United Nations/Finland Workshop on the Applications of
Global Navigation Satellite Systems

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Classifying GNSS Signals in Terrestrial Environments using Deep Learning

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Sardar Vallabhbhai Institute of Technology, Surat, Gujarat, India.

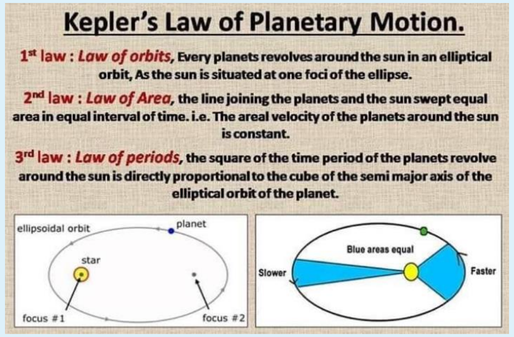
Contents

GNSS

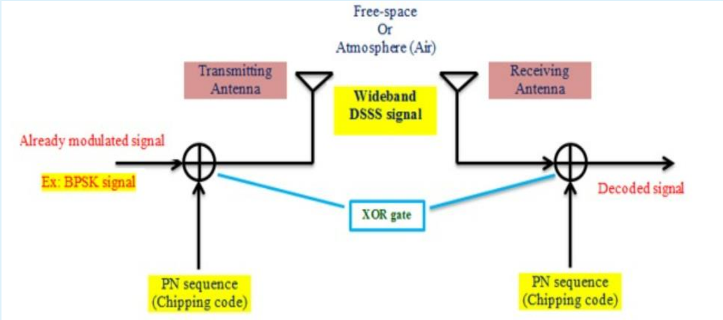
GPS, Galileo, Glonass, Beidou

NavIC, QZSS

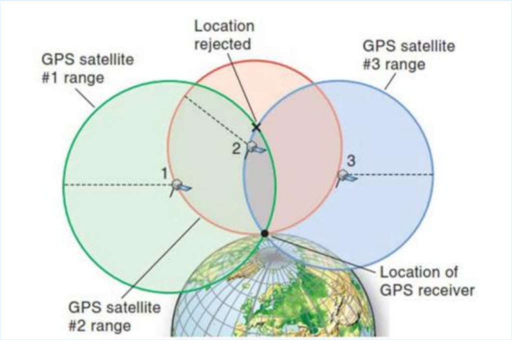
Satellite Navigation



Kepler's laws of planetary motion



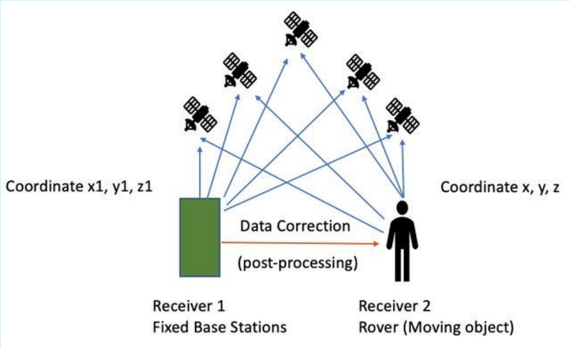
Spread-spectrum Technique

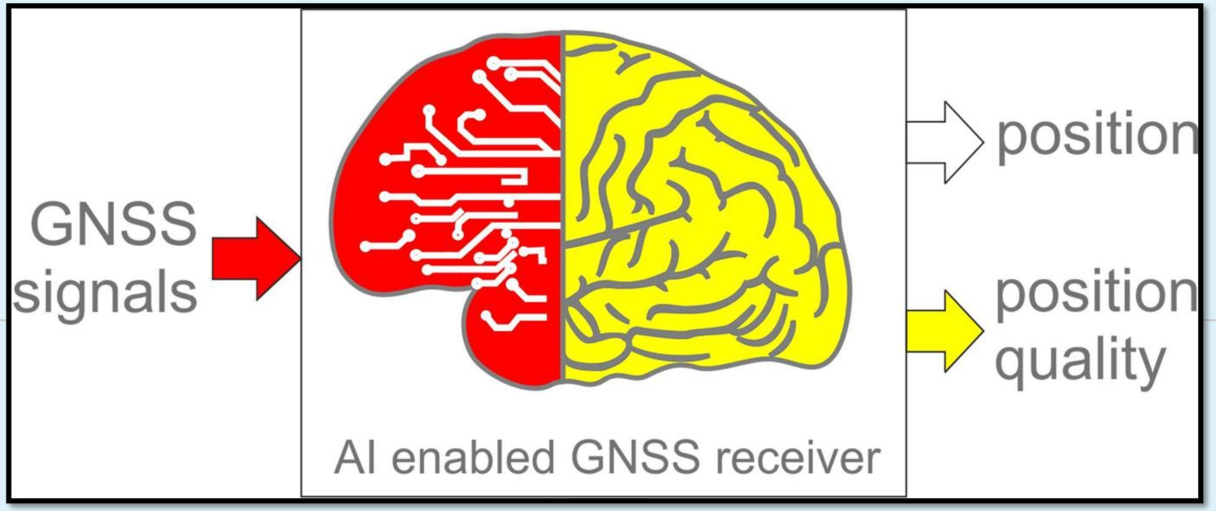


Trilateration model

DGPS (Differential GP

l-Time Kinematic)

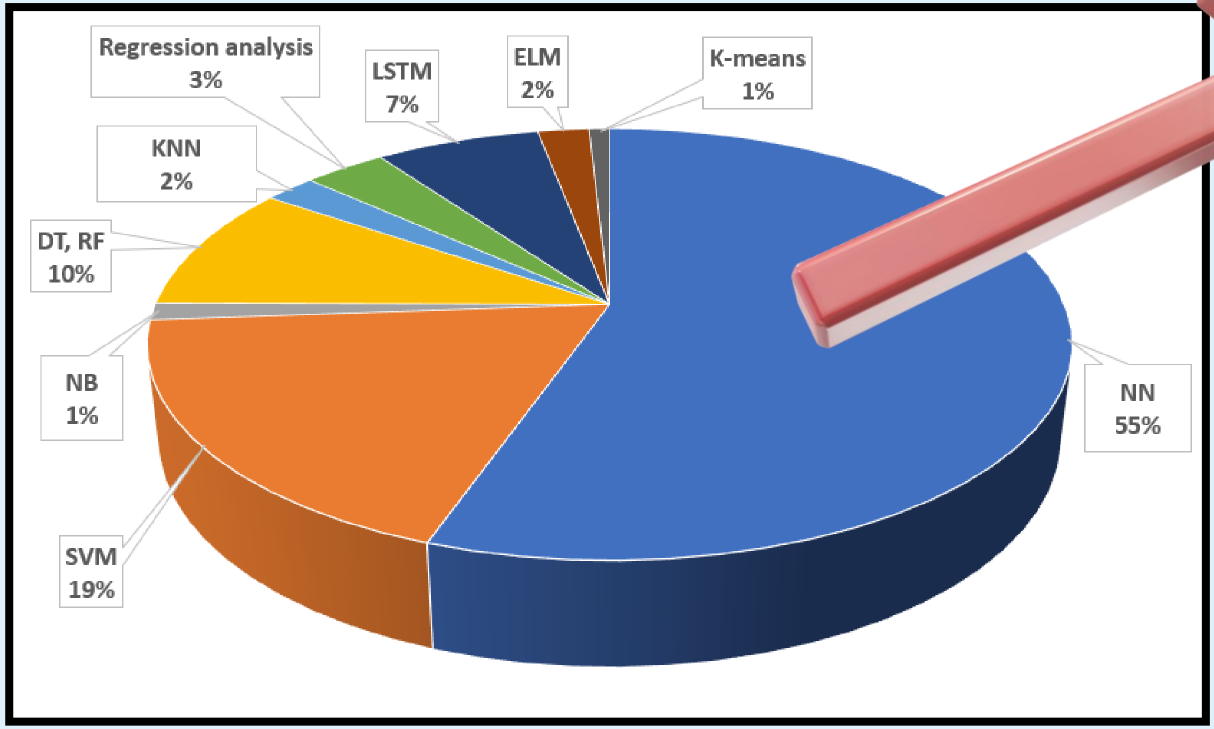




New Era in GNSS

GNSS with AI brings researchers' attention to precise positioning, navigation in complex areas, interference cancelation and mitigation etc…

