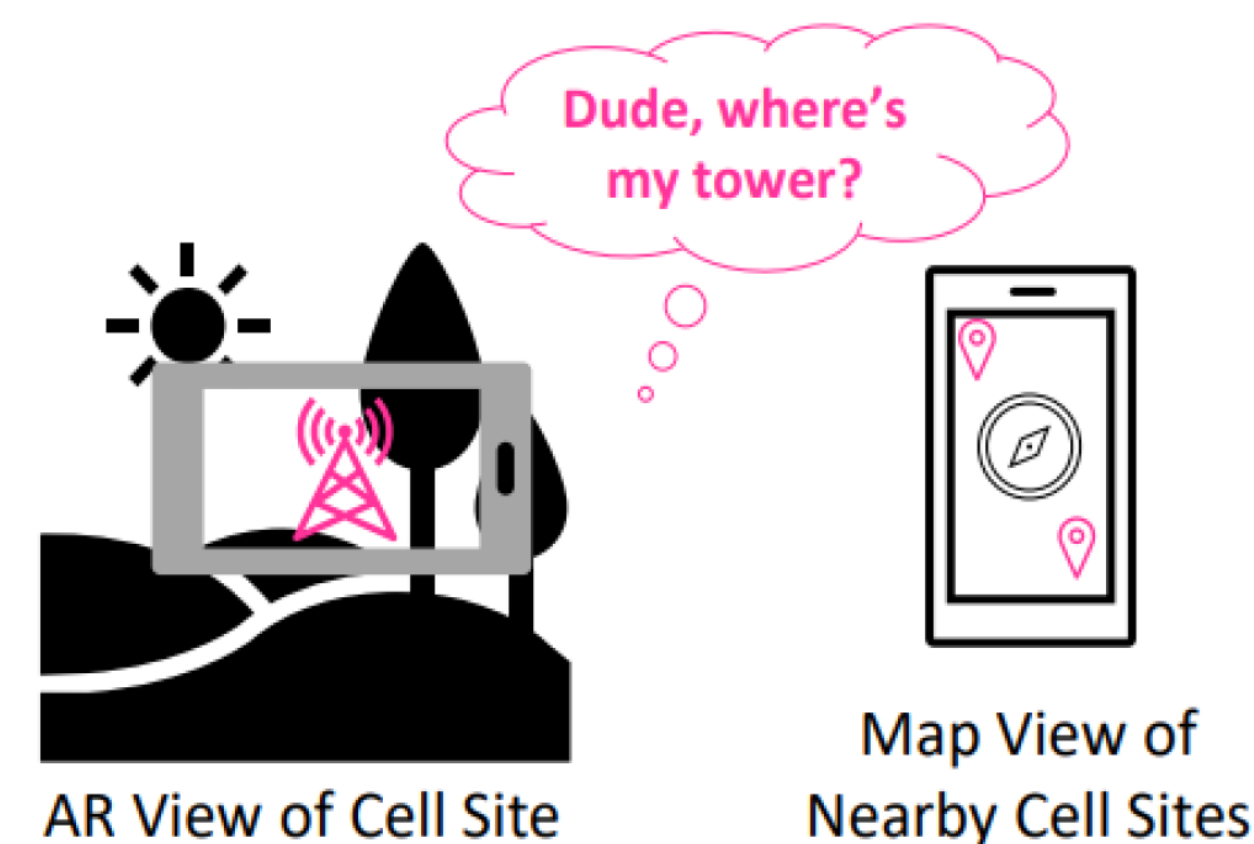


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Introduction

This app will give users of the T-Mobile home internet device an accurate prediction of the best spot to place the device inside of their home. This will ensure that the user is getting the best internet service possible



