Federated Learning for Distributed Sensing Aided Beam prediction in 5G Networks

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Intro about presenter – Adwitiya Pratap Singh

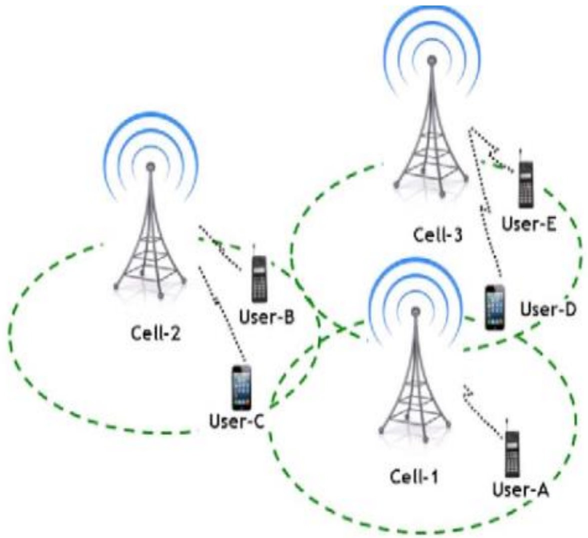
Adwitiya Pratap Singh received his bachelor’s in technology degree in Information Technology from the Manipal University, Jaipur in 2022. He is currently working at Hughes Systique Corporation as a software engineer.

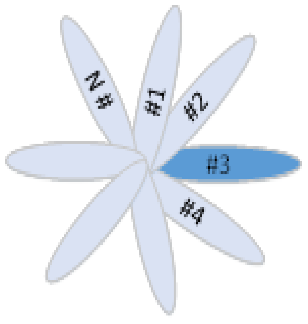
He is currently working in the CoE (Centre of Excellence) department at the company concerned with advancements in wireless technology with the aid of AI.

Cell Selection and Beam Selection

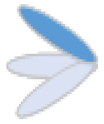
- ➢ Cell Selection Procedure:
  - ❑ 35 parameters for System Information
  - ❑ 10 parameters for speed dependent Selection
  - ❑ 13 parameters for interworking
  - ❑ New technology of Beam Selection and Sweeping

- ➢ Larger Bandwidth at millimeter waves is the Key for achieving higher Data rate.
- ➢ Attenuation in millimeter wave is very High as a result signal can not travel longer distance.
- ➢ To overcome this, Using Multiple Antennas in MIMO system. Directional signal called Beam can be used for Transmission.





