Comparative Study of Machine learning Models for Fall Detection

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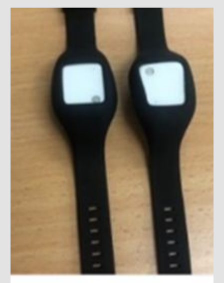
Motivation

- Existing smartwatch-based fall detection system based on the LSTM model is underperforming
- The Transformer model which has the advantage of processing longer sequence time series data could outperform LSTM model

Methodology

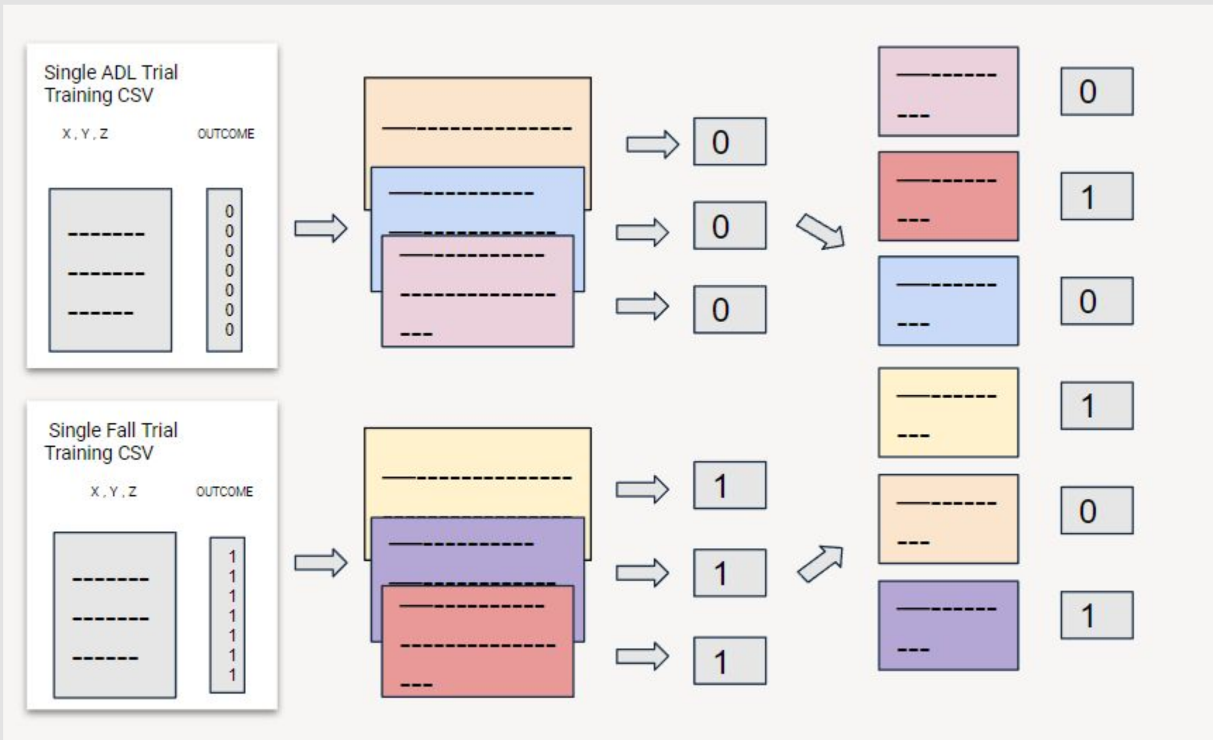
DATA

- Models trained on right-wrist x,y,z acceleration data collected by meta sensors from 12 students