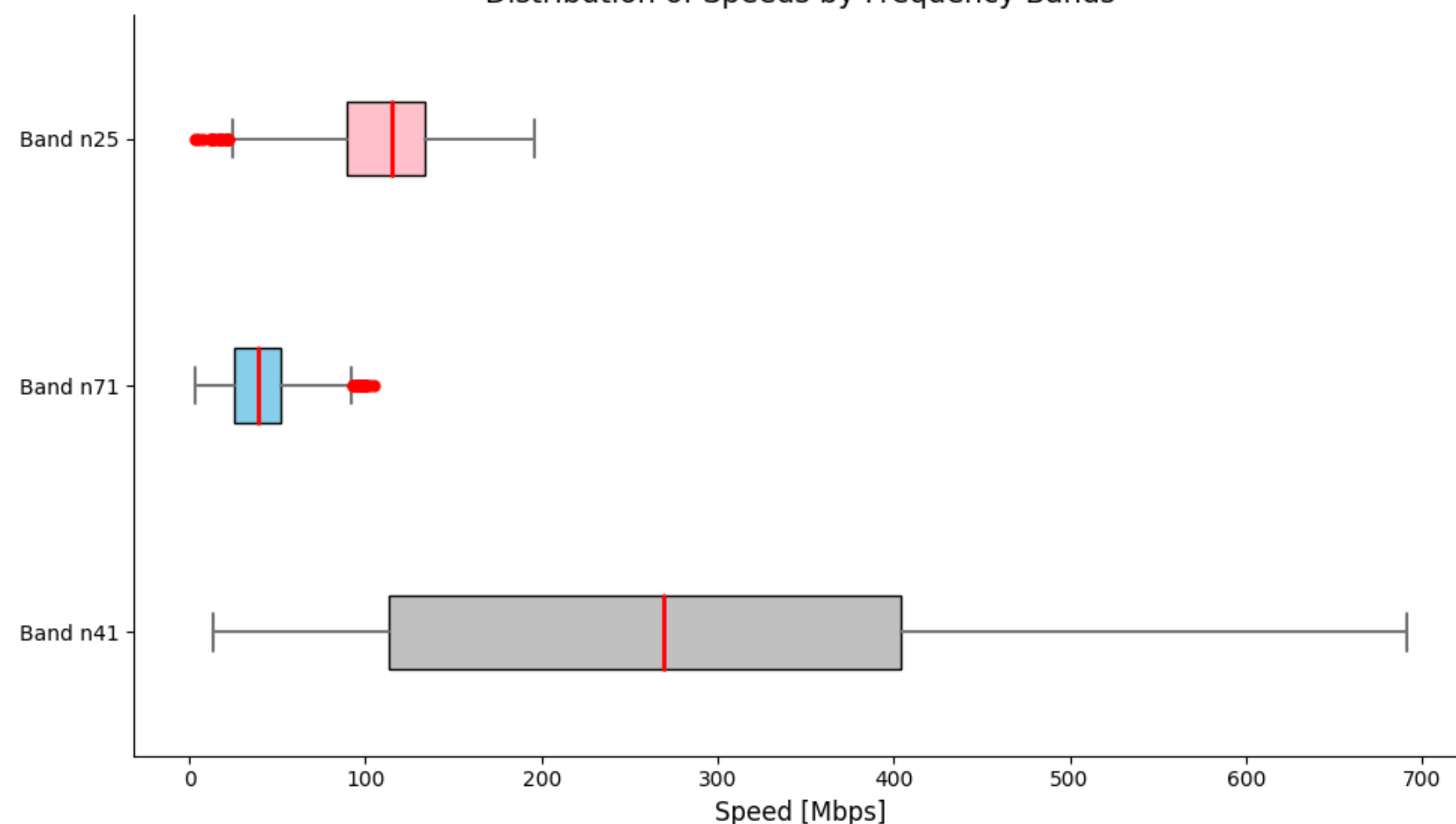
Objectives

The objective of this project is to create an accurate prediction for the placement of T-Mobiles Home Internet Device. We completed this through the creation of an AR visual app that displays the closest cell tower and collects RF data. After the data is collected, the app uses a REST API from Microsoft Azure to gain access to a well-trained ML model that will then predict and display if the camera's location will be the most effective place to place the device