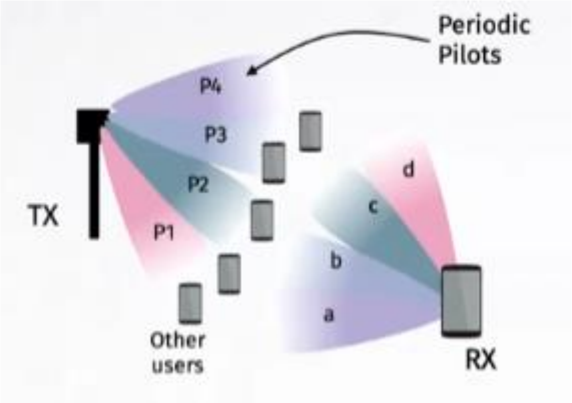
gNB's Beams

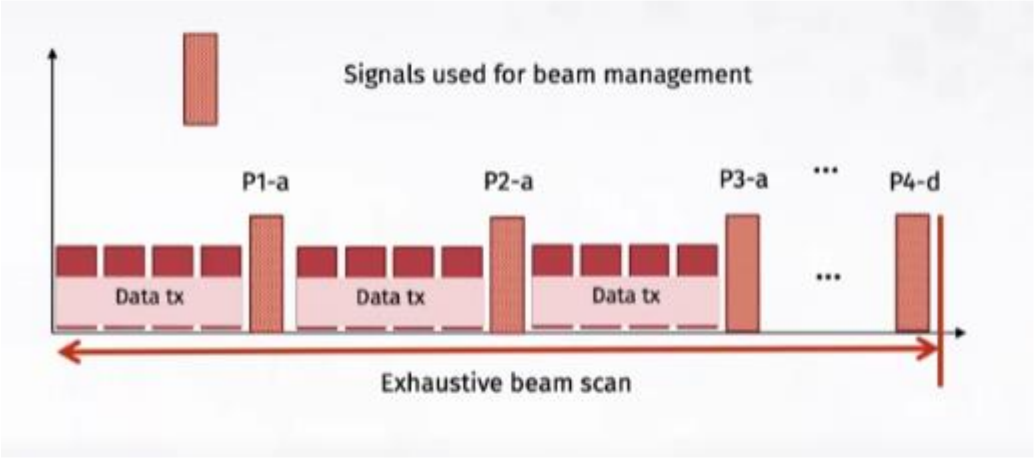

UE's Beams

Input Data e.g. UE Location ,Speed, Signal Strength → **Beam Selection With AI** → Faster Selection i.e. Reduced Latency

Traditional Beam Selection in 5G

- There is a need of tracking which is one of the directionality challenges of 5g mmWaves. And also in some cases change the base station.
- Traditional Beam Management : There is a need for pilots that are transmitted by the TX and also an exhaustive scan by the receiver to find the optimal beam. Results in High latency and overhead .
- Both the TX and the RX need to discover each other by finding the initial beamforming vectors that yield sufficient Signal-to-Noise-Ratio (SNR) to establish a link. This crucial procedure is usually called initial access