Meta Sensors

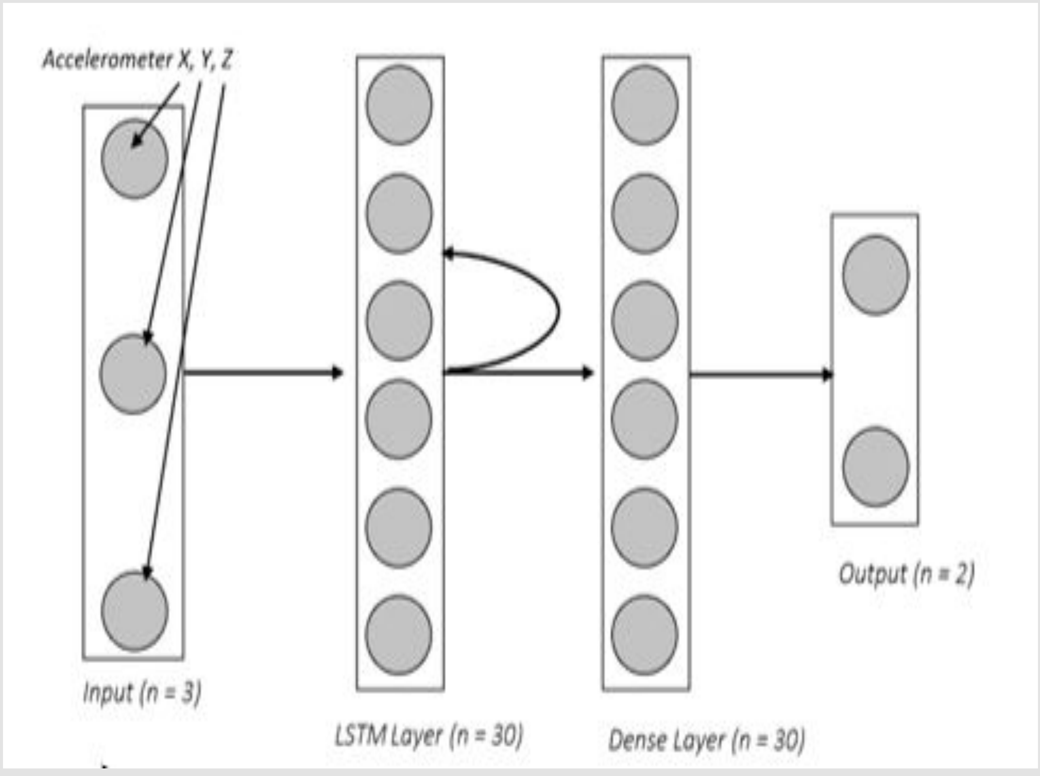
- Dataset included:
  - Total ADL Activities : 435
  - Total Fall Activities :320
- Data fed to the LSTM model in form of 99% overlapping windows and into the Transformer model as input sequences



EVALUATION

- We used leave one out cross-validation with 12 students data set
- The F1 score and AUC metric was used to measure the effectiveness of the model
- The most effective model is re-trained with 12 student of Huawei's watch data with transfer learning for real-world model testing

