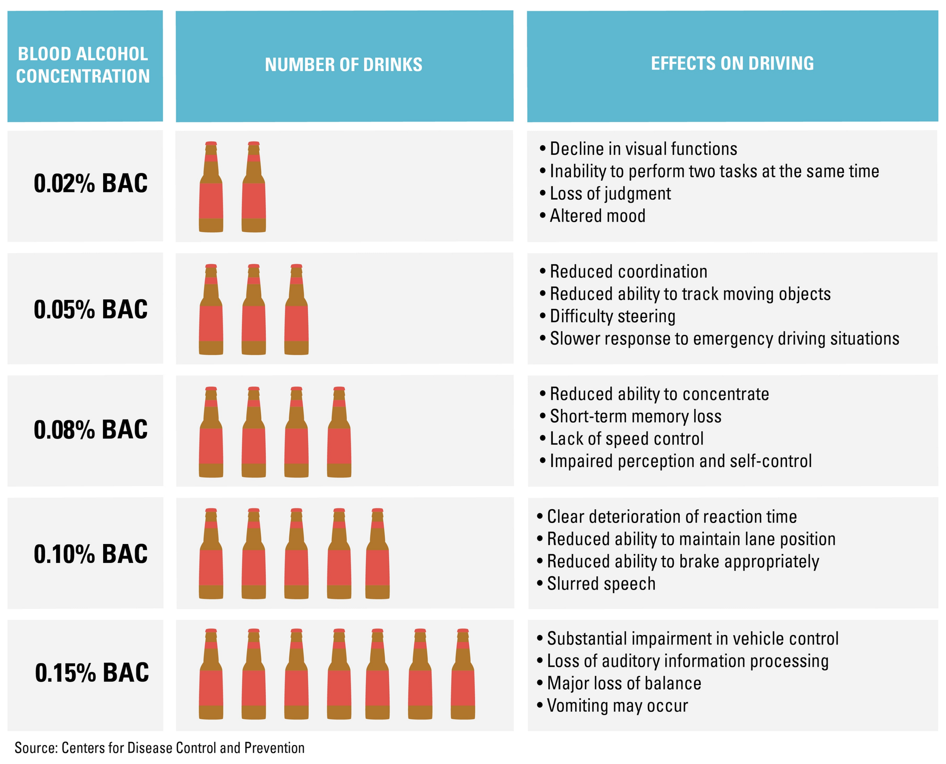
Motivation

Driving under the influence (DUI) caused a significant number of deaths. However, there are two traditional ways to determine person's the blood alcohol content(BAC) including Widmark's equation and detect BAC directly. Aside from traditional methods, since the smart phone is a convenient wearable tool in the daily life with wearable sensors, using deep learning application to detect BAC is possible.



BLOOD ALCOHOL CONCENTRATION	NUMBER OF DRINKS	EFFECTS ON DRIVING
0.02% BAC		• Decline in visual functions • Inability to perform two tasks at the same time • Loss of judgment • Altered mood
0.05% BAC		• Reduced coordination • Reduced ability to track moving objects • Difficulty steering • Slower response to emergency driving situations
0.08% BAC		• Reduced ability to concentrate • Short-term memory loss • Lack of speed control • Impaired perception and self-control
0.10% BAC		• Clear deterioration of reaction time • Reduced ability to maintain lane position • Reduced ability to brake appropriately • Slurred speech
0.15% BAC		• Substantial impairment in vehicle control • Loss of auditory information processing • Major loss of balance • Vomiting may occur

Source: Centers for Disease Control and Prevention

Figure 1: BAC Level and Effects.

This study aims to detect BAC through deep learning algorithms using the human motion data obtained by smart phone sensors.And build a mobile application to alert the drunk drivers and avoid possible accidents[1].

Background

Data Collection: The experiments collect smartphone's accelerometer and gyroscope data through subject walking. At the same time, we also collect subjects' BAC value. In the prior studies, sensors data contains gait level information and is able to utilized to detect subject's anomalies [2].

Data Preprocessing: After collecting 70 individuals' accelerometer and gyroscope data with different BAC, the data are preprocessed in several steps: filter smoothing, overlapping and segmenting.