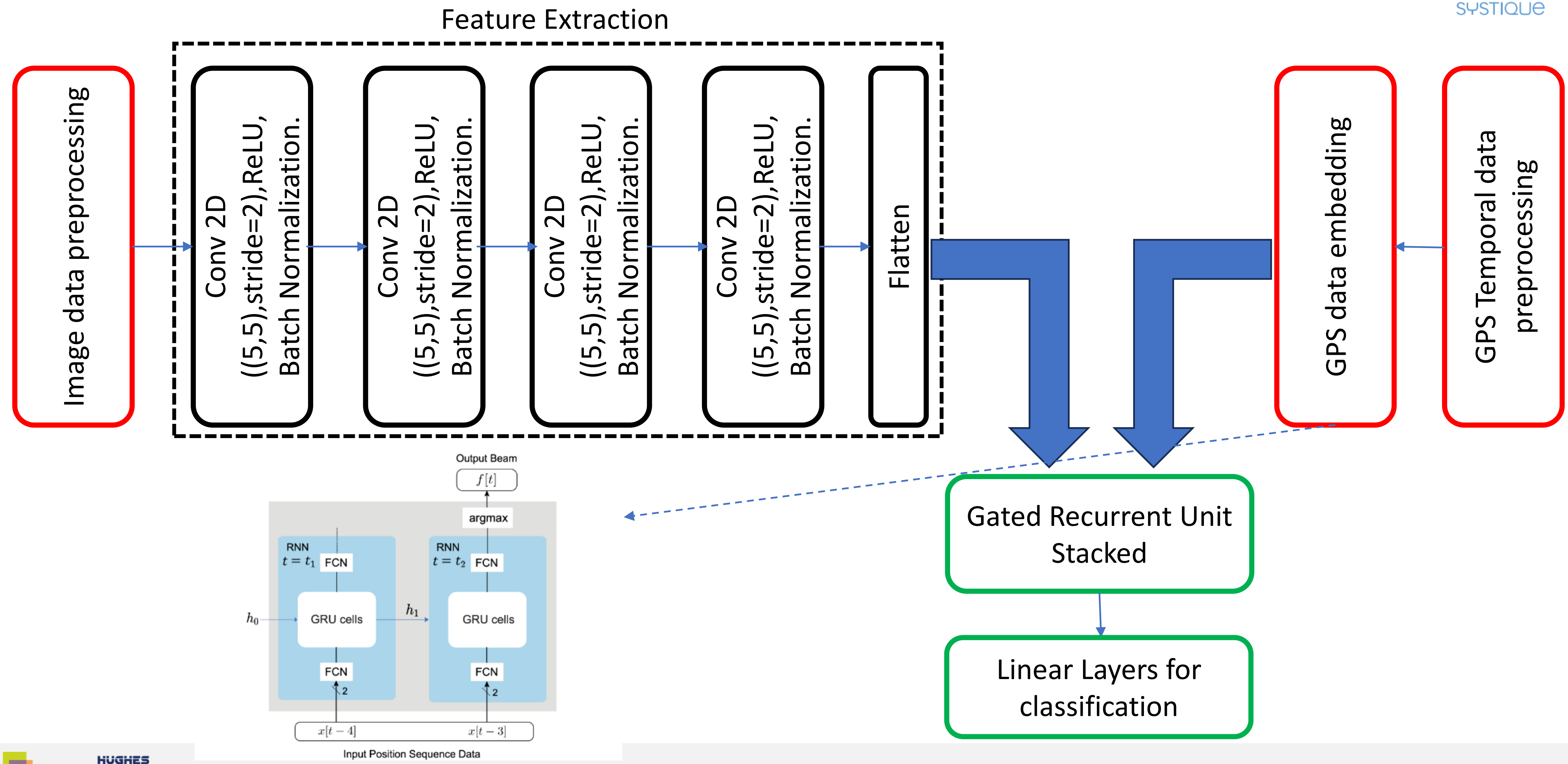


Aim and Contributions of Our Paper

- Aim of the paper :
  - Create a sensory aided deep learning model to reduce the time taken to perform beam-selection.
  - Implement this in a simulated federated learning environment to gauge practical feasibility.

- Contributions:
  - Created a multi-modal time-series model to perform beam selection aided by GPS and Image data.
  - Experimented with multiple aggregation techniques to use during federated learning and compared their results with centralized learning.

Model Visual Representation



Multi-modal data Preprocessing

- Camera data
  - Using pretrained MIRnet to brighten/enhance data with low brightness conditions.
  - Background masking to focus on important features retaining the road.
  - Using PIDnet to focus on the cars on the streets.
- GPS data
  - Converted latitude-longitude cordinates to cartesian coordinates.
  - Min-max normalization.
  - Calibrated angle normalization
    - The 0-degree angle for all images were calibrated to its center pixel.

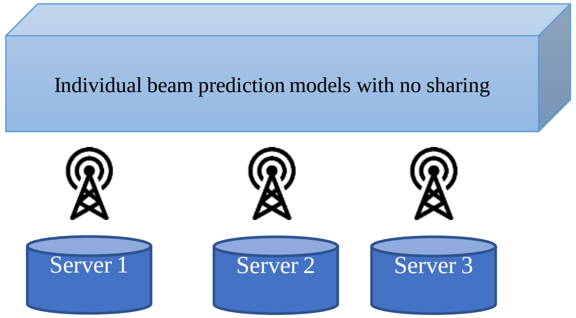
Challenges of Centralized Model

- In a real-life deployment, each gNodeB would have a view of only a specific location/scenario. To create and run a centralized model the gNodeB should have access to all possible data or scenarios.

- However, it is prohibitively **expensive computationally** to get the data in one centralized place.