LSTM MODEL



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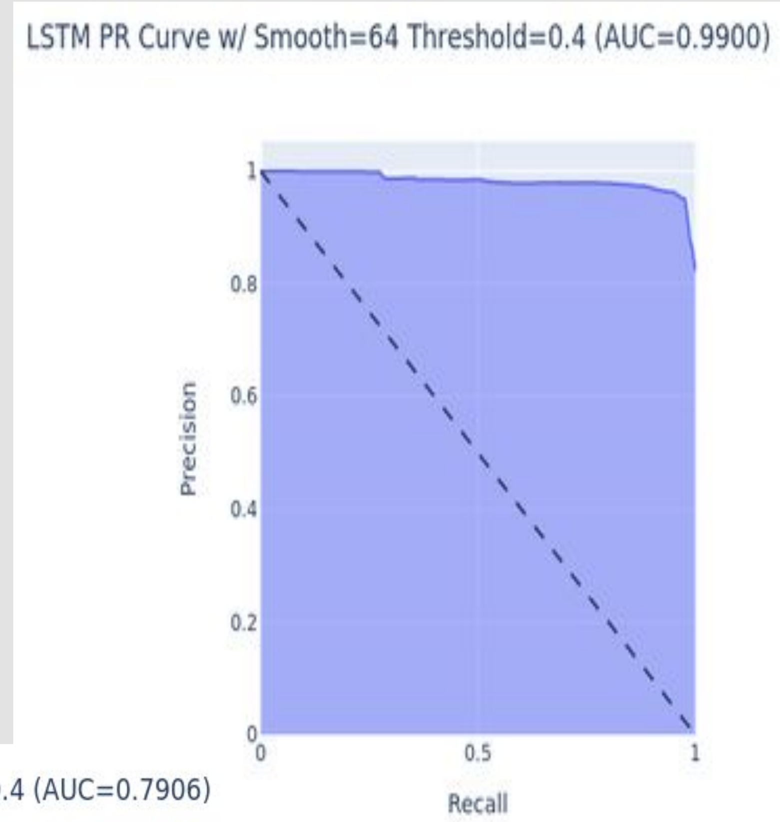
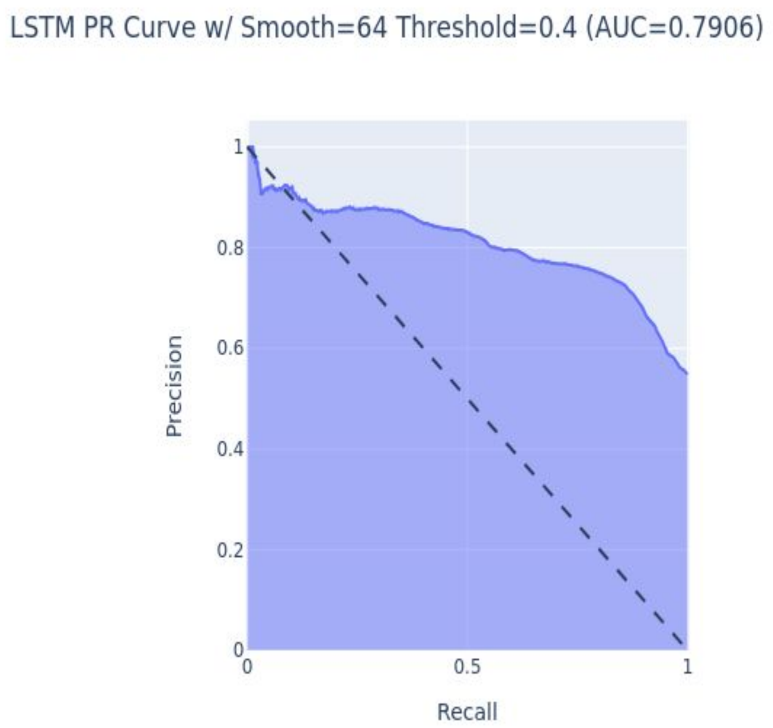
- Processes data in 99% overlapping windows
- Two dense layers with 256 neurons
- Total parameters : **333,313**
- Training Time: **668.31s**
- Total Inference Time: **5.51s**