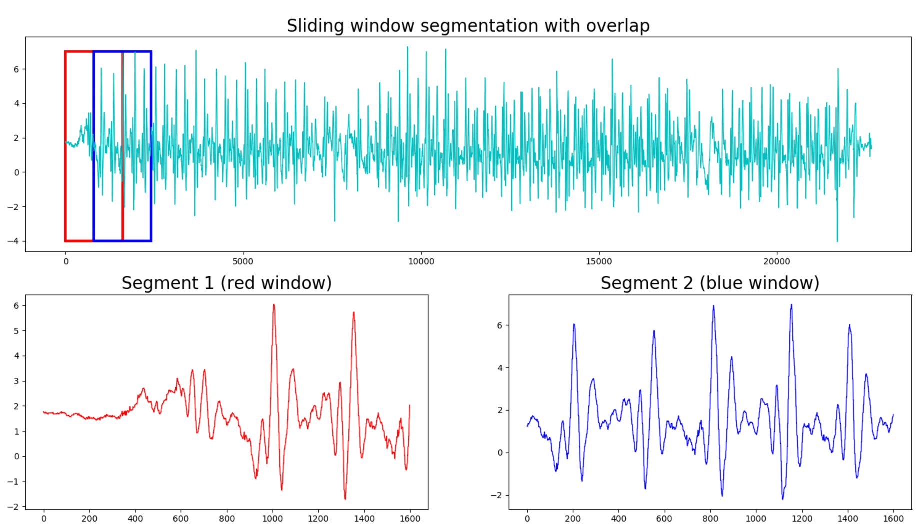


Figure 2: Overlap and Segment.

We hand-craft time, frequency and energy features, since the feature extraction is popular in human activity recolonization area[1]. But the existed research also demonstrates the confined features may limit generalization capabilities[3]. We propose the a variety of long short-term memory-based models (LSTM) without feature extraction, including LSTM and Bidirectional LSTM(Bi-LSTM). Comparing to Random Forest, Multilayer Perceptrons and Convolution Neural Networks, Bi-LSTM is proved to be the faster and higher-accurate algorithm.
Comparing with the feature dataset, the original signal achieve the lower error in the regression.

LSTM: LSTM is demonstrated to be especially effective for sequence long term data.

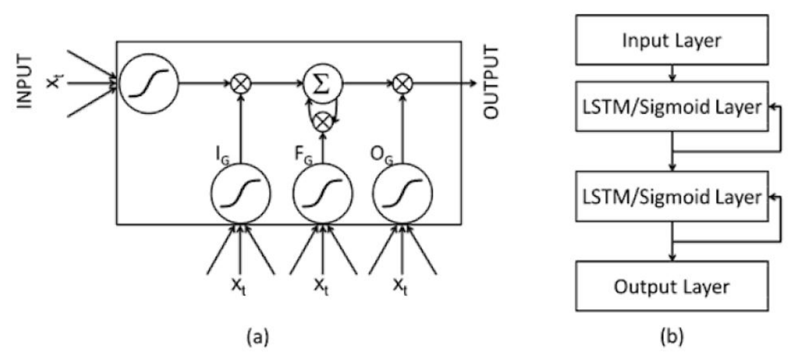


Figure 3: (a)LSTM cell (b)Stacked Architecture.

Bi-LSTM: Experiments uses Bi-LSTM neural network on MXNet Framework and Tensorflow Framework.

