WN Project Report (Group 16)

Daksh Laur(2020191) | Kshitij Makkar(2020213) | Mrinal Anand(2020222) | Vardaan Abrol(2020258)

Project Title:
Activity Recognition using Wifi channel state information (comparative analysis using sequential and non-sequential models)

Work Distribution:
The project was a collaborative effort, with each team member contributing to all aspects. However, the major work done by each member was as follows. Vardaan led the literature review, while Daksh and Mrinal worked on methodology and took charge of model implementation and fine-tuning, and Kshitij led the result analysis and explored optimizations. Together, we conducted a comprehensive study on WiFi-based Human Activity Recognition.

Background Information:
In wireless communications, Channel State Information (CSI) comprises the known channel properties of a communication link. This information describes how a signal propagates from the transmitter to the receiver and represents the combined effect of scattering, fading, power decay with distance, etc.
The movement of humans and objects changes the multipath characteristics of the wireless channel, and hence, the estimated channel will have a different amplitude and phase. When the person is not moving, the CSIs for all antennas are relatively stable; however, when the activity starts, the CSIs start changing drastically. Using this knowledge of the characteristics of CSI data for human activity, we can use different machine-learning techniques for multi-class classification.

Problem Statement:
WiFi access points emit signals that cover the surrounding area. Using smartphones that have WiFi, it is possible to see the changes in these WiFi signals with respect to various users in the area. This data, known as Channel State Information, contains a sequence of phase and amplitude values of the signals in the area and can be used to determine the user's movement and current activity. Using this data, we can train Machine Learning and Deep Learning models to perform multiclass classification and classify the user's activities.

Related Work:
Human activity recognition (HAR) utilising WiFi Channel State Information (CSI) has garnered significant attention in recent years due to its applicability in diverse fields such as health monitoring, contextual awareness, and energy-efficient smart homes.

Traditional Activity Recognition Systems

Historically, activity recognition systems have relied on wearable devices equipped with motion sensors like accelerometers and gyroscopes. These systems, though effective, suffer from the inconvenience of individuals consistently wearing devices. Moreover, camera-based solutions present line-of-sight restrictions and privacy concerns, limiting their deployment in various environments.

WiFi-Based Activity Recognition Techniques

WiFi signals have emerged as a promising medium for passive activity recognition, leveraging the ubiquitous availability of WiFi access points (AP) and devices in indoor spaces. Traditional WiFi-based approaches involve hardware or specialized equipment modifications, such as the WiFi Universal Software Radio Peripheral (USRP).

WiFi Signal Power Techniques

This method explores various techniques based on WiFi signal power, including Received Signal Strength (RSS) and modified hardware like the USRP. While RSS is simple to use, it struggles to capture real changes in the signal due to environmental dynamics. Techniques like WiSee address this limitation by measuring Doppler shifts in OFDM signals.

WiFi Channel State Information (CSI) Techniques

Recent advancements focus on using WiFi CSI, providing detailed information about the channel characteristics. CSI captures the amplitude and phase of WiFi signals for different subcarriers, allowing for a richer representation of the wireless environment. Techniques like CARM, employ Principal Component Analysis (PCA) de-noising and Discrete Wavelet Transform (DWT) for feature extraction.

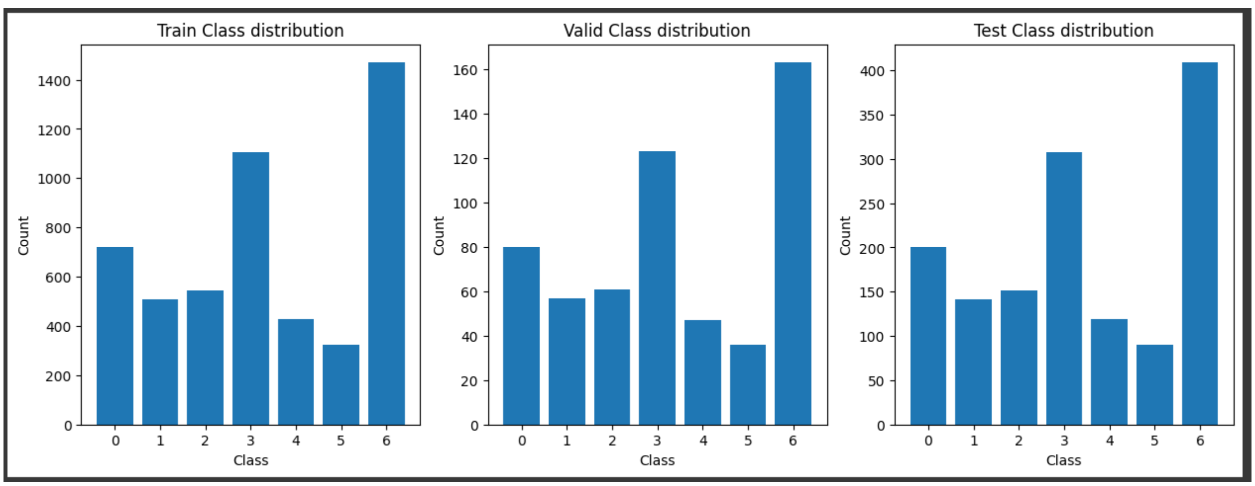
Comparative Analysis of Sequential and Non-Sequential Models