Literature Review



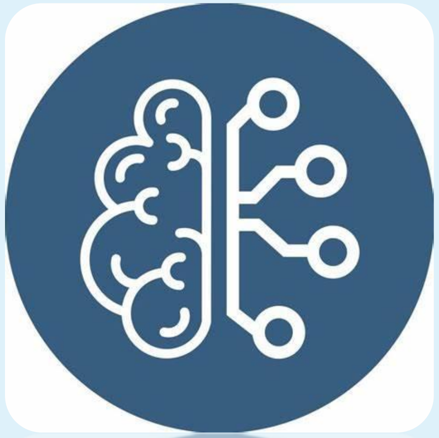
GNSS Use Cases

- GNSS Signal Acquisition
- Signal Detection and Classification
- Earth Observation and Monitoring
- GNSS Navigation and Precise Positioning
- GNSS Denied Environments and Indoor Navigation
- GNSS Anomaly Detection and Atmospheric Effects
- GNSS Security: Spoofing and Jammer Attacks
- GNSS/INS Integration
- Satellite Selection

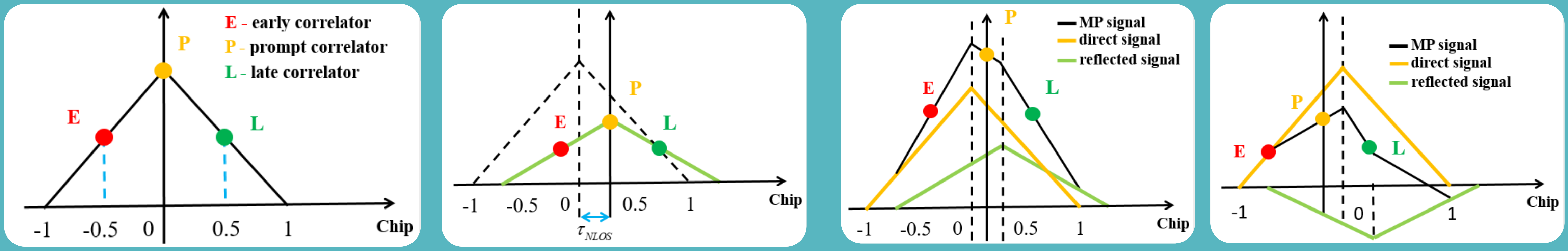
Siemuri, Akpojoto, Kannan Selvan, Heidi Kuusniemi, Petri Valisuo, and Mohammed E. Elmusrati. "A Systematic Review of Machine Learning Techniques for GNSS use Cases." IEEE Transactions on Aerospace and Electronic Systems, Nov. 2022.

Literature Review

Convolutional Neural Networks (CNNs) are valuable in enhancing GNSS technology by improving accuracy, robustness, and reliability in various scenarios, making them an essential component in modern navigation and positioning systems.



- **Satellite Constellation Prediction**
- **Terrain and Obstacle Mapping**
- **Image-Based Positioning**
- **Signal Strength Prediction**
- **Indoor and Urban Navigation**
- **Sensor Fusion**
- **Real-Time Updating**
- **Signal Authentication**
- **Signal Processing and Interference Reduction**



LOS signal

NLOS signal

Constructive Multipath signal

Destructive Multipath signal

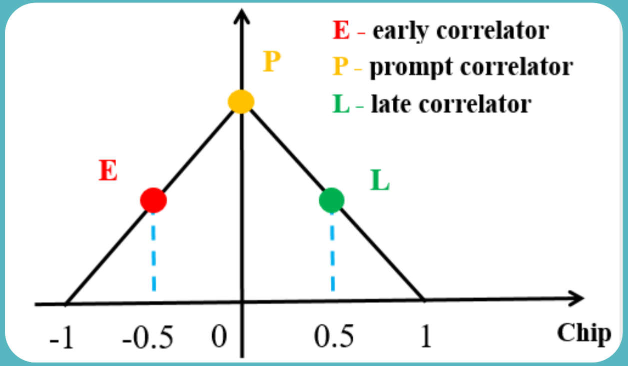
<u>Correlators outputs</u>

Jiang, C., Chen, Y., Xu, B., Jia, J., Sun, H., He, Z., Wang, T. and Hyyppä, J., 2022. Convolutional Neural Networks Based GNSS Signal Classification using Correlator-Level Measurements. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *46*, pp.61-66.

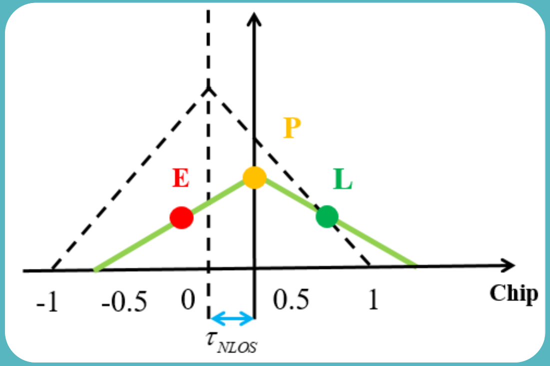
under LOS condition: the correlator peak is consistent with the prompt correlator, however, there is code phase bias between prompt correlator output and correlator peak under

NLOS condition; in addition, the correlators magnitude is lower than that of LOS signal due to the power loss caused by the signal reflection.

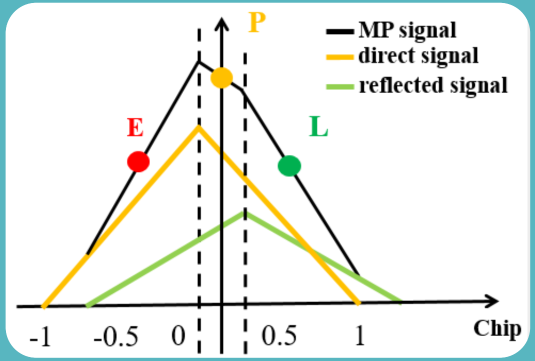
under MP condition, the correlator peak is not consistent with prompt correlator, the correlators curves are not triangle due to the superposition of the LOS and reflected signals.



