



Deep Learning-Based Multipath Detection in GNSS Signals

Using Delay-Doppler Correlation Maps and CNN Classification

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Introduction

GNSS Multipath Problem & Motivation

GNSS Multipath Problem



Urban Challenge

Signal Reflections

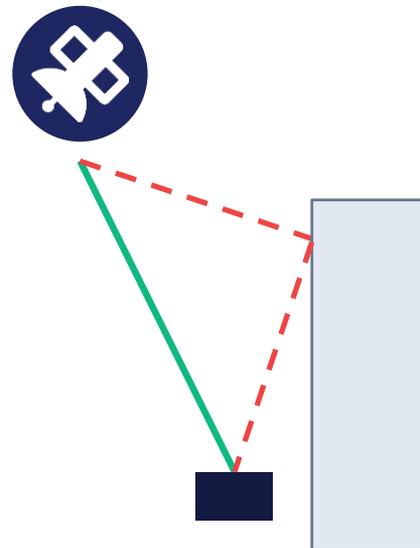
Signals bounce off buildings, vehicles, and terrain before reaching the receiver

Correlation Distortion

Multiple signal paths distort the correlation function used for ranging

Position Errors

Pseudorange errors can reach tens of meters in severe conditions



— LOS Signal

- - - Reflected

Multipath Signal Model

Received Signal Model

$$r(t) = s(t) + \sum \alpha_k \cdot s(t - \tau_k) \cdot e^{j(2\pi f_{\{d,k\}}t + \phi_k)} + n(t)$$

LOS signal + K multipath reflections + noise

α_k

Amplitude ratio

[-20, -3] dB

τ_k

Path delay

10-300 m

$f_{\{d,k\}}$

Doppler offset

Variable Hz

ϕ_k

Phase offset

[0, 2π]



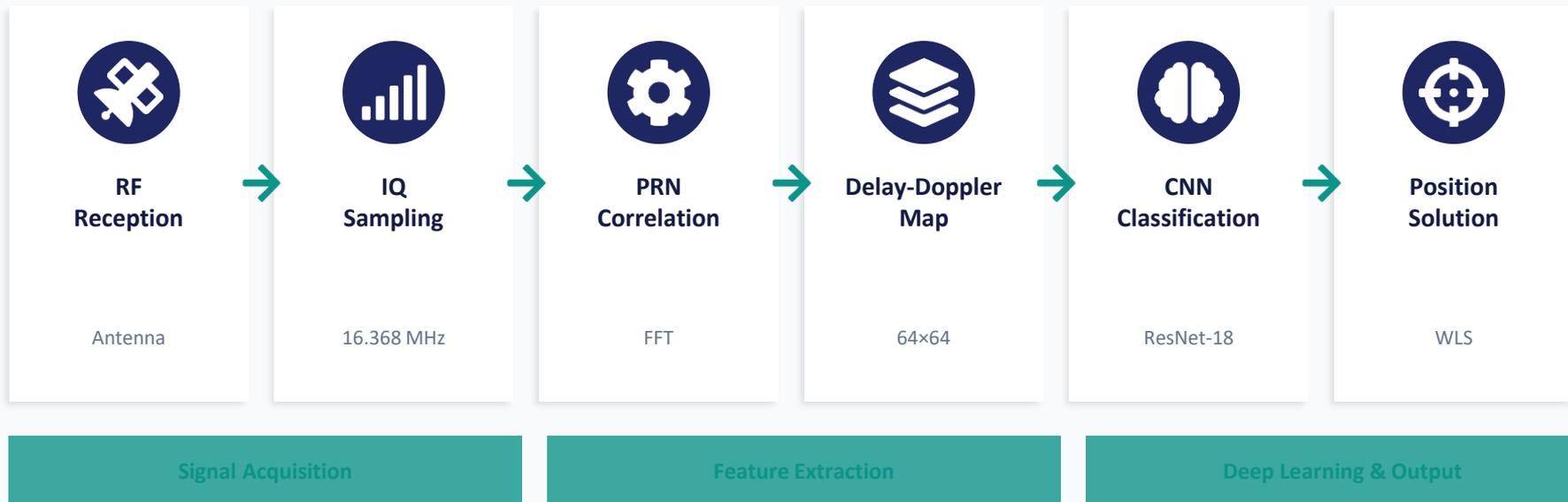
Key Insight: If we can estimate α , τ , and phase relationship, we can correct the pseudorange measurement