The new research introduces a comparative analysis between sequential and non-sequential models for WiFi-based activity recognition. It evaluates the performance of Random Forest, HMM, and LSTM, showcasing the advantages of deep learning techniques like LSTM in terms of accuracy. The research underscores the importance of considering temporal dependencies in activity recognition tasks, and the potential of LSTM to extract features and preserve temporal state information automatically.

Methodology:

We chose the paper **A Survey on Behavior Recognition Using WiFi Channel State Information** from IEEE 2017 as the basis of our experiments. The paper provides a comprehensive dataset and a preliminary model of a BiLSTM with Attention Layers against which we can compare the results of our models as a benchmark.

The dataset employed in this research comprises CSI data from an indoor office scenario, featuring a 3-meter LOS setup between a transmitter and a receiver. Each 20-second trial involves a participant engaging in activities such as "Lie down," "Fall," "Walk," "Run," "Sit down," and "Stand up." Video recordings accompany the trials, ensuring precise alignment between CSI data and activities. We collected data from six people doing various activities like walking and sitting in an indoor setting. Each person repeated each activity 20 times. This carefully prepared dataset helps us test and study how well models can recognize different activities using WiFi signals in changing indoor conditions.
We observe that there is an imbalance in the class distribution in the dataset so don't use accuracy as a metric for comparison instead we use the F-1 score to compare the various models.



Distribution of the Dataset

Since we have to perform a comparative analysis of various models based on their performance on Human Activity Recognition, we pick several different types of models, both sequential and non-sequential and test them on the same dataset. The models include Random Forest and XGBoost as the tree-based models and BiLSTM, BiGRU, Neural Networks, 2D-CNN, and combinational models like 1-D CNN + Dense and CNN + GRU as the Deep Learning models.

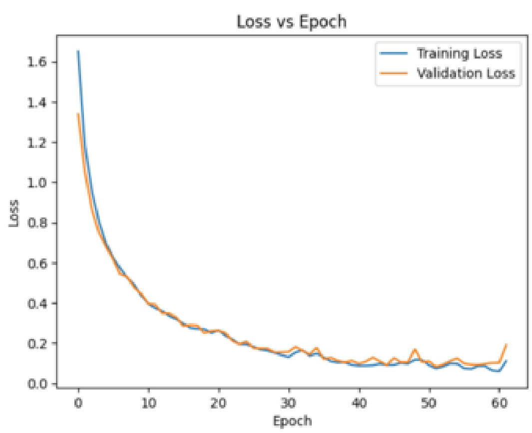
After finalizing the best performance models, we also perform various optimizations to reduce the model size and complexity without harming the performance, so that we can deploy the model on-device such as on mobile phones, instead of the model being present on a server, leading to faster predictions and responses.

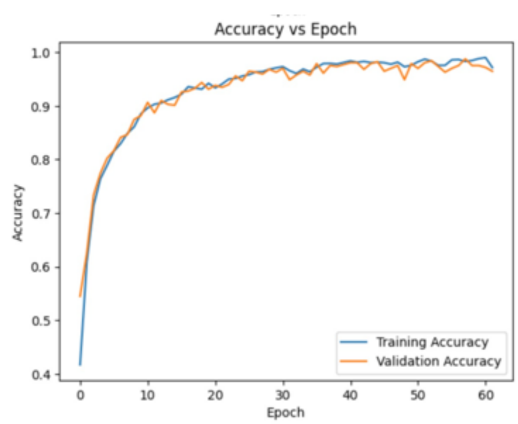
Results:
Using the models mentioned above, we performed training and testing on the available dataset to get a comparative analysis of the models. The results are shown in the table below.