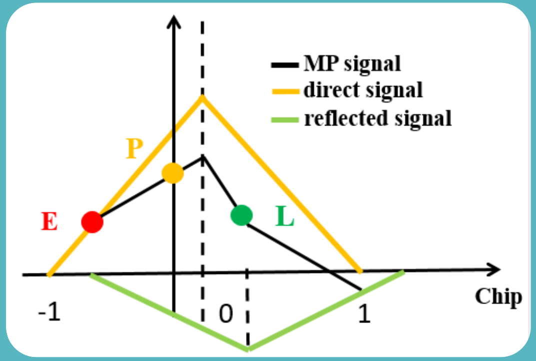
LOS signal



NLOS signal



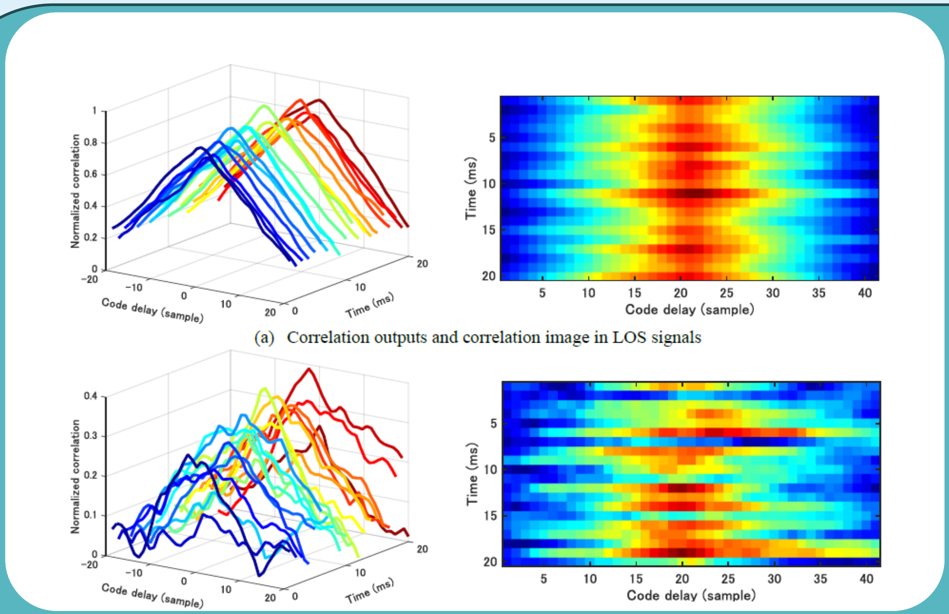
Constructive Multipath signal



Destructive Multipath signal

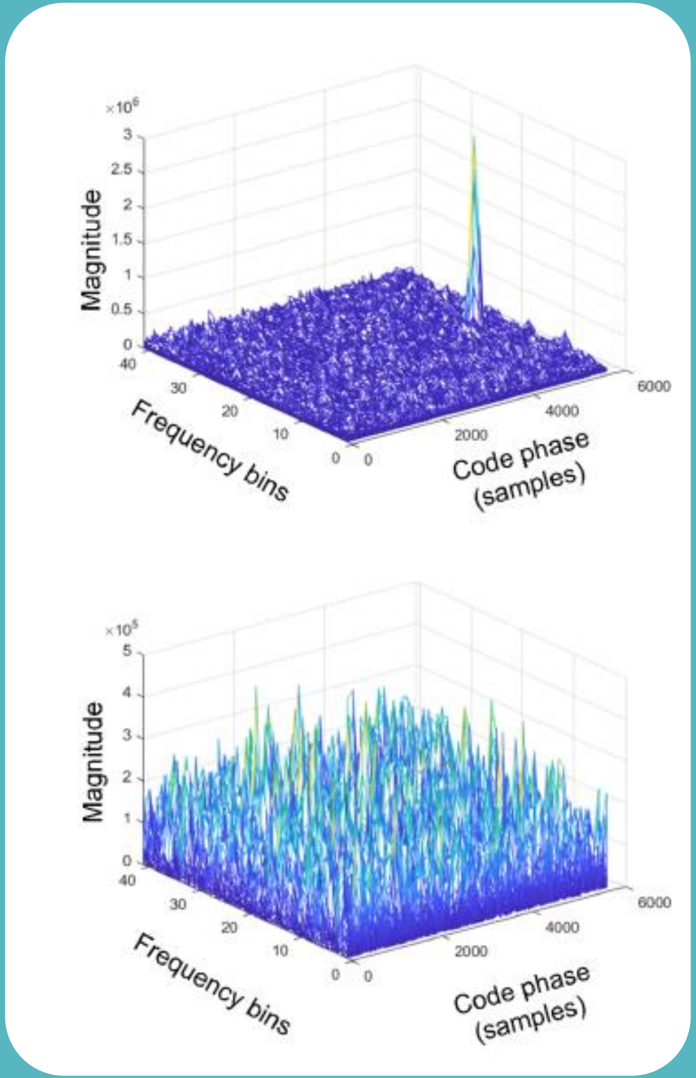
<u>Correlators outputs</u>

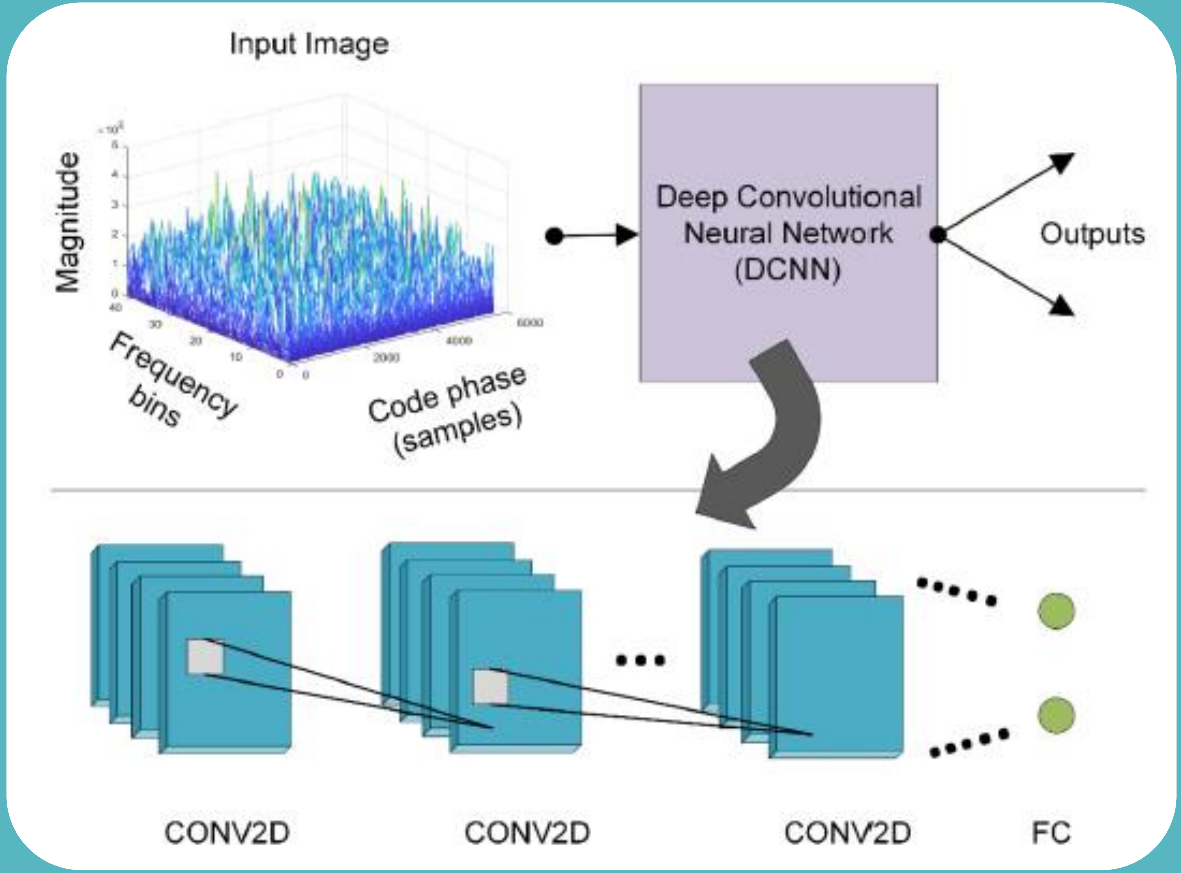
Jiang, C., Chen, Y., Xu, B., Jia, J., Sun, H., He, Z., Wang, T. and Hyyppä, J., 2022. Convolutional Neural Networks Based GNSS Signal Classification using Correlator-Level Measurements. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *46*, pp.61-66.



<u>CNN to learn the NLOS features in GNSS signal correlation outputs</u>

Suzuki, T., Kusama, K. and Amano, Y., 2020, September. NLOS multipath detection using convolutional neural network. In Proceedings of the 33rd International Technical Meeting of the Satellite Division of the Institute of Navigation (ION GNSS+ 2020) (pp. 2989-3000).





<u>Detection outline of GPS signal acquisition by using the CNN and fully connected layer</u>

<u>CAF results for code phase/Doppler grid in the: (top) presence, and (bottom) absence of signal</u>

Moradi, N., Nezhadshahbodaghi, M. and Mosavi, M.R., 2023. GPS signal acquisition based on deep convolutional neural network and post-correlation methods. GPS Solutions, 27(3), p.132.

Brief Methodology

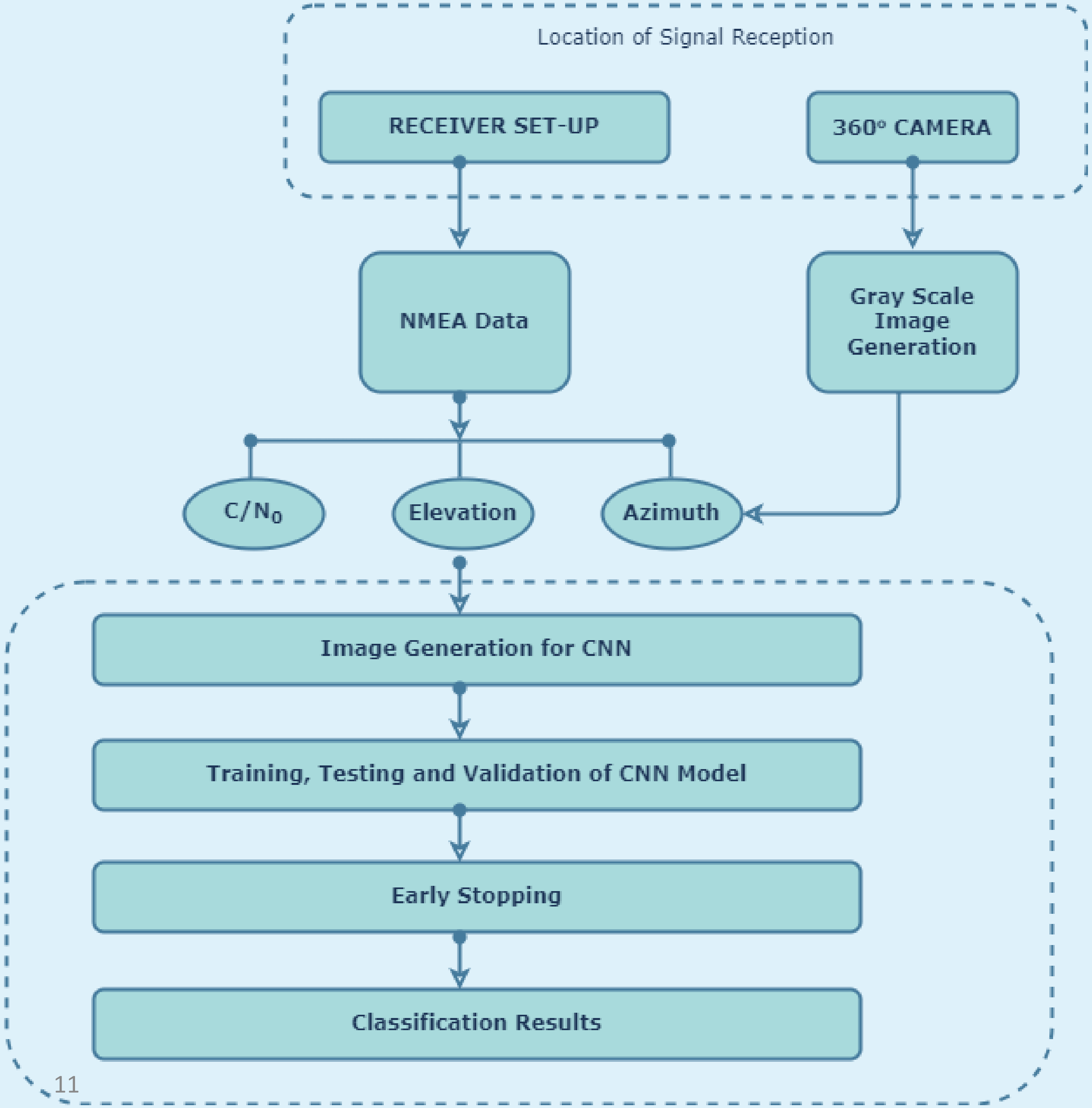
The methodology is divided into different steps:

1. Data Collection: The dataset containing many LOS, NLOS, and multipath signals has been used to train the DL algorithm. The NavIC/GPS measurements have been collected in several urban canyon environments with proper data marking.

2. Data Analysis and Feature Engineering: The DL-based algorithm is used to train the marked training dataset to extract classification rules. The extracted rules are then used to classify newly collected unlabelled NavIC/ GPS measurements. The values of C/N_0, elevation, and azimuth details of the individual satellite have been taken from the NMEA data for the GPS and NavIC systems. Along with that, the 360^0 images of the specific location are acquired, and grayscale images are generated through image processing. These details have been combined to generate the skyplot classification image as an input to the CNN model.

3. Designing a neural network for the task: Depending on the data, network architecture is chosen. Here, CNN is applied to classify the signal in terms of LOS, NLOS, and multipath signals.

4. Hyperparameter tuning until convergence is achieved: Hyperparameter tuning will be done depending on the architecture. To prevent overfitting or underfitting, proper methods for regularization is adopted. In this study, the early stopping regularization technique is employed to identify the training phase's optimal point at which the model achieves strong generalization and mitigates the risk of overfitting.

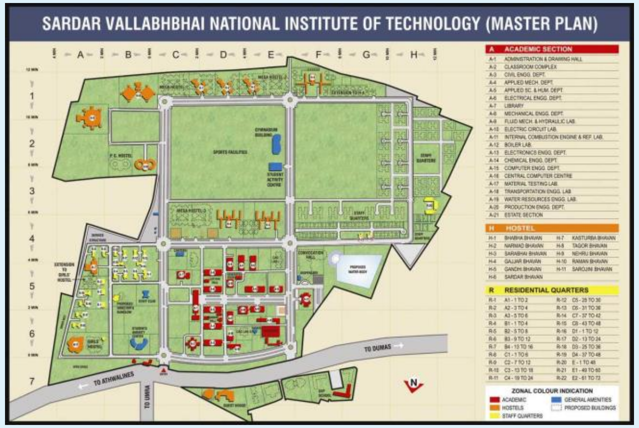


Data Collection:

- Locations with varied sky-views
- Data collected from SVNIT and Outside of Campus

Inside SVNIT Campus		Outside SVNIT Campus	
A.1	ECED	B.1	Green City 1
A.2	Above ECED	B.2	Green City 2
A.3	Between ECED & CHED	B.3	Green City 3
A.4	Behind NCRC	B.4	Green City 4
A.5	Behind SVB	B.5	Pal Umra bridge
A.6	SAC Ground	B.6	Suman Bhargav
A.7	SAC Ground Entrance		
A.8	Residential Quarters		

Data Collection: Inside SVNIT Campus



250 acres of area

A.1 ECED

A.2 Above ECED

A.3 Between ECED & CHED

A.8 Residential Quarters

A.4 Behind NCRC

A.5 Behind SVB

A.6 SAC Ground

A.7 SAC Ground Entrance

Location: Sardar Vallabhbhai National Institute of Technology, Ichchhanath,Surat-395007, Gujarat, INDIA.

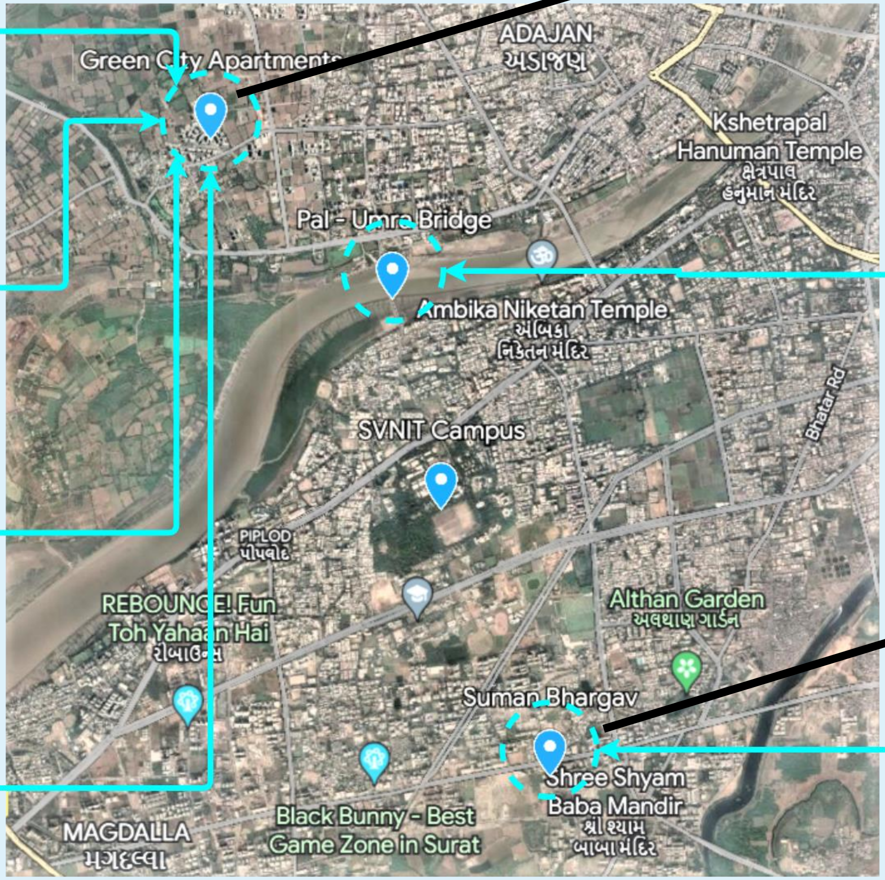
Data Collection: Outside SVNIT Campus

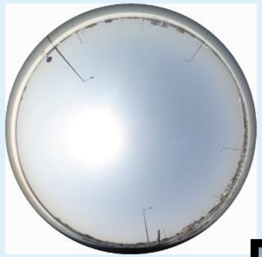
B.1 Green City 1

B.2 Green City 2

B.3 Green City 3

B.4 Green City 4





B.5 Pal Umra Bridge

B.6 Suman Bhargav

Location: Green City Apartments, PAL, Surat-395009, Gujarat, INDIA. (B.1 to B.4), Pal Umra Bridge (B.5), Suman Bhargav apartments Vesu , Surat (B.6)

Data Analysis and Feature Engineering

Real-Time Data Collection

1. Setting up the Receiver System & Camera

- **Ensuring proper position and orientation of the Camera**
- **North-South alignment of the camera axis**

2. Configuring System Parameters

- **UBLOX ANN Antenna + NTLab 103 Receiver**
- **Multiple frequency band support**
- **Variety of configuration options**
- **Constellation : GPS & NavIC**
- **Message Format: NMEA**

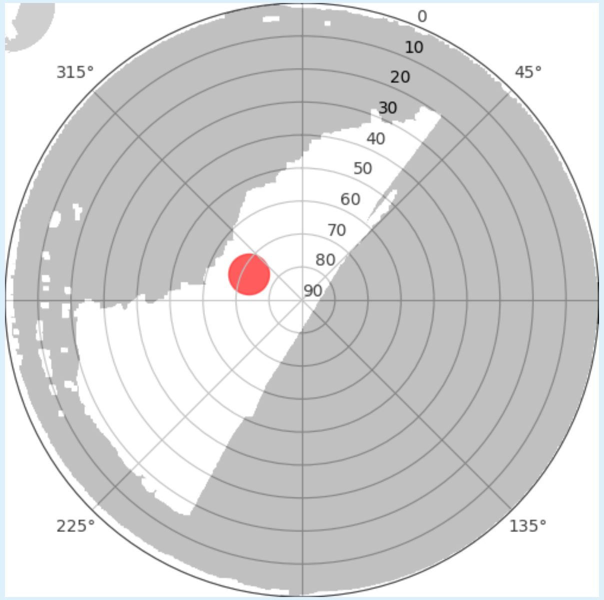
3. Initialization and Monitoring

- **Data was collected for at least 15-20 minutes at each location.**
- **System was monitored throughout the process to ensure proper recording**