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Methodology

Correlation Maps & CNN Classification

End-to-End Processing Pipeline



Novel contribution: 2D Delay-Doppler maps as standardized CNN input → enables transfer learning across receivers

Delay-Doppler Correlation Maps

Correlation Function

$$R(\tau, f^d) = |\sum r[n] \cdot c^*[n-\tau] \cdot e^{(-j2\pi f^d n T_s)}|^2$$

τ spans code delay search range

f^d spans Doppler frequency range

Result:

64x64 2D image capturing signal characteristics

Correlation Map Examples

Clean

Weak MP

Severe MP

NLOS

Four-Class Severity Classification

Class 0

CLEAN

No multipath

Class 1

LOS_WITH_MP

Weak ($\alpha < -10$ dB)

Class 2

SEVERE_MP

Strong ($\alpha > -6$ dB)

Class 3

NLOS

LOS blocked

03

CNN Architecture

Network Design & Training Strategy

CNN Architectures Evaluated

SimpleCNN

2.2M

parameters

3-layer baseline with batch norm

ResNet-18

11.2M

parameters

Skip connections for deep learning

★ BEST

VGG-Small

2.5M

parameters

Sequential 3×3 convolutions

ShallowConv

47K

parameters

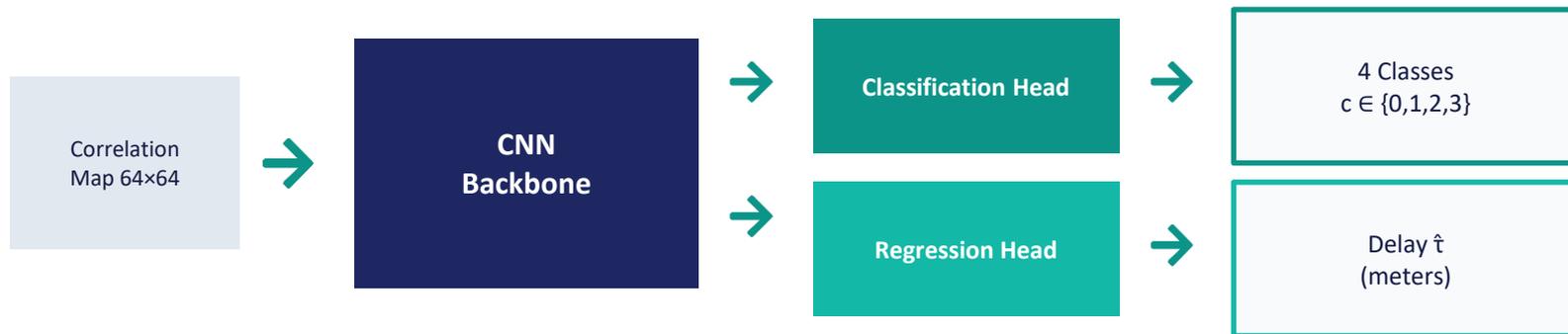
Minimal 2-layer lightweight

ResNet-18: Residual Learning

$$y = F(x, \{W_i\}) + x$$

Skip connections allow gradients to flow directly through the network, mitigating vanishing gradient problem and enabling deeper feature extraction.

MultipathEstimator: Joint Classification & Regression



Multi-task Loss

$$L = L_{cls} + \lambda_{reg} \cdot L_{reg} + \lambda_{conf} \cdot L_{conf}$$

Weighted cross-entropy + MSE regression

Pseudorange Correction

$$\Delta\rho = \alpha_c \cdot \min(\hat{\tau}, 30m) \cdot \gamma$$

$\rho' = \rho - \Delta\rho$ (corrected pseudorange)

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Experimental Results

Classification & Position Accuracy

Dataset & Training Configuration



Dataset

- GPS L1 C/A signals (PRN 1-5)
- Sampling: 16.368 MHz
- Map resolution: 64×64
- SNR: 35-45 dB-Hz
- 10,000 total samples
- Train/Val/Test: 70/15/15%



