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

F. D. Suárez Bonilla, J.M. de la Rosa, G. Liñán-Cembrano
Instituto de Microelectrónica de Sevilla, IMSE-CNM (CSIC/Universidad de Sevilla), Spain
Email: felix.suarez@imse-cnm.csic.es

***Abstract*—This paper presents a Neural Architecture Search (NAS) approach for automatic classification of telecommunication signals using Convolutional Neural Networks (CNNs). Our optimized CNN architecture achieved 96.29% accuracy using Neural Architecture Search with only 91,367 trainable parameters, demonstrating improved computational efficiency compared to manually designed architectures. We explored 63 million possible architectural configurations using Bayesian optimization to systematically identify optimal network designs for spectrogram-based signal classification. The search process evaluated 20 different trials over approximately 1 hour and 21 minutes, ultimately discovering an architecture that balances accuracy and computational efficiency. This work demonstrates how automated architecture search can effectively optimize telecommunication signal processing applications for spectrum monitoring, electronic defense, and cognitive radio systems.**

***Keywords*—Neural architecture search, signal classification, convolutional neural networks, telecommunication signals, software-defined radio, spectrum monitoring, Bayesian optimization, over-the-air signals**

I. Introduction

Neural Architecture Search (NAS) has emerged as a powerful paradigm for automatically discovering optimal neural network architectures for specific tasks, eliminating the tedious process of manual architecture design and hyperparameter tuning [1], [2]. In telecommunication signal classification, selecting appropriate network architectures presents unique challenges due to the distinctive characteristics of signal data and the demanding requirements of real-world deployment scenarios.

Traditional approaches to signal classification have typically relied on manually designed architectures based on general deep learning principles or adaptations from computer vision domains [3], [4]. However, the optimal architecture for signal classification often differs significantly from those designed for image processing, since signals exhibit distinct temporal, spectral, and statistical properties that require specialized processing approaches.

Among the various NAS methodologies, we selected Bayesian optimization due to its superior sample efficiency and principled uncertainty quantification in scenarios with expensive function evaluations [5], [6].

We evaluate our approach using the RadComOta2.45GHz dataset [7], [8], which provides a realistic testing environment with actual transmitted signals containing real-world impairments in the critical 2.4-2.5 GHz frequency band for modern telecommunication systems.

Our main contribution consists of a comprehensive Neural Architecture Search that explored 63 million configurations using Bayesian optimization across 20 trials, achieving 96.29% accuracy with an optimized CNN model containing only 91,367 trainable parameters.

The rest of the paper is organized as follows. Section 2 contains the literature review. Section 3 contains the methodology. Section 4 contains the results and discussion. Section 5 contains the conclusions and future work.

II. Background and Related Work

NAS has evolved from manual hyperparameter optimization to sophisticated automated design methodologies [1]. Key developments include reinforcement learning-based approaches like NASNet [2], evolutionary methods [9], gradient-based techniques like DARTS [10], and subsequent developments such as iDARTS [11].

Recent advances in deep learning for telecommunication signal classification have shown significant progress [12], [13]. However, most existing methods suffer from either excessive computational complexity or limited performance on real-world signals, with the majority relying on synthetic datasets that may not capture over-the-air signal characteristics.

Modern CNN-based approaches for automatic modulation classification have demonstrated improved robustness under realistic channel conditions [14]–[16]. Advanced preprocessing techniques [17] and attention mechanisms [18] have further enhanced classification performance.

Bayesian optimization techniques for NAS have gained attention due to their efficiency in exploring large search spaces [5], [6], [19], providing principled uncertainty quantification and sample-efficient search strategies.

Table I presents a comprehensive comparison highlighting the performance landscape for signal classification methods.

Existing approaches show significant limitations. [20] uses hybrid data but relies partially on synthetic samples with unoptimized parameter complexity (60M vs 7M parameters). [4] and [21] achieve low complexity (4.3k and 3.3k parameters respectively) but use synthetic data, limiting real-world applicability. [22] demonstrates over-parameterization (¿10.7M parameters) despite using real signals, while [23] employs controlled laboratory conditions failing to capture realistic channel impairments.

Our NAS-optimized CNN model distinguishes itself by achieving competitive accuracy (96.29%) on real over-the-air signals while maintaining very low complexity across a wide SNR range (-20 dB to 18 dB).

III. Methodology

We use the RadComOta2.45GHz dataset [7], [8] containing approximately 567,000 labeled signal records from radar and communication applications, captured over-the-air using USRP N210 hardware in the 2.4-2.5 GHz band. For our experiments, we selected 35,000 records (5,000 per class) across seven signal categories with 70%/15%/15% train/validation/test splits.

A. Input Data Preparation

The spectrogram representation (33×7×1) was generated using parameters specifically optimized for telecommunication signal characteristics:

- Signal duration: 12.8 μs (128 I + 128 Q samples)
- Sampling rate: 10 MS/s
- Spectral parameters: nperseg=64, noverlap=32
- Frequency resolution: 33 frequency bins
- Time resolution: 7 time segments

The Short-Time Fourier Transform (STFT) uses 64-sample windows with 50% overlap, with noverlap=32 ensuring sufficient temporal overlap for smooth spectral transitions.

B. Search Space Definition

The NAS algorithm systematically explored 63M possible configurations across multiple architectural dimensions. Preprocessing options included data augmentation strategies and Gaussian noise levels ranging from 0.05 to 0.2. Convolutional architecture choices encompassed initial filter counts (16, 32, 48, 64), kernel sizes (3×3, 5×5, 7×7), batch normalization options, activation functions (ReLU, ELU, Swish[1]), and pooling strategies (max, average). Advanced mechanisms such as attention mechanisms and residual connections were systematically evaluated. Dense layer configurations varied the number of units (64 to 256), dropout rates (0.2 to 0.5), and the inclusion of secondary dense layers. Optimization parameters included optimizer selection (Adam, RMSprop) and learning rates spanning from 1e-5 to 1e-2 on a logarithmic scale.