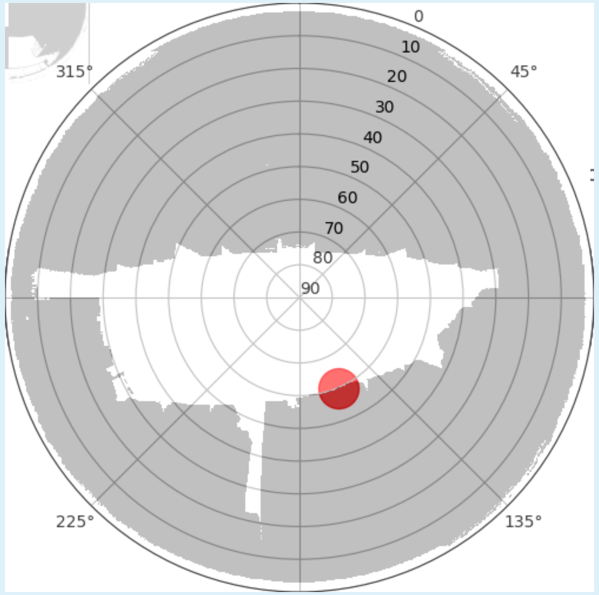
Data Post Processing

- **Some of the Generated Images (for NavIC Constellation):**

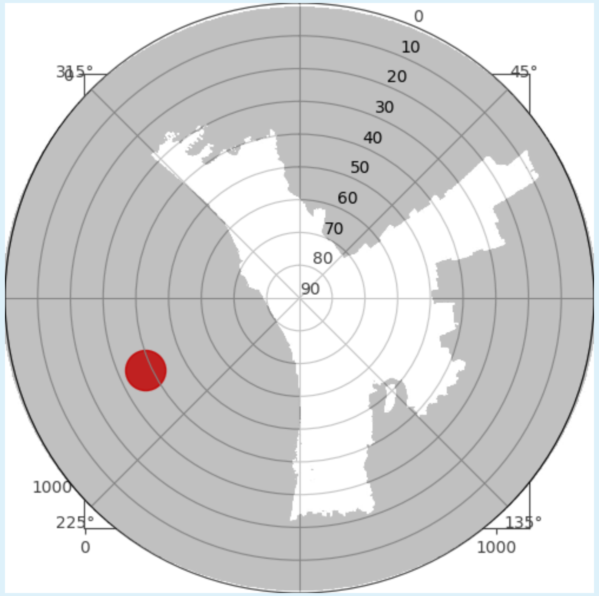
LOS



Multipath



NLOS

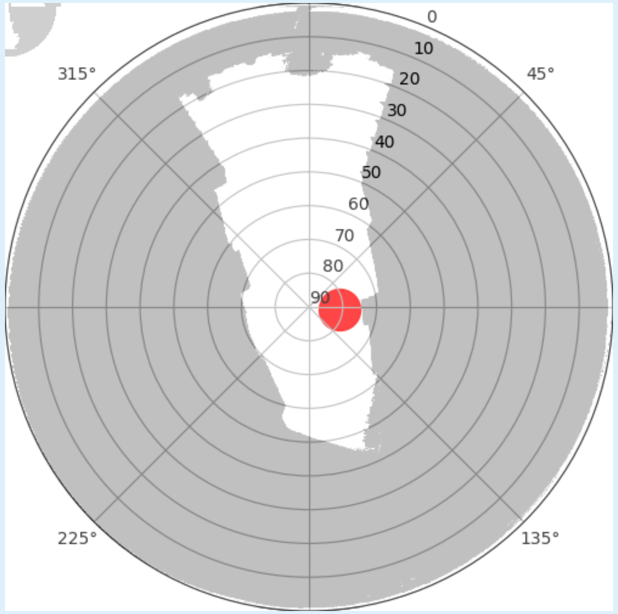


The opacity of the dot is shown according to the value of C/N_0 in above figures.

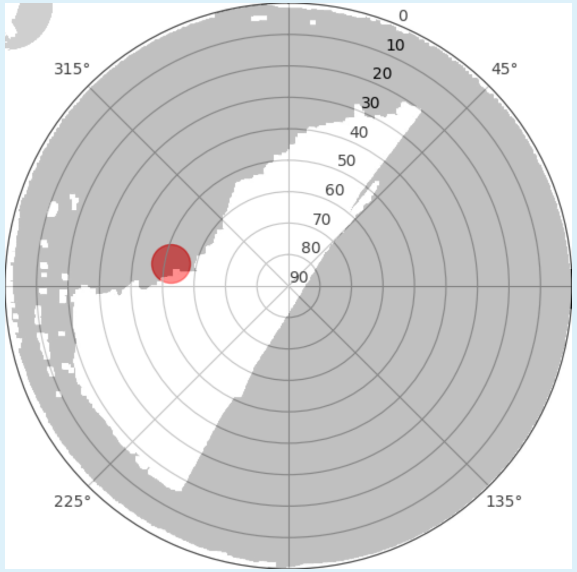
Data Post Processing

- **Some of the Generated Images (for GPS Constellation):**

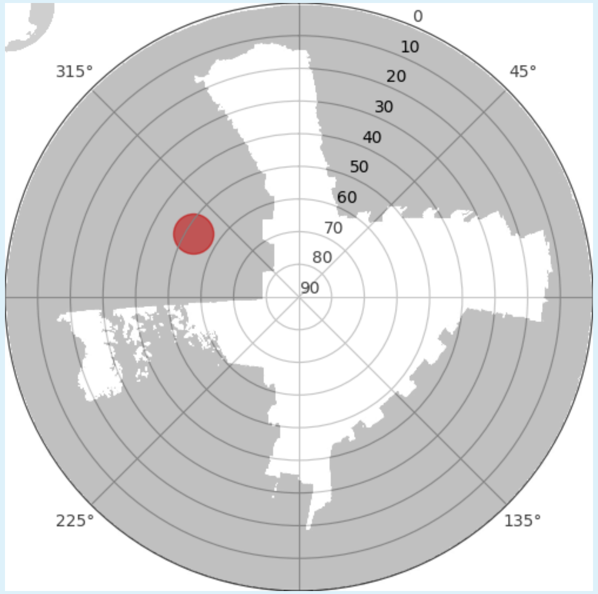
LOS



Multipath



NLOS



The opacity of the dot is shown according to the value of C/N_0 in above figures.