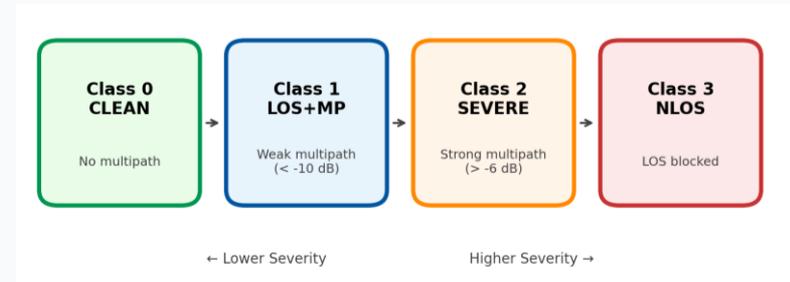
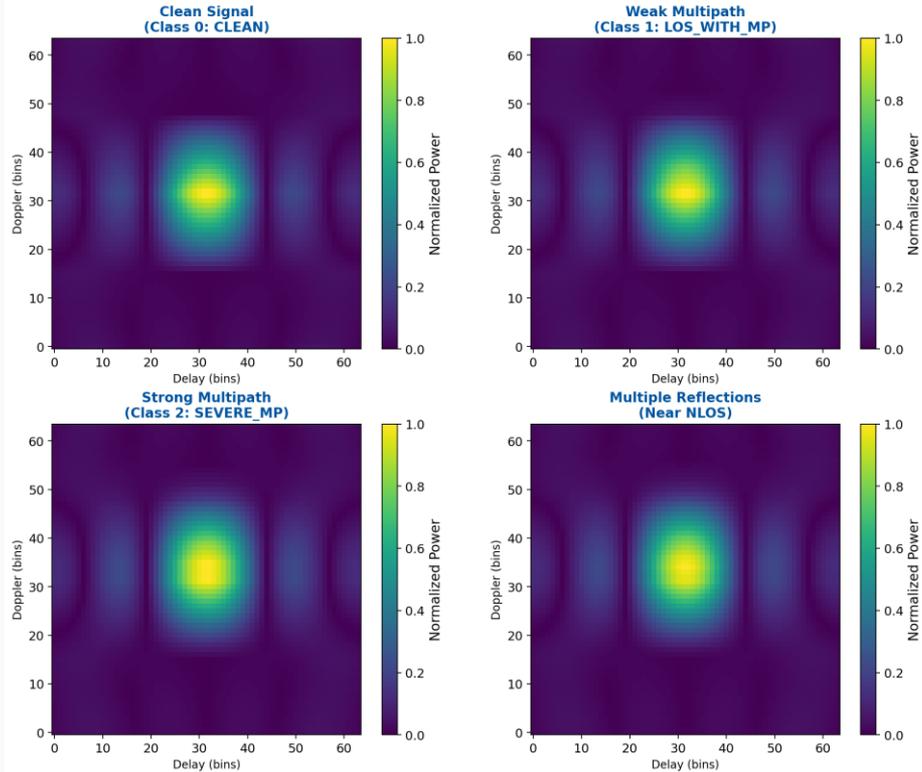
Training

- Optimizer: AdamW
- Learning rate: 10^{-3} (cosine)
- Batch size: 64
- Early stopping: 10 epochs
- Mixed precision (FP16)
- Hardware: RTX A4000

Class Distribution: 25% Clean | 75% Multipath (distributed across severity levels)