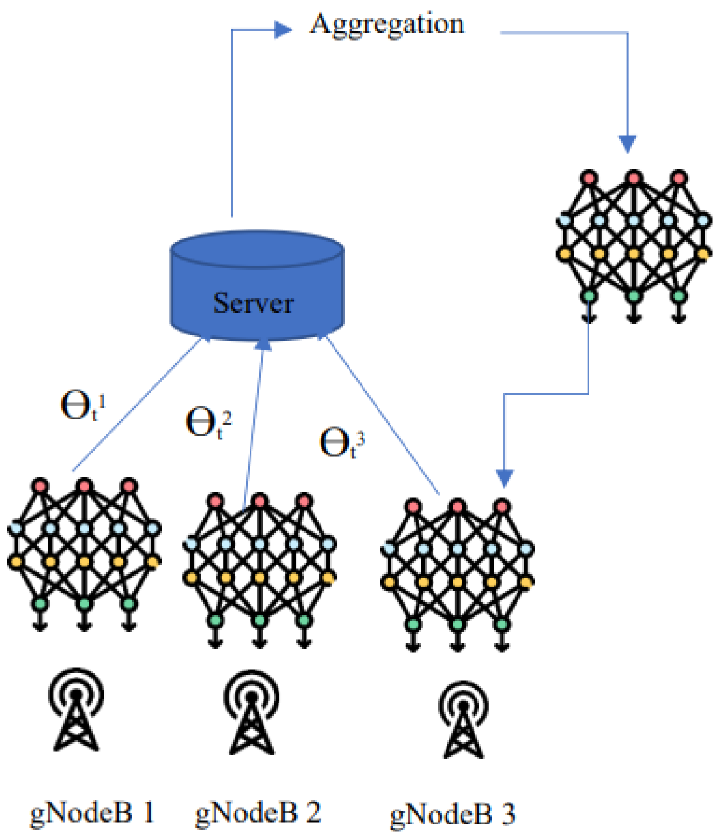
- **Security** of data is also at risk if the cumulative data is stored and processed at one position, one breach would cause a major loss.

- In a centralized learning system, the central controller becomes a **single point of failure**.



Federated Learning

- Data is distributed across different gNodeB depending on locality.
- Using gNodeB as local servers reduces chances of local server dropping out of model training.
- Each model is trained based on local data and skews with a different bias.
- Model weight is sent to local server hence reducing single point failure.
- Updated aggregated model is then uploaded to all gNodeB.