Classification Algorithm

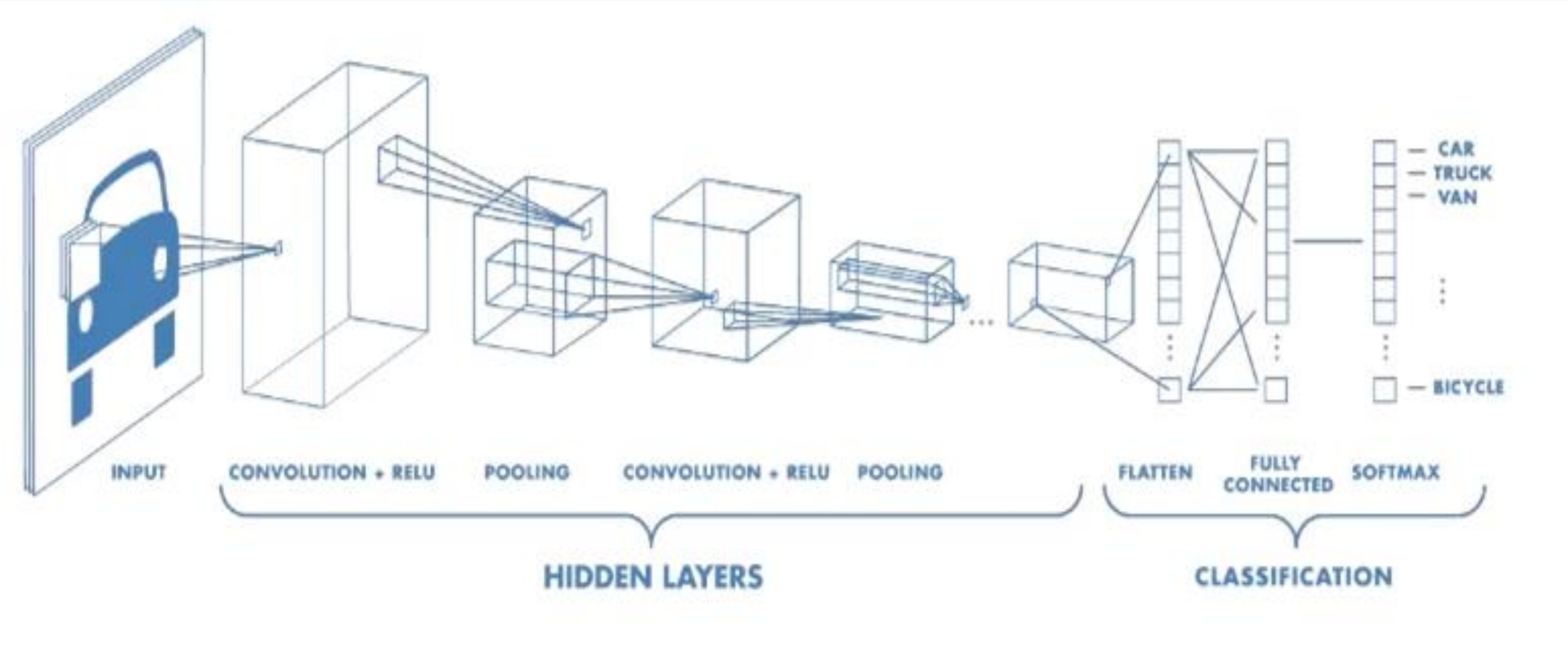
Convolutional Neural Networks

- **A CNNs, is a class of neural networks that specializes in processing data that has a grid-like topology, such as an image.**

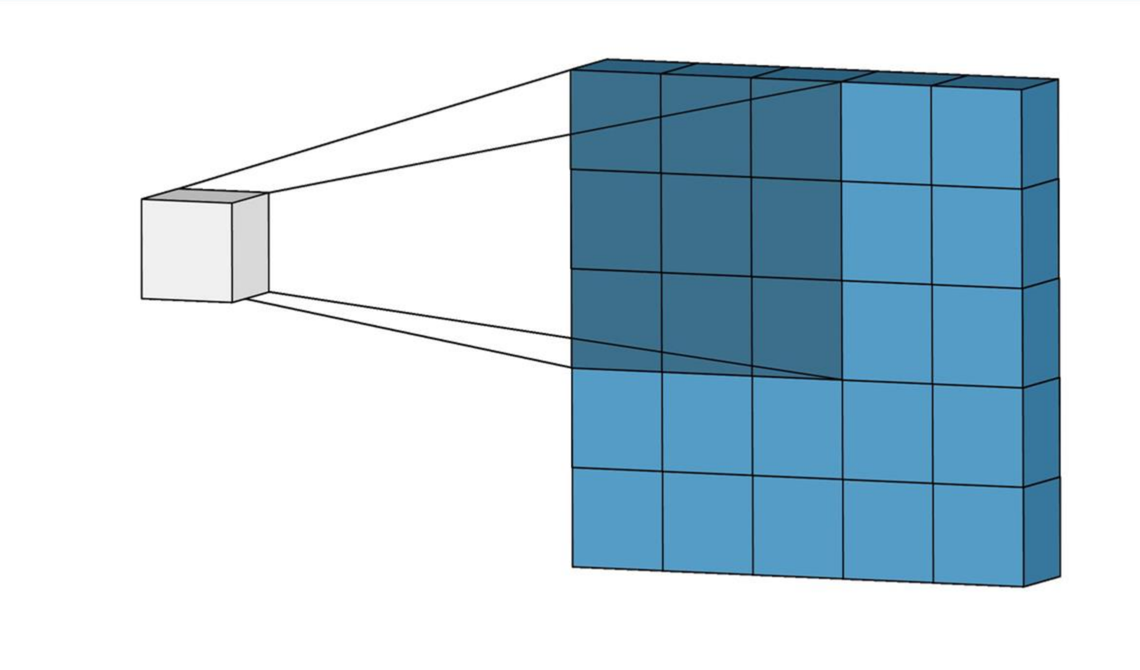
- **A typical CNN has three layers:**
  - **Convolution layer**
  - **Pooling layer**
  - **Fully connected layer**

Convolutional Neural Network

A convolutional layer is designed to extract features. Multiple kernel filters are employed in the convolutional layer to extract the features and characteristics from the input data.



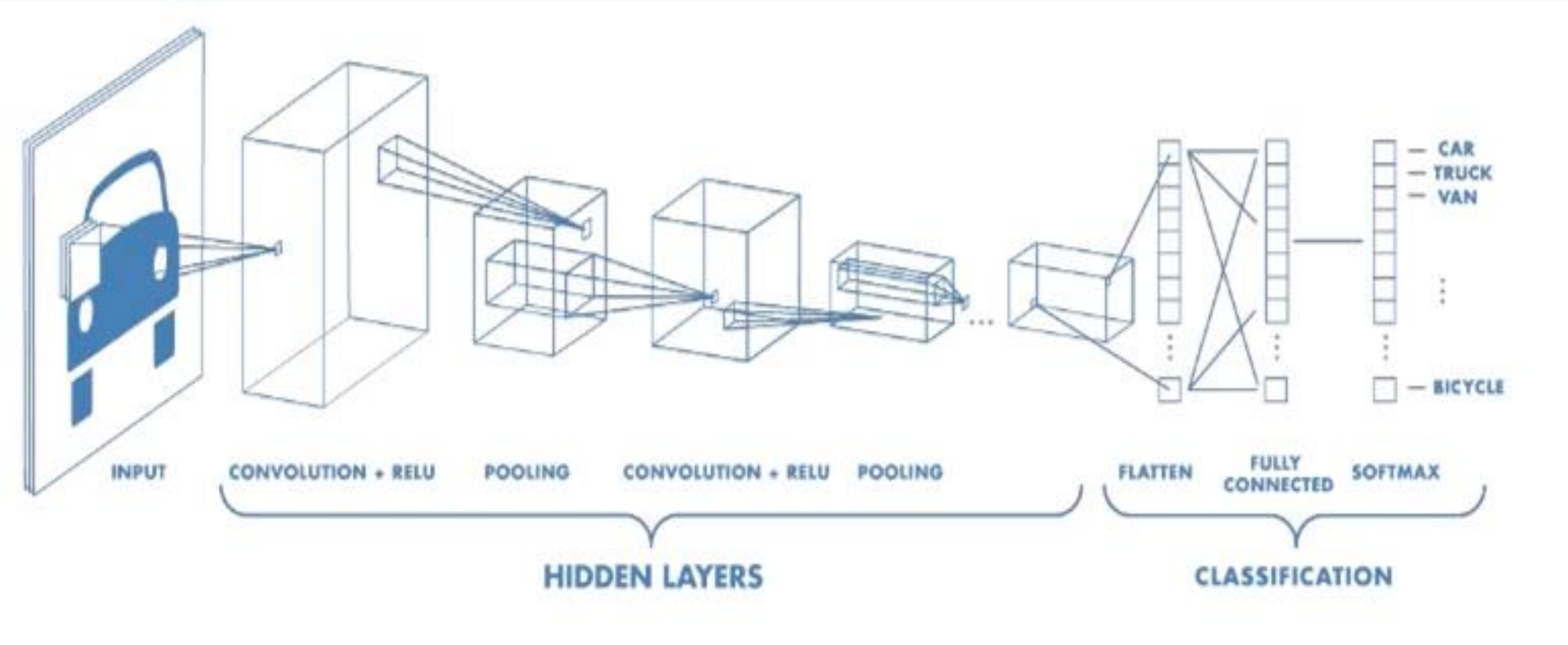
Convolutional Neural Network



- The **CONVOLUTION LAYER** performs a dot product between two matrices, where one matrix is the set of learnable parameters otherwise known as a kernel, and the other matrix is the restricted portion of the receptive field.