Model (Tree Based)	**Accuracy**	**F1-Score**
Random Forest	75%	0.84
XGBoost	81%	0.88

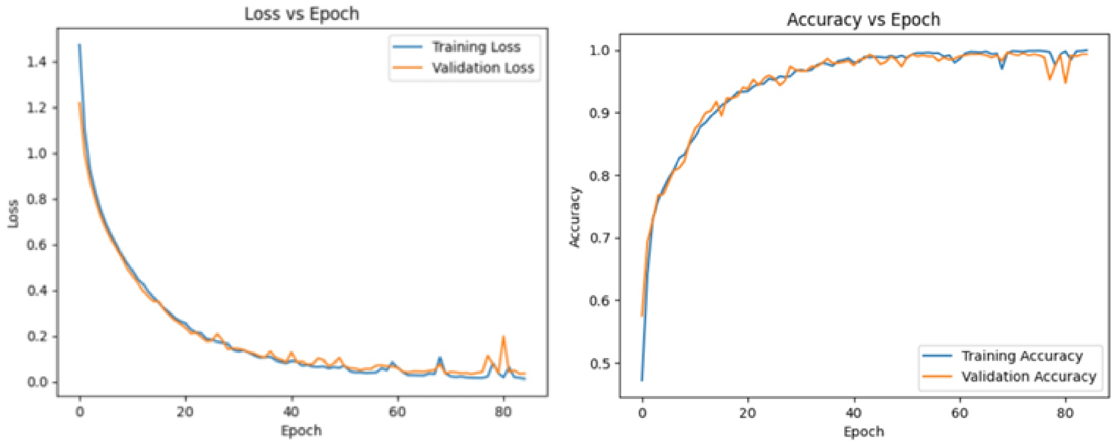
DL Model	**Accuracy**	**F1-Score**	**Number of Parameters**	**Model Size (on disk)**
Original BiLSTM	97%	0.97	629207	7.25MB
BiGRU	99%	0.98	514007	5.93MB
Neural Network	74%	0.69	23188743	88.46MB
2D CNN	98%	0.97	668423	7.7MB
1D CNN + Dense	98%	0.98	372295	4.4MB
CNN + GRU	99%	0.99	115601	1.25MB

We also generated Loss and Accuracy curves for the training process for the Deep Learning Models.