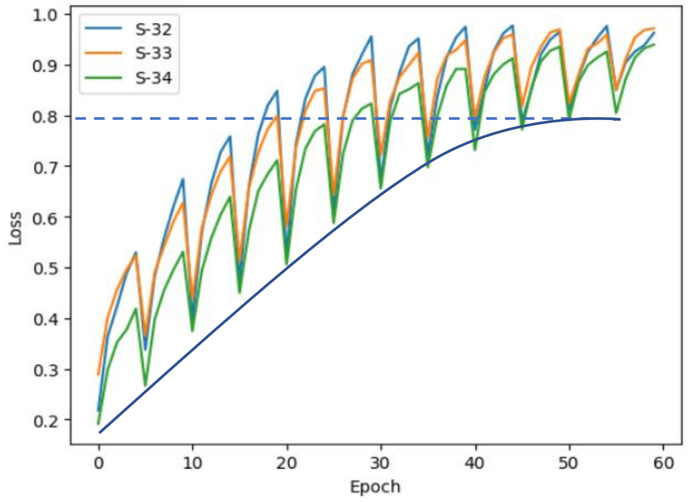


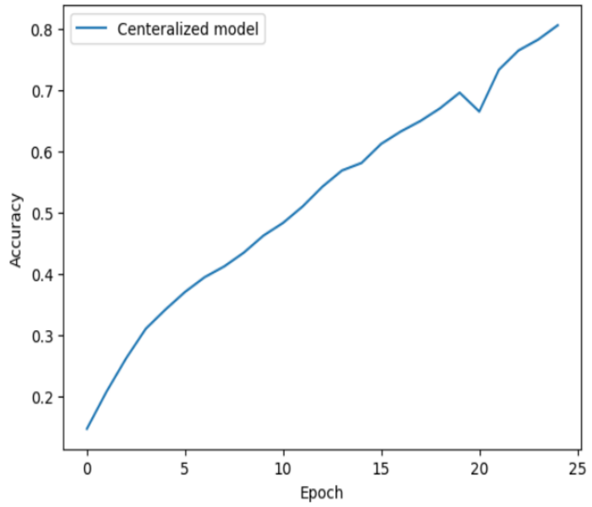
Aggregation Techniques

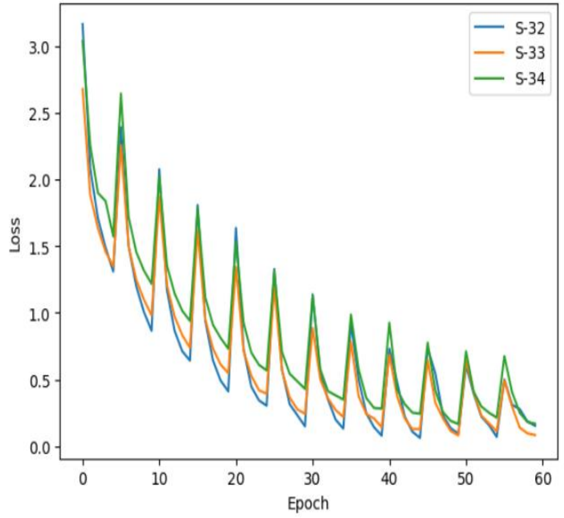
An aggregation technique is used to accurately combine and average the local model weights at the central server.

- Federated stochastic Gradient Descent (FSGD):
  - In the case of FSGD after the weighted average is formed of the given clients then the difference between the current global model weights is computed after which we subtract the difference to move opposite to the rising gradient.
- Federated average momentum:
  - This is an extension of the Federated Average technique that includes momentum in the aggregation step.
- Federated Proximal:
  - Federated Proximal is a technique that uses a proximal operator to enforce sparsity in the model updates.

Results and Analysis







- The centralized implementation is identical to the federated model except that we used the entire dataset at one node to train the model at once.

- We are emphasizing the minimum accuracy amongst the peaks since that is the result after aggregation. This dip in accuracy is due to the new scenario data weights that is introduced to the global model, it maxes out at 80% accuracy in beam selection.

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Models	Top 5 of 64	Top 10 of 64
Baseline model (GRU)	77 %	80%
Centralized model	83%	90%
Federated Model	64%	80%

Models	Top 5 of 64	Top 10 of 64
FSGD	64 %	80 %
Proximal	60 %	75 %
Fed Avg	65 %	76 %

- As seen above federated stochastic gradient descent worked best amongst all. This can be corroborated with theory as well since FSGD is slightly immune to the non-iid imbalanced dataset since it allows for more local model updates.
- The best federated model results do lag the centralized model, but it covers in time to process, since parallel processing of three models at three different nodes allowed the model to train 37% faster on the CPU. This would be increased even further if the data is loaded on to the GPU.

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- Some applications require immediate or near-real-time model updates to respond to dynamic data patterns or changing conditions. Faster training in federated learning allows for quicker updates to the global model.
- Since bulk of the training is done at the gNodeB containing the sensors itself, the communication overhead is reduced.
- Increasing the number of local nodes will help us generalize a set pattern of close by areas hence further increasing the model accuracy while keeping the training time at a minimum.

Future Work

- The use of other sensors can also prove to be a viable option in sensor-aided beam prediction such as accelerometers and gyroscopes.
- Different aggregations techniques can be explored to analyze the resultant effect in the performance of federated learning.
- The federated model falls prey to overfitting if given a small number of clients, we can investigate the behavior by varying the number of active clients in federated learning.
- A grad norm clipping algorithm can also be used. To only use a certain section of data from the gNodeBs which might help remove outliers.