RF Data Collection and Analysis

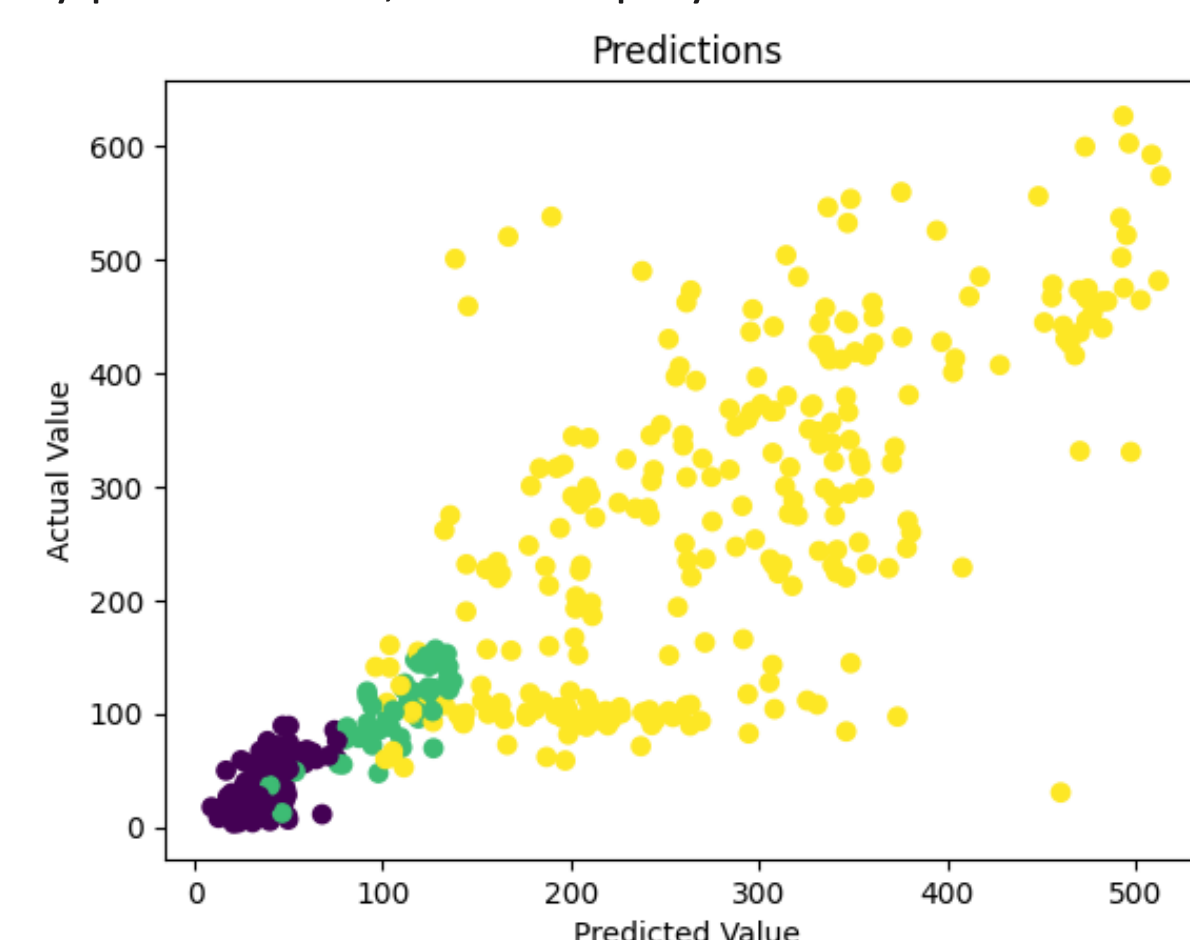
- Collection Locations: Data was collected in the lab space, halls, elevators, and other lab spaces within the ECE building, as well as in a residential building.
- Amount of Data: Approximately 77 locations with 26 timestamps per location were collected with Ookla, while iPerf data included 11 general locations with varying timestamps (ranging from 730 to 2100) depending on signal availability.
- Data Collection: RF data was collected using Ookla and iPerf in a lab space and various locations within the ECE building. iPerf3 was chosen for comprehensive RF data collection, allowing measurement of bandwidth, loss, and other metrics.

Figure 1: Distribution of 5G PDSCH Throughput Speeds across Frequency Bands.
Distribution of Speeds by Frequency Bands