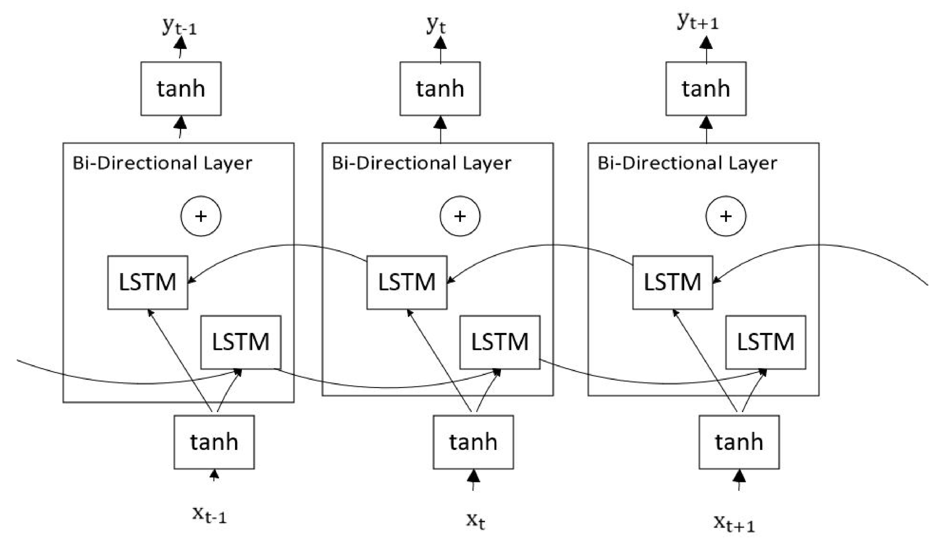


Figure 4: Unfold Bidirectional LSTM Structure.

GAF: Another method called Gramian Angular Field(GAF) encode the raw time-series data to image and achieve highly competitive results in classification with CNN[4].

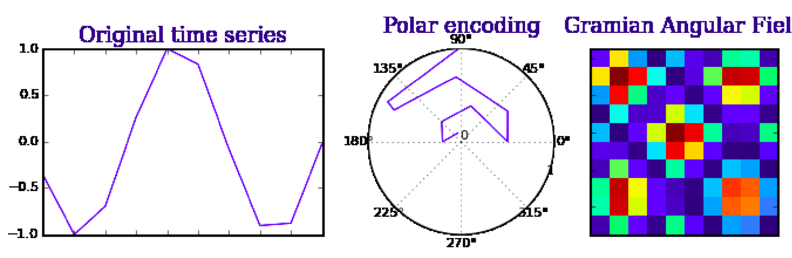


Figure 5: Imaging Time series by Gramian Angular Field.

Methods

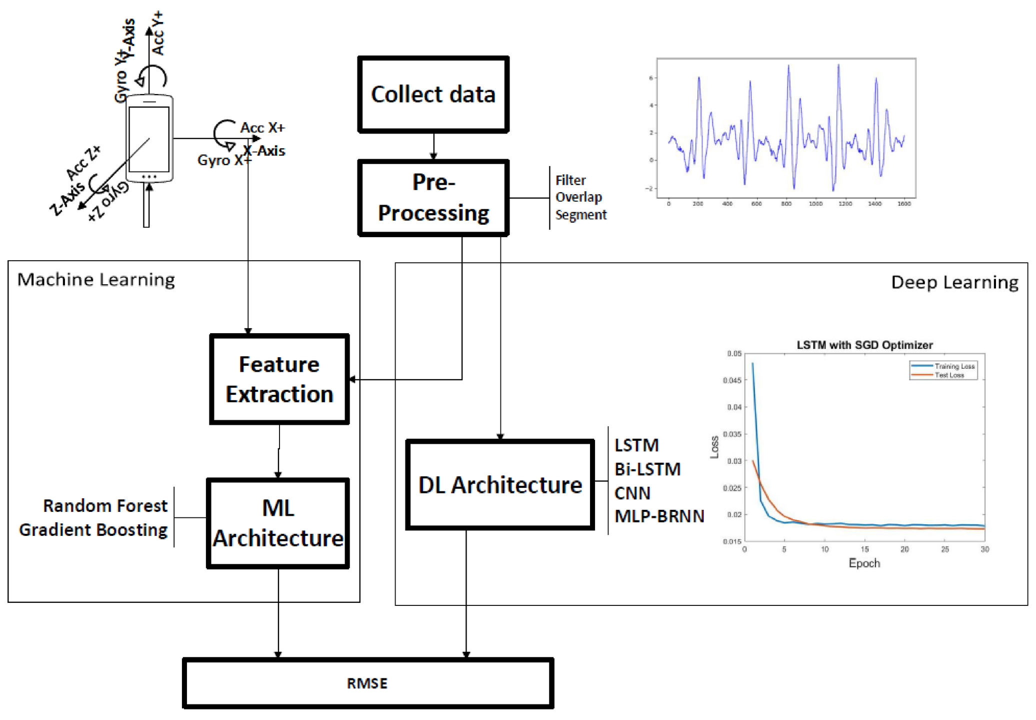


Figure 6: Flow chart of our system.

