Neural Architecture Search for Over-the-Air Telecommunication Signal Classification

Achieving 96.29% Accuracy with Optimized CNN Architecture

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November 10, 2025

Outline

Introduction

The Challenge

Traditional approaches to signal classification rely on manually designed architectures, often suboptimal for telecommunication signal characteristics.

Current Limitations:

- Manual architecture design is tedious
- General CNN designs not signal-optimized
- Limited exploration of design space
- Computational efficiency often overlooked

Applications:

- Spectrum monitoring
- Electronic defense systems
- Cognitive radio networks
- Software-defined radio

Research Hypothesis

Systematic exploration of CNN architecture space can yield networks that better exploit time-frequency signal representations while maintaining computational efficiency.

Main Contributions

1. **Comprehensive NAS Framework:** Explored 63M configurations using Bayesian optimization

2. **High-Performance Model:** 96.29% accuracy with only 91,367 trainable parameters

3. **Efficient Search Process:** 20 trials in 1h 21m, discovering optimal architecture in trial 17

4. **Real-World Validation:** Tested on over-the-air signals with wide SNR range (-20 dB to 18 dB)

5. **Architectural Insights:** Identified key design principles for signal classification CNNs

Dataset & Methodology

Dataset Specifications

Parameter	Value
Total Records	567,000 labeled signals
Selected Records	35,000 (5,000 per class)
Signal Classes	7 types
SNR Range	-20 dB to 18 dB
Center Frequency	2.4–2.5 GHz
Sampling Rate	10 MS/s
Sample Length	256 samples (128 I + 128 Q)
Hardware	USRP N210 + VERT2450
Data Split	70%/15%/15% (train/val/test)

Signal Categories

- AM Combined
- BPSK SATCOM
- FMCW Radar Altimeter
- PULSED Air-Ground-MTI
- PULSED Airborne Detection
- PULSED Airborne Range
- PULSED Ground Mapping

Spectrogram Configuration

Time-Frequency Representation:

- Signal duration: 12.8 μs
- Spectral parameters: nperseg=64, noverlap=32
- Output dimensions: 33×7×1
- Frequency bins: 33
- Time segments: 7

STFT Parameters

Short-Time Fourier Transform:

- Window size: 64 samples
- Overlap: 50% (32 samples)
- Good temporal-spectral balance
- Preserves spatial structure
- Computationally efficient

Design Rationale

This configuration captures essential time-frequency characteristics while maintaining computational efficiency for real-time applications

Neural Architecture Search Framework

Search Space Design

Explored 63M configurations across multiple dimensions:

Convolutional Layers

- Initial filters: 16, 32, 48, 64
- Kernel sizes: 3×3, 5×5, 7×7
- Batch normalization options
- Activation: ReLU, ELU, Swish
- Pooling: max, average

Advanced Mechanisms

- Attention mechanisms
- Residual connections
- Progressive filter scaling
- Global average pooling
- Dropout regularization

Optimization

- Optimizer: Adam, RMSprop
- Learning rate: 1e-5 to 1e-2
- Gaussian noise: 0.05-0.2
- Dense units: 64-256
- Dropout: 0.2-0.5

Objective Function

Balanced classification accuracy with model complexity:

$$\text{Objective} = \alpha \cdot \text{Accuracy} - \beta \cdot \log(\text{Parameters}) \qquad (1)$$

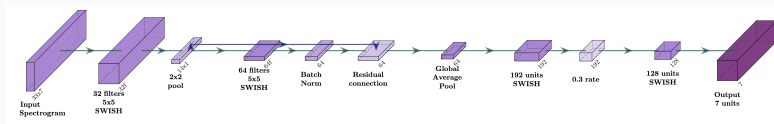where $\alpha = 1.0$ and $\beta = 0.01$

Search Configuration

- **Method:** Gaussian Process-based
- **Acquisition:** Expected Improvement
- **Total trials:** 20
- **Training limit:** 30 epochs per trial
- **Validation:** Cross-validation

Search Results

- **Search time:** 1h 21m 28s
- **Best trial:** 17 out of 20
- **Convergence:** Stable at 30 epochs
- **Efficiency:** Progressive improvement

Optimal Architecture

Key Architectural Features

Progressive filter expansion (32→64) | Uniform 5×5 kernels |
Residual connections | Swish activation | Strategic pooling

NAS Model Specifications

Component	Configuration
Conv Layers	2 layers (32→64 filters)
Kernel Size	Uniform 5×5
Activation	Swish functions
Pooling	Average + Global Avg
Residual	Strategic connections
Batch Norm	2nd layer only
Dense Layers	192 + 128 units
Dropout	0.3 rate
Optimizer	RMSprop
Learning Rate	1.48×10^{-4}

Parameter Efficiency

- **Trainable:** 91,367 parameters
- **Total:** 182,864 parameters
- **Model size:** Compact design
- **Memory:** Low requirements
- **Inference:** Fast processing

Design Insights

- 5×5 kernels optimal for signals
- Swish better than ReLU
- Average pooling preserves energy
- RMSprop suits gradient patterns

Results

Performance Results

Main Results

- **Test Accuracy:** 96.29%
- **Test Loss:** 0.0800
- **SNR Range:** -20 dB to 18 dB
- **Test Set:** 5,250 signals
- **Training:** Stable convergence