References

- [1] ITU AI for Good Global Summit ",AI for Good Global Summit 2021", ITU AI For Good Challenge, https://challenge.aiforgood.itu.int/match/matchitem/72
- [2] H. Lindgren and M. Hasselqvist, "The Effects of Battery Aging on the Energy Management of a Parallel Hybrid Electric Vehicle", Proceedings of the 2017 19th European Conference on Power Electronics and Applications (EPE'17 ECCE Europe), Chalmers University of Technology, 2017, pp. 1-6.
- [3] C. Arora and A. Saha, "AI Based Beam Management for 5G (mmWave) at Wireless Edge", IARIA International Journal on Communications (IJCN), vol. 11, no. 3 & 4, 2021, pp. 44-53. DOI: 10.1016/j.ijcon.2021.100038
- [4] J. Smith et al., "A Novel Approach to Federated Learning", IEEE Signal Processing for Wireless Communications (SPAWC), IEEE, 2019, pp. 1-6. DOI: https://doi.org/10.1109/SPAWC.2019.8815569Sdad
- [5] J. Yang et al., "Federated Learning for Intelligent Vehicular Networks: Challenges and Solutions", IEEE Transactions on Vehicular Technology, vol. 71, no. 3, 2022, pp. 3079-3091. DOI: https://doi.org/10.1109/TVT.2022.3142513
- [6] Sharma, Ashish, et al. "Secure Federated Learning for Next-Generation Wireless Communication Networks", IEEE 17th Annual Consumer Communications & Networking Conference (CCNC), 2021, pp. 1-6
- [7] M. Akbari and E. Mohammadi, "Risk and Advantages of Federated Learning for Health Care Data Collaboration", ResearchGate, 2020.
- [8] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Gated feedback recurrent neural networks", arXiv preprint arXiv:1502.02367, 2015.
- [9] Y. Chen, J. Liu, M. Xu, and K. Ren, "Federated learning in mobile edge networks: A comprehensive survey", IEEE Communications Surveys & Tutorials, vol. 20, no. 3, 2018, pp. 2022-2063. DOI: 10.1109/COMST.2018.2834990

Contd.

- [10] M. Karimzadeh et al., "Secure Federated Learning with Homomorphic Encryption: A Review", IEEE Access, vol. 9, 2021, pp. 197789-197814. DOI: https://ieeexplore.ieee.org/document/9862973
- [11] "Deep Learning-Based mmWave Beam Selection for 5G NR/6G With Sub-6 GHz Channel Information: Algorithms and Prototype Validation", ResearchGate, 2020, DOI: 10.13140/RG.2.2.15928.44809
- [12] C. Van Berkel, "Multi-core for mobile phones", In Conference on Design, Automation and Test in Europe, 2009, pp. 1-6.
- [13] A. Kumar Sahu, T. Li, A. Talwalkar, and V. Smith, "Federated Learning: Challenges, Methods, and Future Directions", Carnegie Mellon University, Bosch Center for Artificial Intelligence, and Determined AI, 2019.
- [14] J. Konečnỳ et al., "Federated learning: Strategies for improving communication efficiency", arXiv preprint arXiv:1610.05492, 2016.
- [15] "CS294-163: Federated Learning", University of California, Berkeley, Electrical Engineering and ComputerScience,https://inst.eecs.berkeley.edu/~cs294-163/fa19/slides/federated-learning.pdf.
- [16] G. Charan Alkhateeb et al., "DeepSense 6G: large-scale real-world multi-modal sensing and communication datasets", to be available on arXiv, 2022.

Contd.

- [17] DeepSense6G, "Multi-Modal-Beam-Prediction-Challenge-2022-Baseline", [GitHub repository], https://github.com/DeepSense6G/Multi-Modal-Beam-Prediction-Challenge-2022-Baseline, 2022.
- [18] T. Y. Lin et al., "Focal loss for dense object detection" ,In Proceedings of the IEEE international conference on computer vision, 2017, pp. 2980-2988.
- [19] Brown, M., Thompson, C., and Anderson, B. (2021). “A federated learning approach for beam selection in vehicular mmWave systems”, In Proceedings of the IEEE Global Communications Conference (GLOBECOM), pp. 1-6.