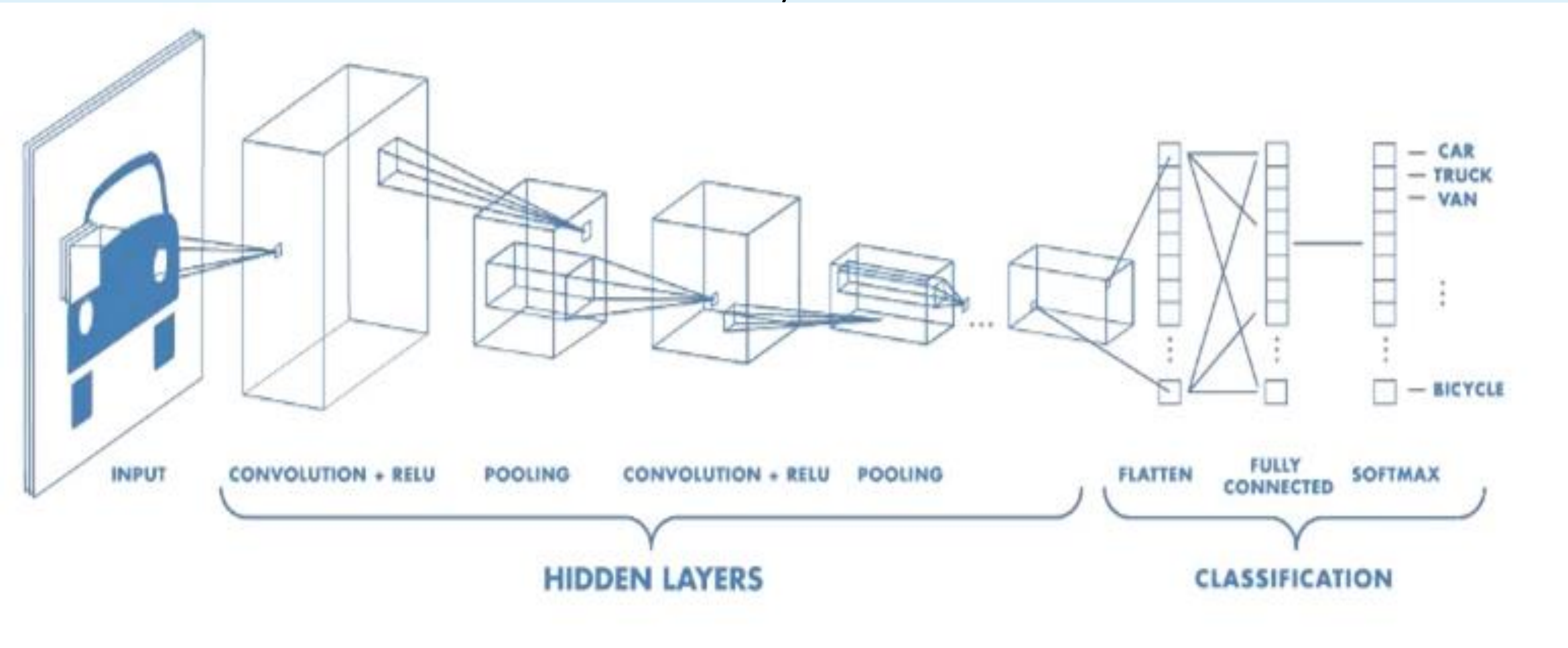
Convolutional Neural Network

After the convolution operation using the kernel filters, the outputs are fed into an activation function

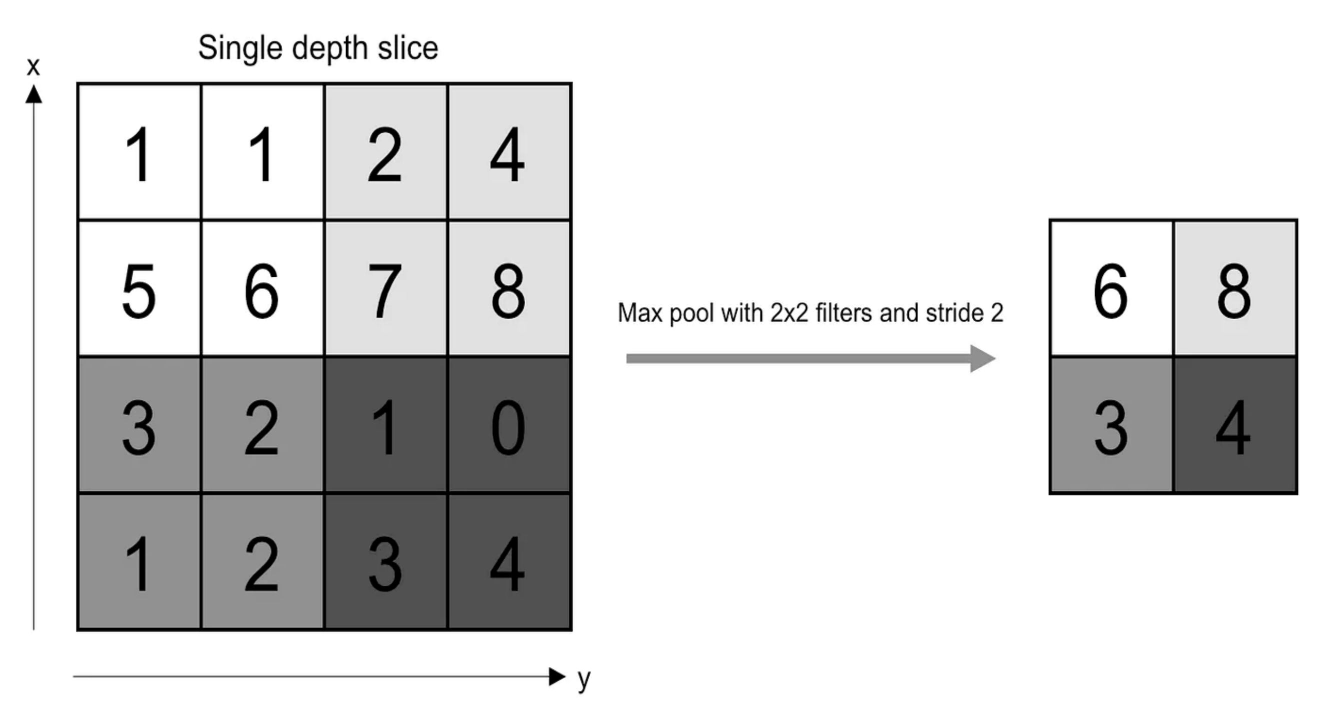


Convolutional Neural Network

Pooling layer is usually added after the convolution layer for spatial reduction through down-sampling the outputs from the convolutional layer. Pooling layer reduces the computation load and time complexity through reducing the tensors’ dimension of the outputs from previous convolutional layer.