Processing Performance

- **Platform:** MacBook Pro M3
- **Speed:** 390 signals/second
- **Feature extraction:** 84% of time
- **Inference:** 16% of time

Table 1: Search Statistics

Metric	Value
Search Time	1h 21m 28s
Total Trials	20
Best Trial	17
Configurations	63M explored
Convergence	30 epochs
Final Accuracy	96.29%
Parameter Count	91,367
Discovery Rate	Progressive

Component Contribution Analysis

Component Removed	Accuracy (%)	Change
Full Model	96.29	-
Residual Connection	95.74	-0.55%
Swish → ReLU	95.21	-1.08%
Global Avg → Flatten	94.97	-1.32%
5×5 → 3×3 kernels	94.68	-1.61%
Dropout Removal	93.49	-2.80%

Key Insights

- **Dropout:** Most critical component (-2.8%)
- **Kernel size:** 5×5 optimal for signals
- **Activation:** Swish consistently better
- **Pooling:** Global avg outperforms flatten
- **Residuals:** Moderate but consistent benefit

Comparison

Comprehensive Performance Comparison

Model	Accuracy	Classes	Type[a]	Dataset[b]	Complexity
Our NAS Model	96.29% (-20 to 18 dB)	7	RDR+CMT	OTA	Low (91k)
Jagannath 2022	82.4% at 0 dB (OTA)	9+11	RDR+CMT	OTA+SYN	Low (253k)
O'Shea 2018	95.6% at 10 dB	24	CMT	SYN	Medium (ResNet)
Wang 2017	100% at 0 dB	7	RDR	SYN	Very Low (4.3k)
Li 2018	95% above 2 dB	7	CMT	SYN	Very Low (3.3k)
Schmidt 2017	95% at -5 dB	15	CMT	HBD	High (16.6M)

[a] RDR: Radar, CMT: Communication
[b] OTA: Over-the-Air, SYN: Synthetic, HBD: Hybrid

Our Competitive Advantages

- **Real OTA signals:** Superior to synthetic datasets across wide SNR range
- **Automated design:** NAS eliminates manual architecture engineering
- **Balanced efficiency:** High accuracy with reasonable parameter count
- **Practical deployment:** Real-time processing capability demonstrated

Table 2: Performance vs. Architecture Comparison

Approach	NAS CNN	Multi-Domain DNN	Spectrogram DNN
Accuracy (%)	96.29	97.72	95.84
Trainable Params	91,367	166,151	145,231
Architecture	CNN + residuals	Dense layers	Dense layers
Input Features	Spectrogram (33×7)	Multi-domain (513D)	Spectrogram (449D)
Search Method	Bayesian NAS	Manual design	Manual design
Processing	Direct 2D	Feature extraction	Flattened 2D

NAS Advantages

- **45.3% parameter reduction** vs. multi-domain approach
- **Direct spectrogram processing** - no complex feature extraction
- **Automated optimization** - eliminates manual design bias
- **Deployment-ready** - suitable for resource-constrained environments

Discussion

Architecture Discoveries

Signal-Specific Design Principles:

- **Swish activation:** Better gradient flow for signal processing
- **5×5 kernels:** Optimal for time-frequency patterns
- **Average pooling:** Preserves energy distribution
- **Progressive filters:** 32→64 expansion effective

Optimization Insights

Training Characteristics:

- **RMSprop** Adam: Better for signal gradients
- **Conservative LR:** 1.48×10^{-4} optimal
- **Selective BatchNorm:** Only 2nd layer beneficial
- **Residual connections:** Help preserve signal features

Practical Implications

- **Real-time viability:** 390+ signals/second processing capability
- **Edge deployment:** Low parameter count suitable for embedded systems
- **Automated ML:** NAS eliminates expert architecture design requirement

Limitations & Future Work

Current Limitations

- **Limited trials:** Only 20 due to computational constraints
- **Single dataset:** RadComOta2.45GHz specific optimization
- **Training limit:** 30-epoch constraint may limit some architectures
- **Search space:** Could explore more advanced mechanisms

Future Directions

- **Multi-dataset validation:** Broader frequency ranges
- **Advanced mechanisms:** Attention, transformer elements
- **Multi-objective NAS:** Energy, latency optimization
- **Hardware-aware search:** Platform-specific optimization

Deployment Roadmap

1. **Embedded optimization:** Raspberry Pi / Jetson deployment
2. **Real-time systems:** FPGA/DSP implementation
3. **Multi-band extension:** Beyond 2.45 GHz validation

Conclusions

Key Achievements

- **Automated discovery:** NAS identified optimal CNN architecture for signal classification
- **High performance:** 96.29% accuracy on real over-the-air signals
- **Computational efficiency:** Only 91,367 parameters with 390+ signals/sec processing
- **Wide SNR robustness:** Effective across -20 dB to 18 dB range
- **Design insights:** Identified signal-specific architectural principles

Scientific Contribution

- First comprehensive NAS for OTA signal classification
- Systematic exploration of 63M configurations
- Domain-specific design principles
- Real-world validation methodology

Practical Impact

- Spectrum monitoring systems
- Electronic defense applications
- Cognitive radio networks
- Edge computing deployment

Thank you for your attention!

Questions & Discussion

Project Repository:
`github.com/felixsuarez0727/ICECS_2025`