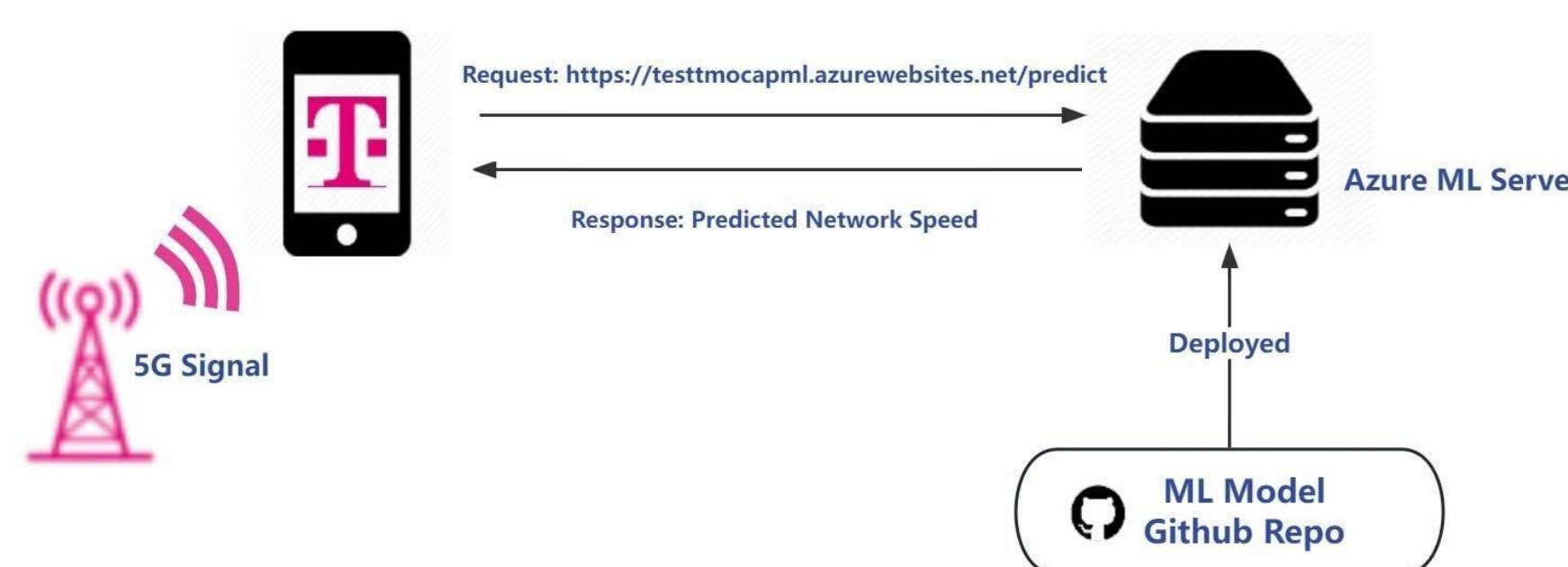
Machine Learning Model and Approach

- Goal: The objective of the machine learning (ML) model was to predict internet speed in MBPS based on RF metrics obtained from the placement of the home internet device. The predicted speed would then be utilized by the app.
- ML Architectures: Several ML architectures were tested, including Decision Tree Regressor, RandomForest Regressor, Support Vector Machine Regression, and Neural Networks.
- Best Performance: After thorough evaluation, the RandomForest regressor yielded the best performance results for the given task. This choice aligns with the fact that RF information, such as the connected band, has a significant impact on internet speed.
- RandomForest Regressor: The RandomForest Regressor is an ensemble learning algorithm that combines multiple decision trees to make predictions. It is known for its ability to handle complex relationships between input features and the target variable.
- RF Metrics: Initially, the model was tested using 2 RF metrics. However, it was found that including additional metrics led to improved performance. The final set of 5 RF metrics used in the model included RSRP, SINR, RSRQ, Band, and Bandwidth.
- Performance and Robustness: The primary aim was to develop a robust ML model that delivers reliable and reasonable internet speed predictions. The model exhibits a high level of robustness, as it can handle various types of RF information. The model achieves an accuracy of approximately 70%, which indicates its capability to make accurate predictions.
- Speed Categorization: For the app's usage, internet speed is categorized into three groups: speeds above 200 Mbps are considered great, speeds between 100 and 200 Mbps are classified as good, and speeds below 100 Mbps are labeled as poor. The ML model has a nearly 95% accuracy in correctly predicting the speed grouping, demonstrating its effectiveness in classifying internet speeds accurately.
- Validation and Deployment: The final ML model was validated using separate validation datasets to ensure its generalizability. Once the model exhibited satisfactory performance, it was deployed onto an Azure server to make predictions accessible for the augmented reality app users.