In the pre-processing part, overlap and non-overlap are both tested.
In the network architecture, We select random forest and gradient boosting with features dataset as the baseline algorithms. And choose LSTM,CNN and MLP using time-series data to compare with random forest and gradient boosting.
In the further experiments, three different optimisers' performance are measured,including adam, adagrad and SGD.

Results

Metrics like Root mean square error(RMSE) are a measure of a models regression performance.

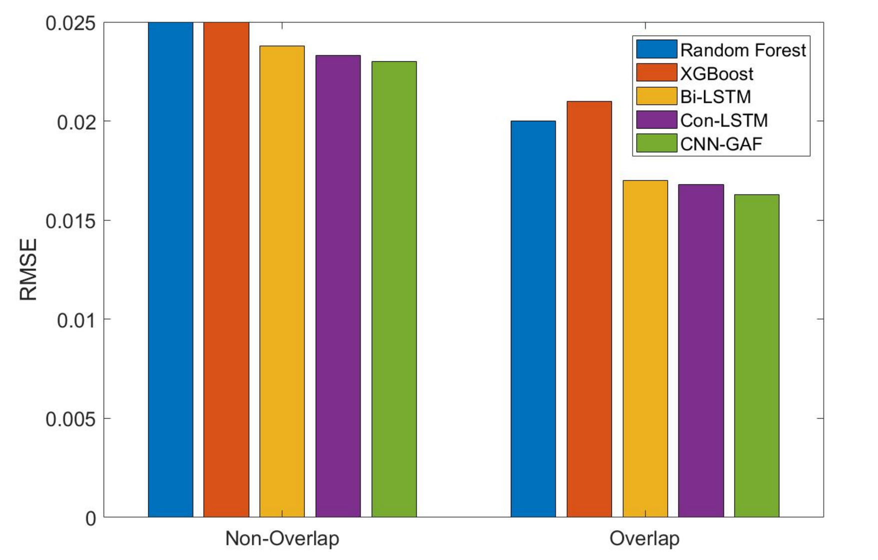


Figure 7: Comparison of Machine Learning with features and LSTM without features.

Figure 7 shows that overlap dataset's RMSE is smaller than non-overlap dataset. Also, random forest and gradient boosting are defeated by the LSTM and CNN.

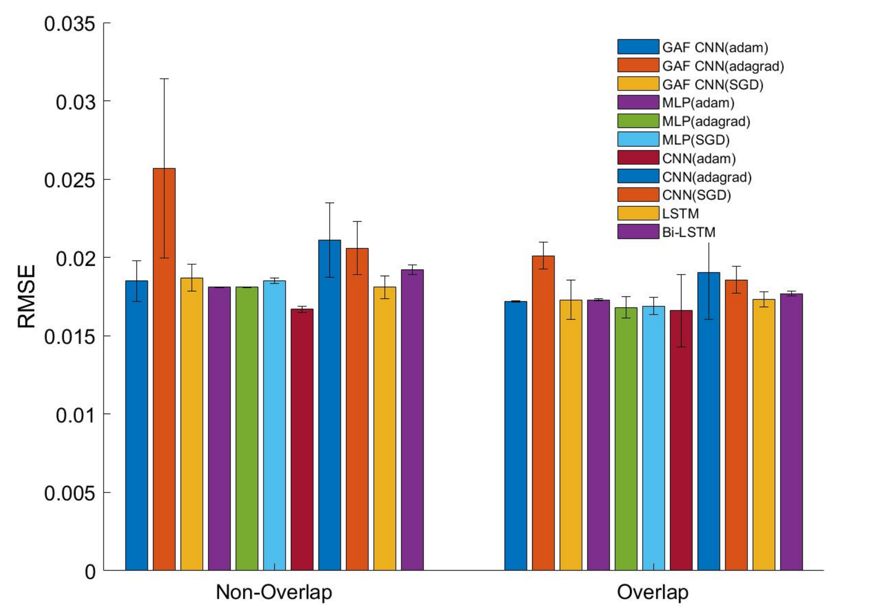


Figure 8: Comparison of LSTM,CNN and MLP with different optimizers.

Figure 8 focuses on the difference between deep learning algorithms and optimizers.

Conclusion

This poster provide the overlapping advantage on the gait level analysis.Moreover shows another possible to do human activity recolonization(HAR) experiments without features engineering.Facing gait-level HAR problem, Adam optimizer defeats adagrad and SGD in many algorithms.

References

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