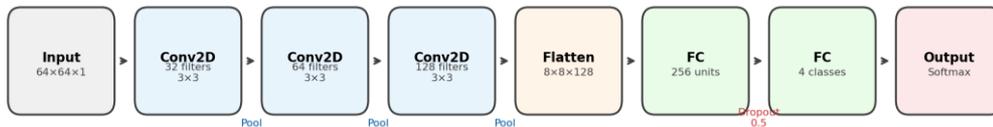
Multipath

Delay-Doppler Correlation Maps: Multipath Effects

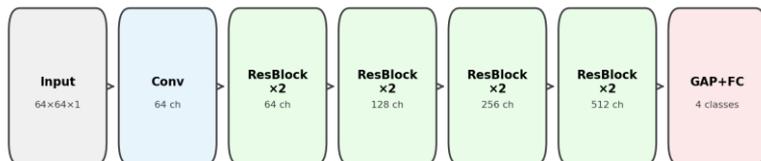


NN Classification

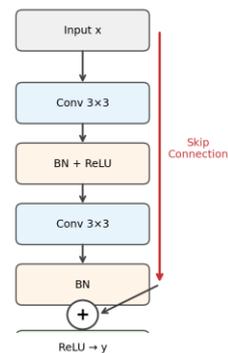
SimpleCNN Architecture



ResNet-18 Architecture



Residual Block



Classification Performance Comparison

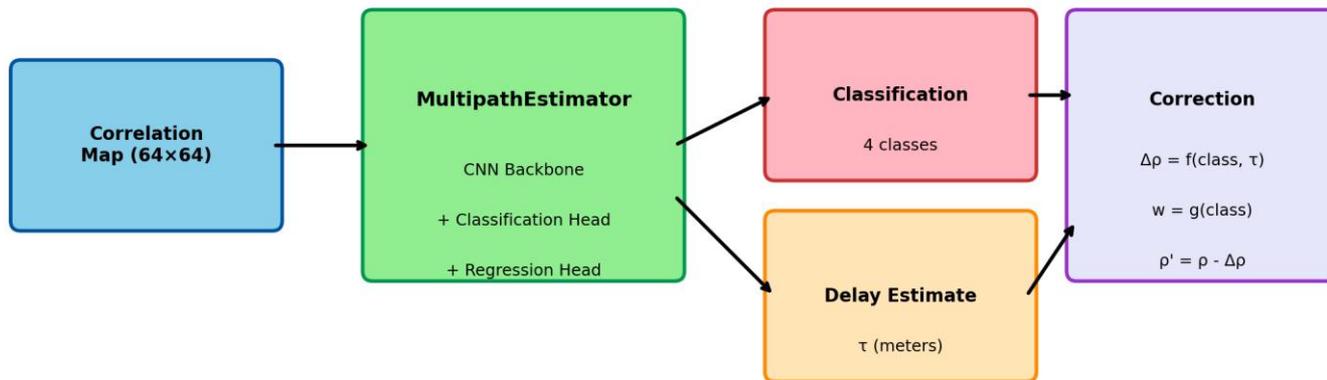
Model	Parameters	Accuracy	F1 Macro	Precision
SimpleCNN	2.2M	70.2%	0.538	0.560
ResNet-18	11.2M	95.4%	0.830	0.768
VGG-Small	2.5M	27.2%	0.156	0.178
ShallowConv	47K	66.9%	0.268	0.241

Key Findings

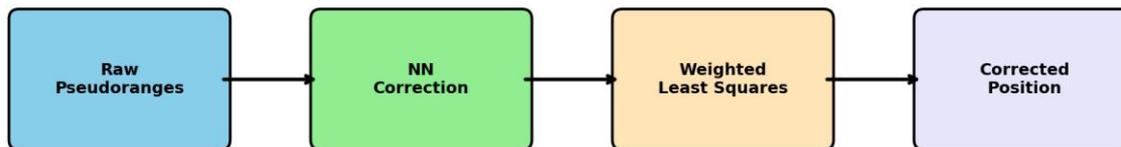
- ResNet-18 achieves best performance (95.4% accuracy, 0.830 F1)
- Skip connections crucial for learning correlation patterns
- VGG suffered from vanishing gradients without residual connections

Classification Performance Comparison

Neural Network Multipath Correction Method



Position Solution Pipeline



Position Accuracy Evaluation

Environment	No MP	No Mitigation	Simple	NN Corr.	Improv.
Open Sky	2.43 m	2.63 m	2.56 m	2.75 m	—
Suburban	2.43 m	5.09 m	3.77 m	4.61 m	9%
Urban	2.43 m	14.25 m	16.14 m	10.98 m	23%
Urban Canyon	2.43 m	21.97 m	35.31 m	18.16 m	17%