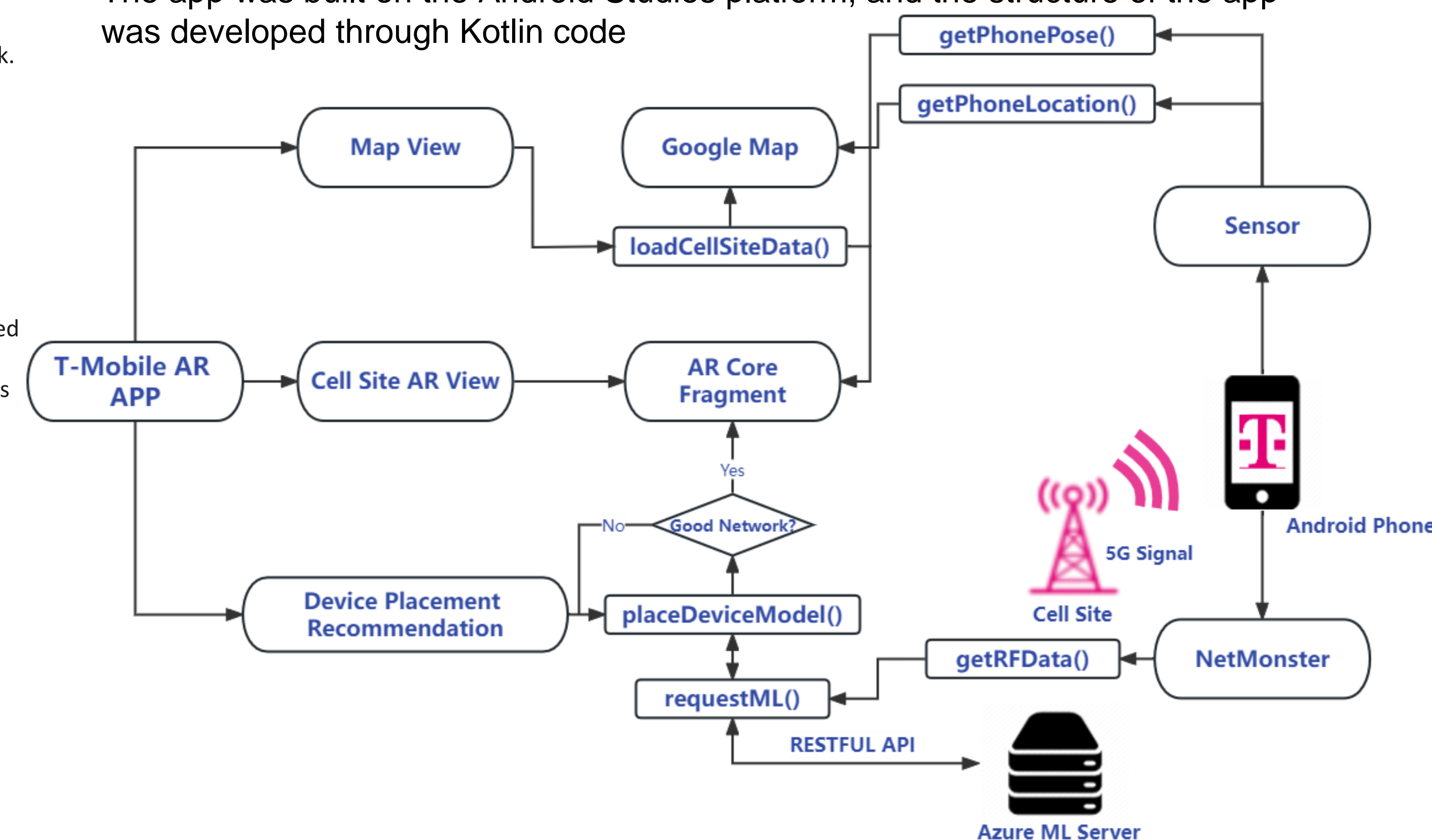
API

- We have set up our REST API specifically to cater to our AR (Augmented Reality) application, providing accurate MBPS predictions. The REST API seamlessly integrates with the AR app, allowing it to leverage the predictive capabilities of the machine learning model for an enhanced user experience.
- The REST API, deployed on an Azure server, offers a notable advantage in terms of model maintenance and evolution. Leveraging Azure's infrastructure, the API enables seamless updates and improvements to the underlying machine learning model over time.
- With Azure, deploying a new version of the machine learning model is straightforward. By creating a new model version, you can easily transition to the updated version without disrupting the existing client implementations that rely on the API.
- The Azure server hosting the API provides a robust environment for managing model updates. You can upload the new model version to Azure, configure the API endpoint to use the updated model, and gradually switch the traffic to the new version while monitoring its performance.
- Leveraging Azure's versioning capabilities, you can maintain a history of model versions, facilitating experimentation, A/B testing, and comparison of different models' performance and accuracy.



AR App

The app was built on the Android Studios platform, and the structure of the app was developed through Kotlin code



Results, Future Work, References, and Acknowledgments

Future work on the app could include, larger data collection for a more fine-tuned ML model, and therefore a better placement of the HINT, and adding user friendly features to the app.

References throughout the project were given to us by our T-Mobile industry mentors. They created documents describing how to log the RF data and gave us a skeleton code for the ML model. The one aspect that was not given any direction on was creating the REST API.

[1]BryanLa. (2023, April 4). *Azure REST API reference documentation*. Microsoft Learn. <https://learn.microsoft.com/en-us/rest/api/azure/>