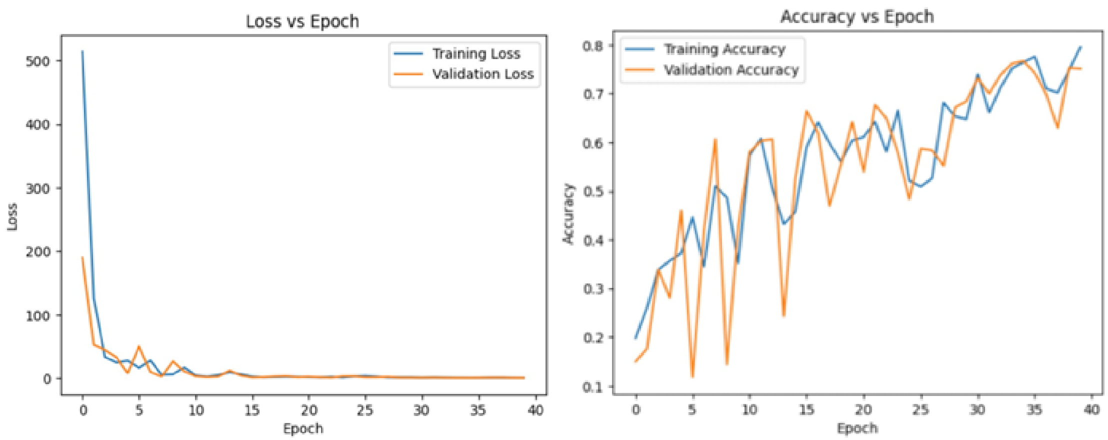




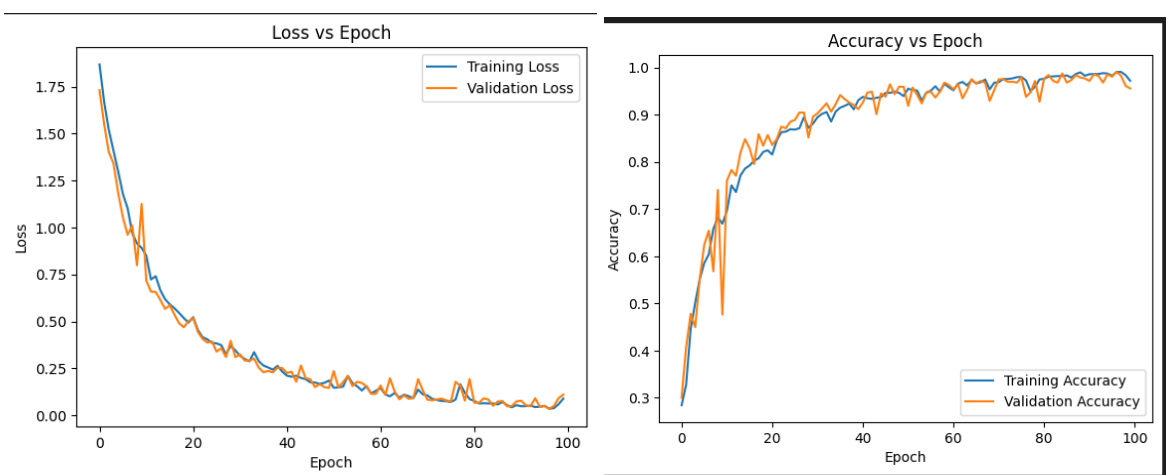
Plots for BiLSTM



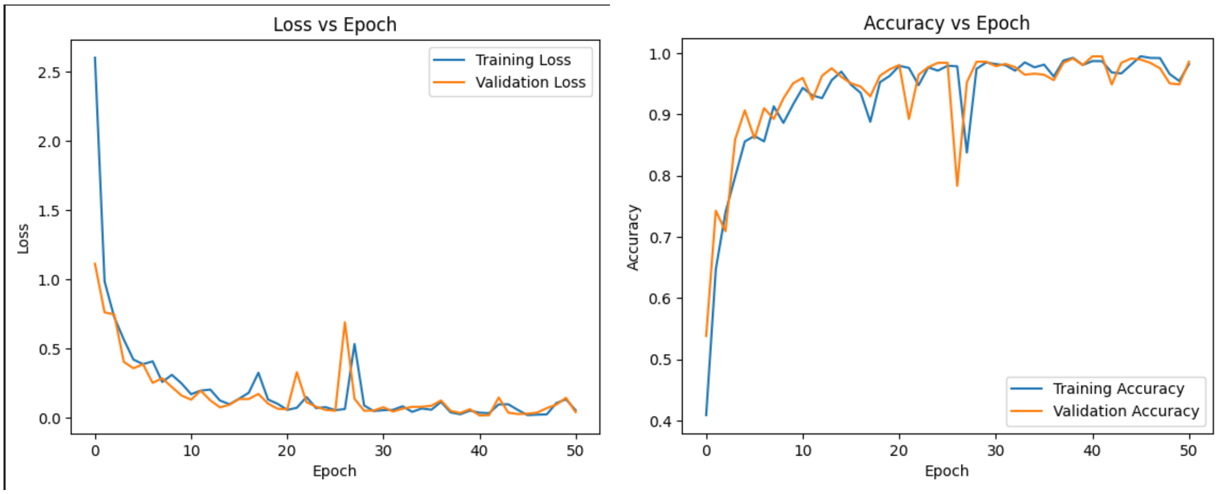
Plots for GRU



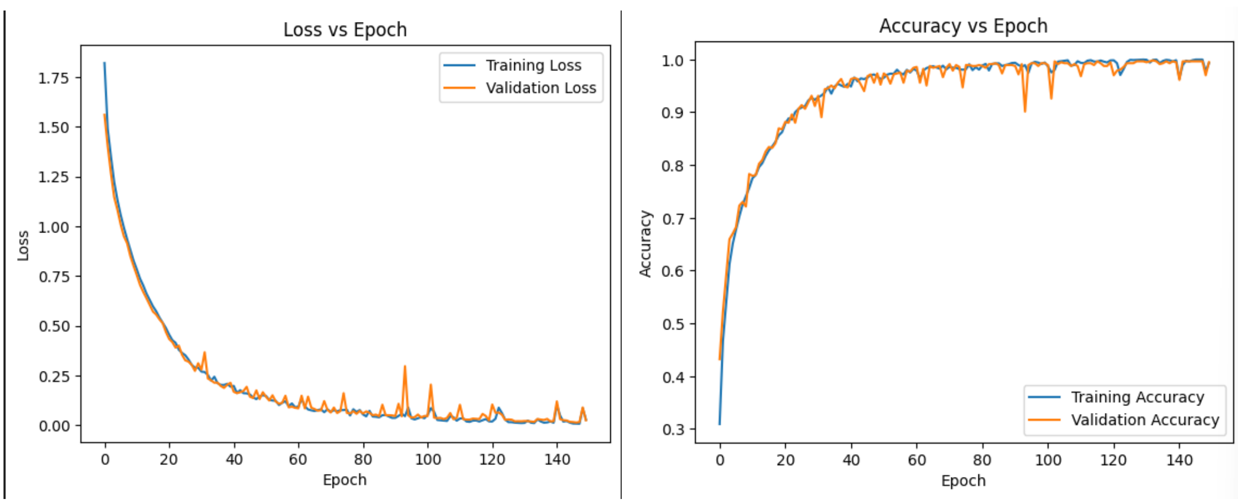
Plots for Neural Network.



Plots for 2D CNN



Plots for 1D CNN + Dense



Plot for CNN+GRU

These results highlight a few key points regarding the dataset distribution and the application of Classification Models:

- We see that the tree based models (RF and XGBoost) do not perform well on the given dataset. This is also the case with vanilla Neural Networks, containing only dense layers. All the other models containing CNN or LSTM layers perform much better.
- This discrepancy in results highlights the sequential nature of the CSI data. Since the data itself is sequential in nature, the sequential models, like models containing LSTM, GRU and CNN layers, perform much better than their non-sequential counterparts.
- Models with combination of layers, like CNN with Dense and CNN with GRU perform the best, while being the smallest when it comes to the size and number of parameters.

According to the results, we find that CNN+GRU model performs the best with an accuracy of 99% and F1-score of 0.99. We perform optimizations on this model in an effort to reduce its size and complexity.

We used TensorFlowLite in order to compress the model and reduce its overall footprint while maintaining similar performance. The confusion matrix and classification report of the resultant model on the same test dataset is as follows, along with the size comparison:

```
[[199   0   0   0   1   0   0]
 [  0 141   0   0   0   0   0]
 [  0   1 150   0   0   0   0]
 [  0   0   0 307   0   0   0]
 [  2   0   0   0 117   0   0]
 [  1   0   0   0   0  89   0]
 [  1   0   0   0   0   0 408]]
```

Confusion matrix