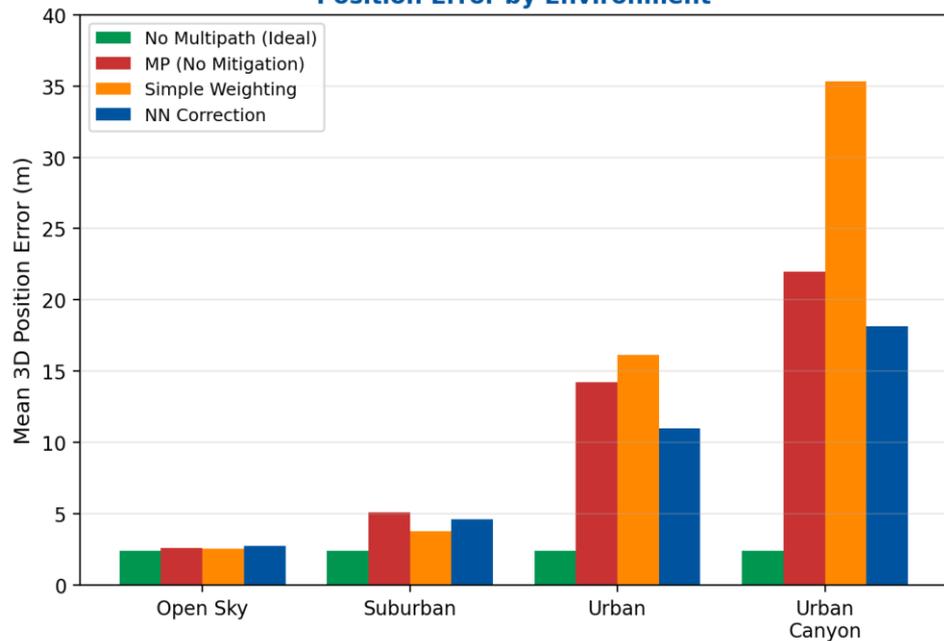


Key Insight: Correction vs Exclusion

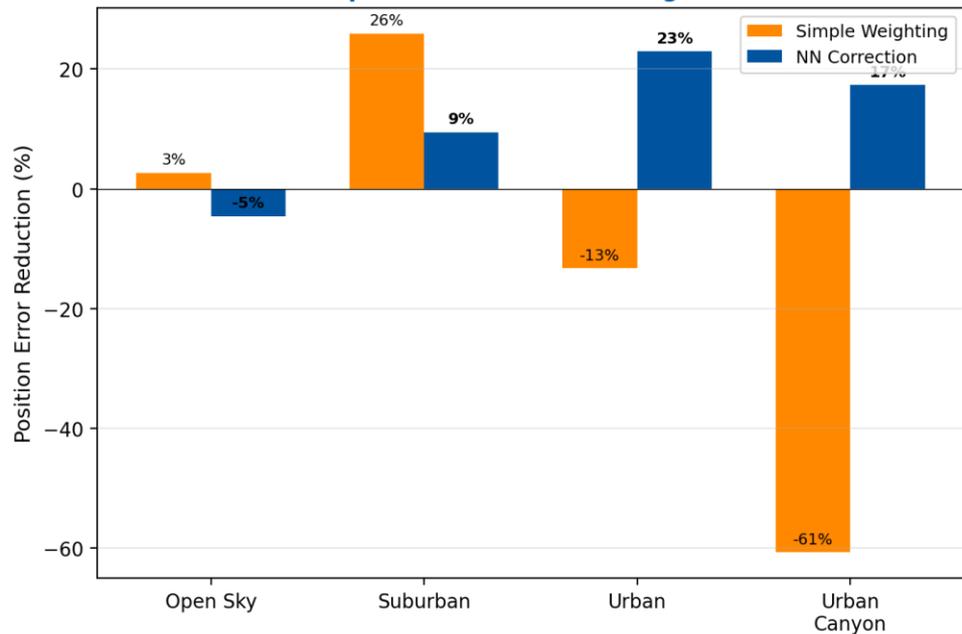
Simple weighting degrades in urban canyons because excluding satellites worsens geometry (DOP). NN correction maintains geometry by correcting measurements rather than excluding them.