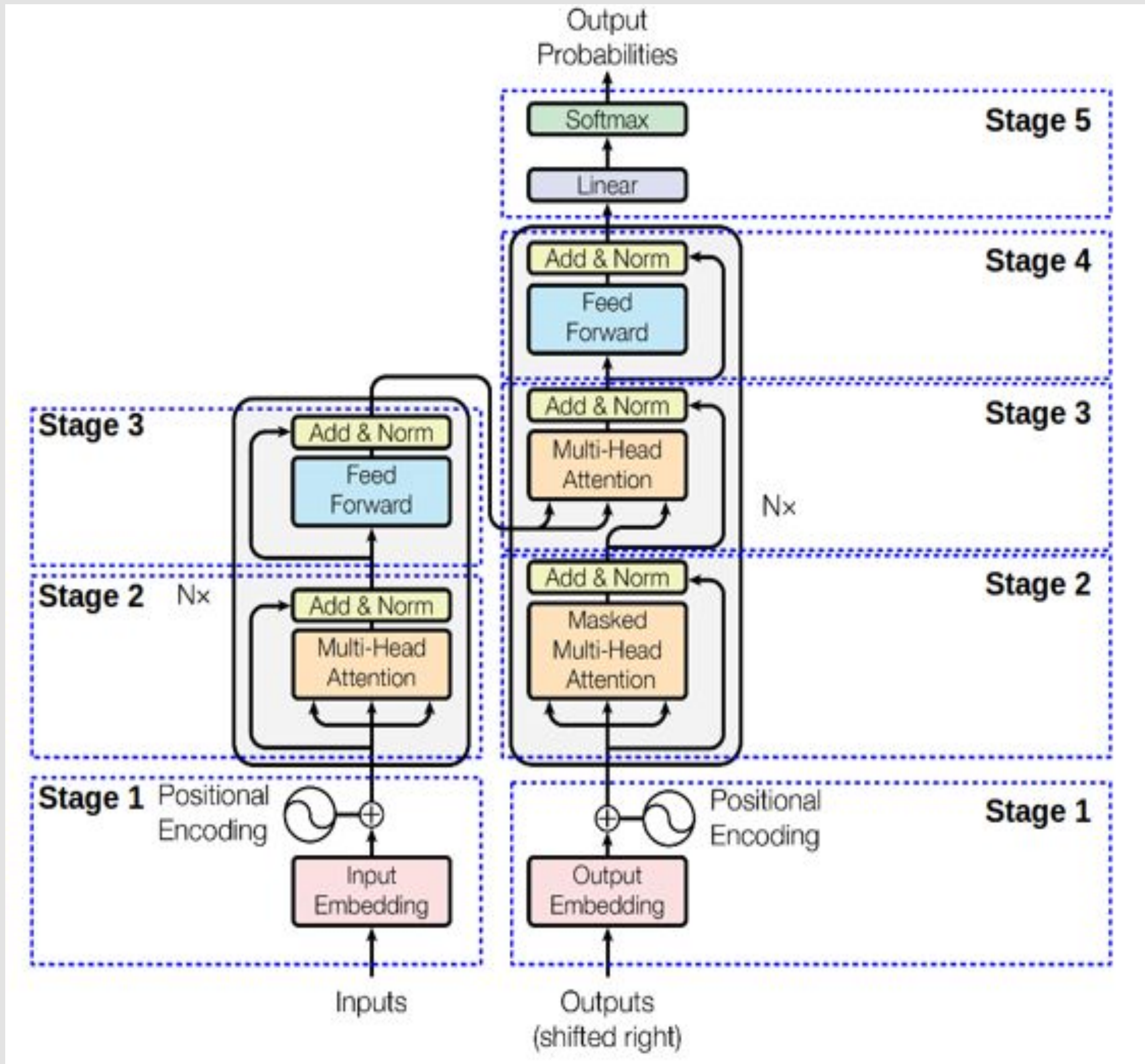
Average F1 Score: *0.893*



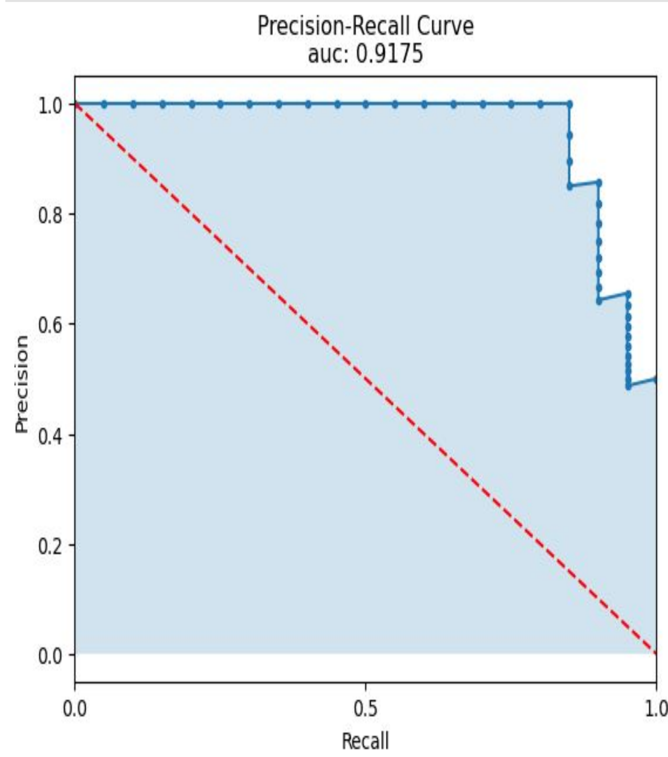


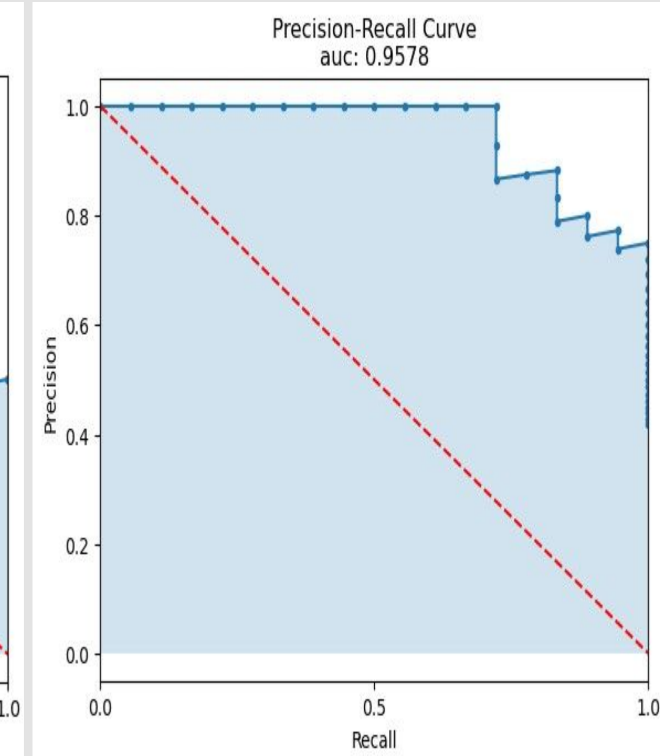
Transfer F1 Score: *0.625*

TRANSFORMER MODEL



- Processes entire data sequences
- Multi-Head Attention mechanism allows for longer term memory
- Employs two self-attention heads
- Requires a large amount of training data
- Total parameters: **72,542**
- Training Time: **402.63 s**
- Inference Time: **0.81 s**





Average F1 Score: *0.714*

Transfer F1 Score: *0.676*

Discussion

CHALLENGES

- Differences in watch data and meta sensor data
- Different devices have different sampling rates leading to differences in accuracy

RESULTS

- Inconclusive with which model works better
  - LSTM unable to trigger activity on the watch
  - Transformer not tested due to model and watch package incompatibilities

CONCLUSION

- Window-size, threshold parameters, and data shuffling impact model results
- Window labelling impacts result
  - User vs code labelled
- Sequence-based evaluation leads to lower F1 scores than window-based evaluation
- Transformer lowers the need for parameter tuning

Future Work

- Use other public datasets, extracting from skeleton data, utilize a dummy
- Create watch model using meta sensor data
- Preprocess data before transfer learning

References

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[5] Thiruvengadam, A. (2019, March 26). *Transformer architecture: Attention is all you need*.Medium.https://medium.com/@adityathiruvengadam/transformer-architecture-attention-is-all-you-need-aeccd9f50d09

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