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.99       200
           1       0.99      1.00      1.00       141
           2       1.00      0.99      1.00       151
           3       1.00      1.00      1.00       307
           4       0.99      0.98      0.99       119
           5       1.00      0.99      0.99        90
           6       1.00      1.00      1.00       409

    accuracy                           1.00      1417
   macro avg       0.99      0.99      0.99      1417
weighted avg       1.00      1.00      1.00      1417
```

Classification report

```
Saved quantized and pruned TFLite model to: final_model.tflite
Size of baseline Keras model: 1253.24 KB
Size of TFlite model: 105.31 KB
Percentage of Original: 8.40 percent
```

The model outperforms all existing models while having a much smaller footprint, with more than a 90% reduction in the model size. This model, having only a size of 105.31KB, can be deployed on mobile devices to facilitate on-device machine learning.

Conclusion
In this project, we worked with Wifi-CSI data in order to perform Human Activity Recognition using ML and DL models. We found that the CSI data is sequential in nature, hence sequential models perform better than non-sequential models in classification based tasks. We also did a comparative analysis of various models and performed model pruning and optimization of the best performing models, so that the model size and footprint can be reduced and it can be used on mobile devices.

References:

- S. Yousefi, H. Narui, S. Dayal, S. Ermon and S. Valaee, "A Survey on Behavior Recognition Using WiFi Channel State Information," in IEEE Communications Magazine, vol. 55, no. 10, pp. 98-104, Oct. 2017, doi: 10.1109/MCOM.2017.1700082.
- **https://github.com/ludlows/CSI-Activity-Recognition**
- **https://www.tensorflow.org/lite/models**