Position Accuracy Evaluation

Position Error by Environment



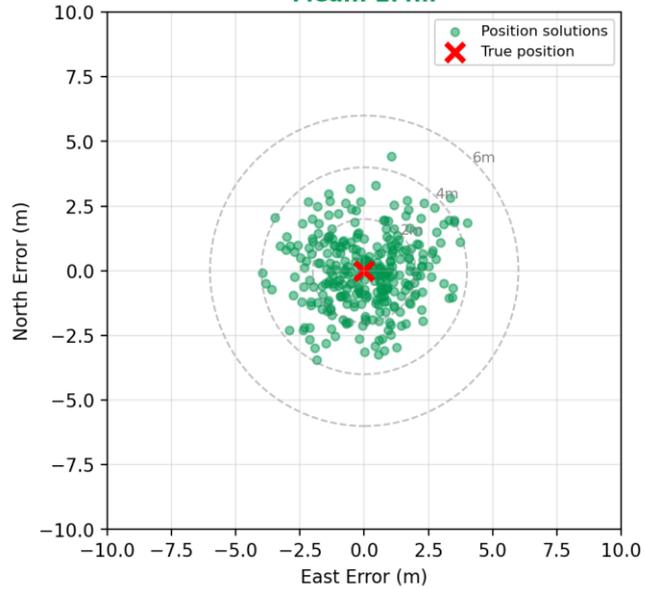
Improvement Over No Mitigation



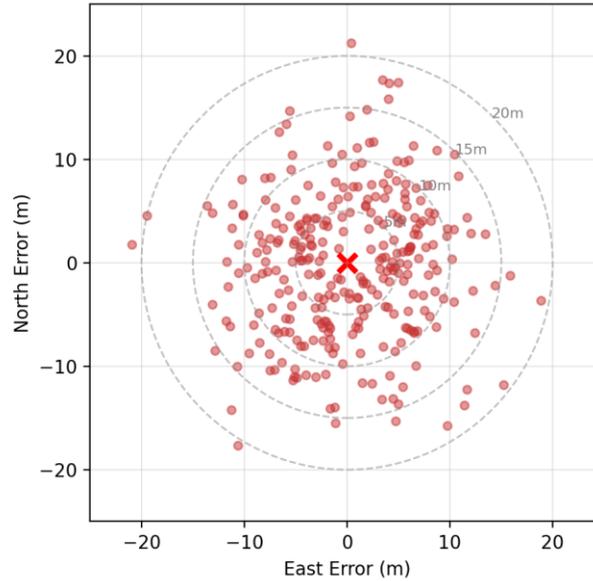
Position Accuracy Evaluation

Position Solution Scatter - Urban Environment

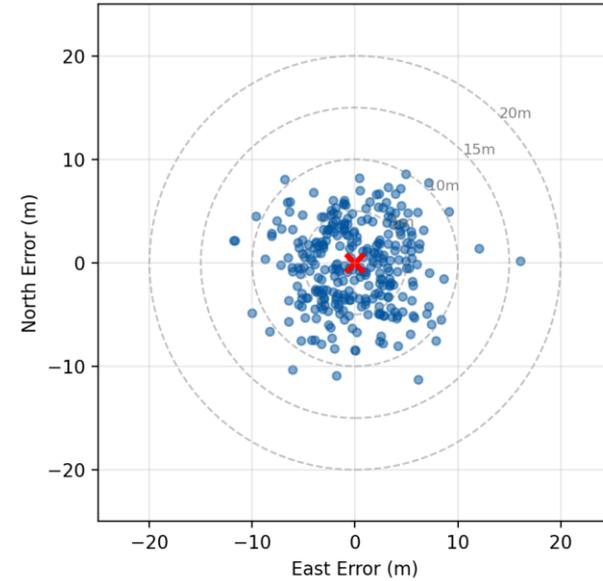
No Multipath (Ideal)
Mean: 2.4m



With Multipath (No Correction)
Mean: 14.3m



With NN Correction
Mean: 11.0m (23% improvement)



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Conclusions

Summary & Future Directions

Key Results & Contributions

95.4%

Classification
Accuracy

23%

Urban Position
Improvement

17%

Urban Canyon
Improvement

~15m

Delay Estimation
MAE

Contributions

- Novel 2D delay-Doppler map representation for CNN-based multipath detection
- Comprehensive architecture comparison (SimpleCNN, ResNet, VGG, ShallowConv)
- Joint classification-regression model enabling pseudorange correction
- Proof that correction outperforms exclusion by preserving satellite geometry

Future Directions



Real-World Validation

Test on actual GNSS receiver data from urban environments

Multi-Constellation

Extend to GPS + Galileo + BeiDou integration



Real-Time Deployment

Optimize for embedded GNSS receiver implementation



Carrier Phase

Extend to carrier phase multipath for high-precision applications

Thank You!

Questions?



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