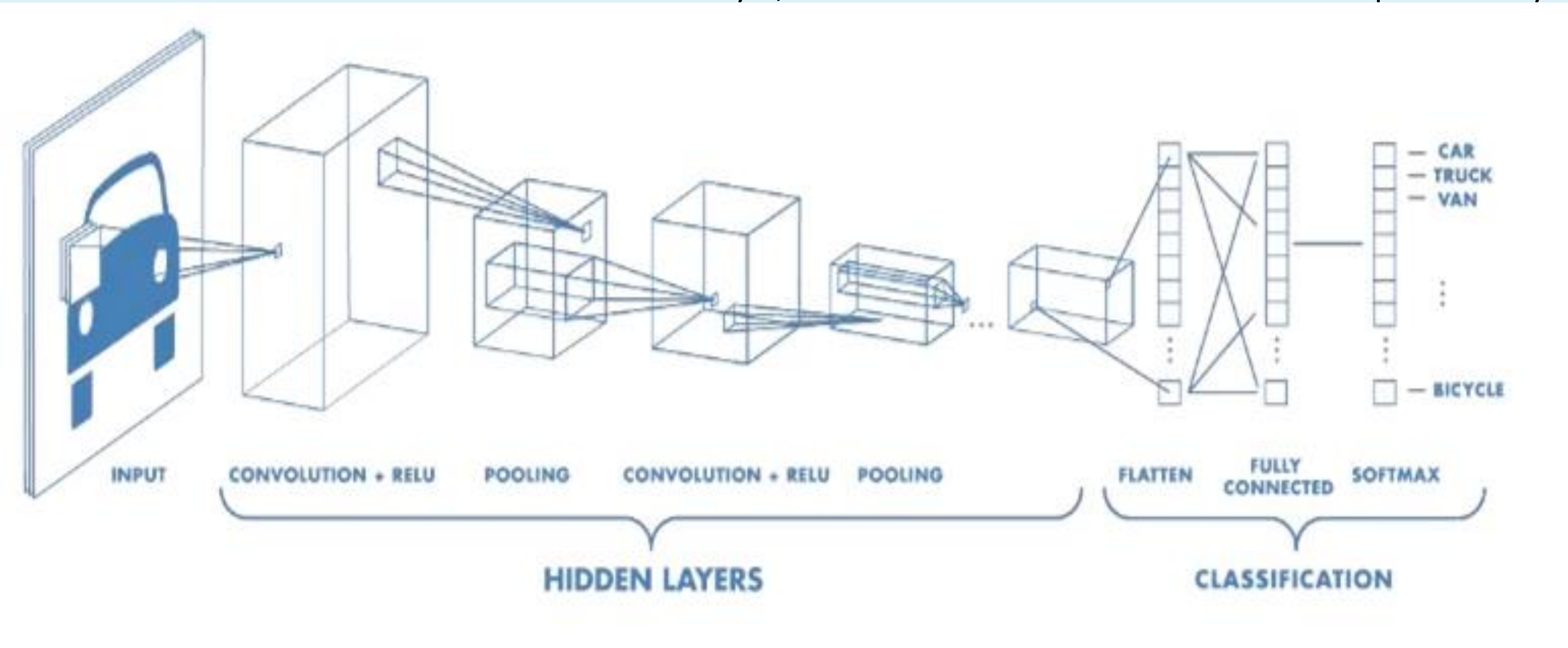
Convolutional Neural Network



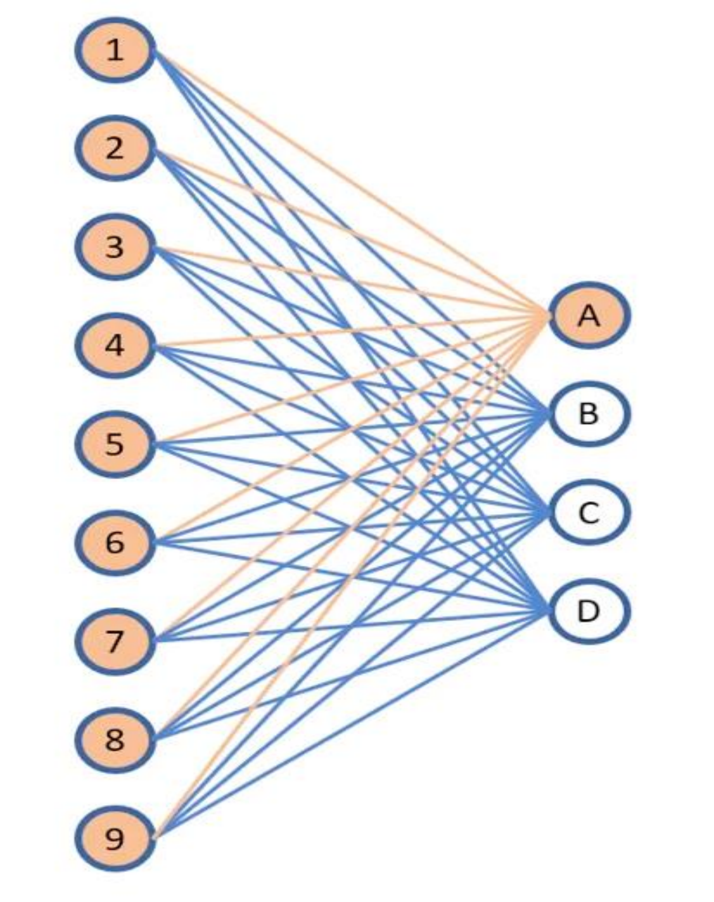
- **The POOLING LAYER replaces the output of the network at certain locations by deriving a summary statistic of the nearby outputs. This helps in reducing the spatial size of the representation.**

Convolutional Neural Network

Convolutional and MaxPooling layers work together to extract the features, and then a fully-connected layer is responsible for selecting the classes' probability using SoftMax function. The class with highest probability is selected as the output of the classifier. In the fully-connected layer, the neurons are all connected to that in previous layer.



Convolutional Neural Network



- Neurons in **FULLY CONNECTED** layer have full connectivity with all neurons in the preceding and succeeding layer as seen in regular FCNN. This is why it can be computed as usual by a matrix multiplication followed by a bias effect.

Convolutional Neural Network

Procedure :

- Considered a single satellite at every epoch
- Used its features like **elevation, azimuth, and C/N$_0$** to plot its position on the corresponding sky-plot (features extracted to be precise).
- Repeat the above for all satellites and for every epoch.
- Generated the dataset from the images, using **ImageDataGenerator** class present in **keras**.
- And finally **train the CNN model** using the generated dataset, 65% for training, 15% for validation, and 20% for testing.
- Have also employed **Early stopping** to prevent overfitting and reduce the overhead of too many excess computations.,

Results

Training	**65%**
Testing	20%
Validation	15%

	GPS	NavIC	GPS + NavIC
No. of Images	39684	24039	63723
No. of Epochs	50	50	50
Early Stopped at	13	10	13
Accuracy(%)	98.46	98.42	98.99
Loss	0.0365	0.0396	0.0263

Results

```
user@workstation:~$ nvidia-smi
Thu Apr 27 15:45:05 2023
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 515.57       Driver Version: 515.57       CUDA Version: 11.7     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  NVIDIA RTX A6000     Off  | 00000000:01:00.0  On |                  Off |
| 30%   46C    P8    20W / 300W |    488MiB / 49140MiB |      2%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|    0   N/A  N/A      3111      G   /usr/lib/xorg/Xorg                 39MiB |
|    0   N/A  N/A      3359      G   /usr/bin/gnome-shell               78MiB |
|    0   N/A  N/A      4707      G   /usr/lib/xorg/Xorg                132MiB |
|    0   N/A  N/A      4839      G   /usr/bin/gnome-shell               62MiB |
|    0   N/A  N/A      6626      G   /usr/lib/firefox/firefox          172MiB |
+-----------------------------------------------------------------------------+
user@workstation:~$ S
```

Conclusion

Strengths of CNN

- High accuracy rates at image recognition and classification
- Robust to noise and distortion
- Automatic feature extraction
- The number of layers and the structure of the layers can be adapted to fit many types of problems

Weaknesses of CNN

- Require large datasets to achieve high accuracy rates
- Computationally intensive to train.
- Require much more experience to tune them (hyperparameters tunning).
- Limited ability to generalize

Conclusion

The basic idea behind using CNNs for satellite signal classification is to extract features from the skyplot image of single satellite and use them to classify the signal type. CNNs are well-suited to this task because they are able to learn and identify patterns within the signal data.

The convolutional layers of the CNN are used to extract features from the skyplot image of a single satellite signal. The pooling layers are used to reduce the dimensionality of the features and to create a feature map. The feature map is then flattened and fed into one or more fully connected layers, which are used to classify the signal.

To train the CNN, a large dataset of labelled sky plot images of a single satellite signal is required. This dataset should include examples of LOS, NLOS, and multipath signals. The CNN is trained using an iterative process known as backpropagation, where the weights of the network are adjusted to minimize the classification error.
The primary advantage of this algorithm is its ability to produce sky-plot images using just NMEA data and a 360° camera.

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4. Xu, Jia, Luo, and Hsu, “Intelligent GPS L1 LOS/multipath/NLOS classifiers based on correlator-, RINEX- and NMEA-level measurements,” Remote Sensing, vol. 11, no. 16, p. 1851, 2019.
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7. Jiang, C., Chen, Y., Xu, B., Jia, J., Sun, H., He, Z., Wang, T. and Hyyppä, J., 2022. Convolutional Neural Networks Based GNSS Signal Classification using Correlator-Level Measurements. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 46, pp.61-66.
8. Suzuki, T., Kusama, K. and Amano, Y., 2020, September. NLOS multipath detection using convolutional neural network. In Proceedings of the 33rd International Technical Meeting of the Satellite Division of the Institute of Navigation (ION GNSS+ 2020) (pp. 2989-3000).
9. Moradi, N., Nezhadshahbodaghi, M. and Mosavi, M.R., 2023. GPS signal acquisition based on deep convolutional neural network and post-correlation methods. GPS Solutions, 27(3), p.132.

Journal Publications

1. Mehul V. Desai, Dr. Shweta N. Shah, "Ionodelay models for Satellite Based Navigation System", IEEE African Journal of Computing & ICT, Vol 8. No. 2 Issue 2, pp: 25- 32, August, 2015
2. Mehul V. Desai, Shah, S.N., Impacts of intense geomagnetic storm on NAVIC/IRNSS system,, Annals of Geophysics, Volume 61, Issue 5, 2018, Article number GE557, DOI: 10.4401/ag-7856
3. Mehul V. Desai, Shah, S.N., "The GIVE ionospheric delay correction approach to improve positional accuracy of NavIC/IRNSS single-frequency receiver", Current Science, Volume 114, Issue 8, 25 April 2018, Pages 1665-1676, DOI: 10.18520/cs/v114/i08/1665-1676
4. Jagiwala, D.D., Shah, S.N., "Impact of Wi-Fi interference on NavIC signal", Current Science, Volume 114, Issue 11, 10 June 2018, Pages 2273-2280, DOI: 10.18520/cs/v114/i11/2273-2280
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7. Priyanka Lineswala, Shweta Shah, "Review of NavIC signals under class II jamming based on power and auto-correlation function monitoring", ACTA GEODAETICA ET GEOPHYSICA, Volume 54, Issue3, Page359-371, 2019
8. Desai, Mehul V., and Shweta N. Shah. "An observational review on influence of intense geomagnetic storm on positional accuracy of NavIC/IRNSS system." IETE Technical Review, 37 (3), 281-295, 2020

Journal Publications

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THANK YOU

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Open for International Collaboration or Research Project

HAPPY FACES…