To guide the architecture search, we employed Gaussian Process-based Bayesian optimization. The objective function balanced classification accuracy with model complexity as follows:

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

where $\alpha = 1.0$ and $\beta = 0.01$. The process utilized an Expected Improvement acquisition function, evaluated 20 total search trials, imposed a 30-epoch training limit per architecture evaluation, and employed cross-validation for robust performance estimates.

[1]A family of functions such that $Swish_\beta(x) = x \cdot sigmoid(\beta \cdot x)$. In our case, $\beta = 1$

IV. Results, Analysis and Discussion

The Neural Architecture Search process successfully identified an optimal CNN architecture that achieved 96.29% classification accuracy on a test set comprising 5,250 signal records with only 91,367 trainable parameters. The search process successfully identified an optimal neural network configuration in trial 17 out of 20. The key performance metrics and search statistics are summarized in Table II. This architecture (Figure 1) features progressive filter expansion (32 to 64 filters), uniform 5x5 kernel sizes in convolutional layers for signal feature extraction, Swish activation functions, strategic residual connections, and a combination of average and global average pooling. It also includes batch normalization only in the second convolutional layer, a moderate dropout of 0.3 in the dense layers (192 and 128 units), and uses the RMSprop optimizer with an optimized learning rate of 1.48×10^{-4}.

We conducted an ablation study to understand the contribution of individual architectural components (Table III). The analysis reveals that dropout regularization demonstrates the most significant impact, with its removal causing a 2.8% accuracy decrease.

Our NAS-optimized model achieves competitive performance while demonstrating superior parameter efficiency compared to traditional approaches (Table IV). Compared to our baseline multi-domain DNN approach (97.72% accuracy, 166,919 parameters), the NAS model achieves 96.29% accuracy with only 91,367 trainable parameters—a 45.3% reduction in parameter count with only 1.43 percentage point accuracy decrease.

The multi-domain DNN utilized comprehensive feature extraction combining time-domain, frequency-domain, and statistical features, while the spectrogram-only DNN processed flattened spectrogram representations through fully connected layers. Both baseline approaches required manual architecture design, demonstrating the advantage of automated optimization.

We processed approximately 390 signals/second on a MacBook Pro M3 (8-core CPU, 10-core GPU, 16GB unified memory), with feature extraction accounting for 84% of total processing time (2.147ms average).

The NAS process revealed important optimal design insights. Swish activation functions consistently outperformed ReLU alternatives, suggesting better signal information preservation for complex spectral patterns. Residual connections preserved low-level signal features, while average pooling outperformed max pooling for capturing distributed signal energy. The preference for RMSprop over Adam optimizer indicates better suitability for spectrogram-based learning with the conservative learning rate of 1.48×10^{-4} ensuring stable convergence.

Current limitations include: computational constraints limiting the search to 20 trials; optimization performed exclusively on RadComOta2.45GHz dataset affecting generalization; 30-epoch training limit potentially preventing full architecture potential; and focus on accuracy-parameter trade-offs without

TABLE I
COMPREHENSIVE COMPARISON OF SIGNAL CLASSIFICATION METHODS

Model	Modulation Accuracy	Signal Classification Accuracy	# Classes	Type[a]	Dataset[b]	Model Complexity
Modulation and Signal Classification - Multi-task						
Our NAS Model (CNN)	**96.29% (-20 dB to 18 dB)**	**96.29% (-20 dB to 18 dB)**	**7**	**RDR and CMT**	**OTA**	**Low (91k parameters)**
Jagannath et al. 2022 [24]	97.58% at 2 dB (SYN) 82.4% at 0 dB (OTA)	90.79% at 2 dB (SYN) 90.1% at 0 dB (OTA)	9 mod., 11 signal	RDR and CMT	OTA & SYN	Low (253k parameters)
Jagannath et al. 2021 [8]	97.87% at 0 dB, 99.53% at 10 dB	92.3% at 0 dB, 99.53% at 10 dB	9 mod., 11 signal	RDR and CMT	SYN	-
Modulation Classification Methods Only - Single Task						
Peng et al. 2019 [20]	less than 80% at 0 dB	-	8	CMT	HBD	High (AlexNet, GoogLeNet)
Jagannath et al. 2018 [25]	98% above 25 dB	-	7	CMT	SYN	Low
O'Shea et al. 2018 [3]	95.6% at 10 dB	-	24	CMT	SYN	Medium (Modified ResNet)
Mossad et al. 2019 [26]	86.97% at 18 dB	-	10	CMT	SYN	Medium
Hermawan et al. 2020 [15]	∼80% at 0 dB, 83.4% at 18 dB	-	11	CMT	SYN	Medium
Wang et al. 2017 [4]	100% at 0 dB	-	7	RDR	SYN	Very Low (4.3k parameters)
Li et al. 2018 [21]	95% above 2 dB	-	7	CMT	SYN	Very Low (3.3k parameters)
Signal Classification Methods Only - Single Task						
Bitar et al. 2017 [22]	-	91% at 15-25 dB, 93% at 30 dB	7	CMT	OTA	High (>10.7M parameters)
Schmidt et al. 2017 [23]	-	95% at -5 dB	15	CMT	HBD	High (16.6M parameters)

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

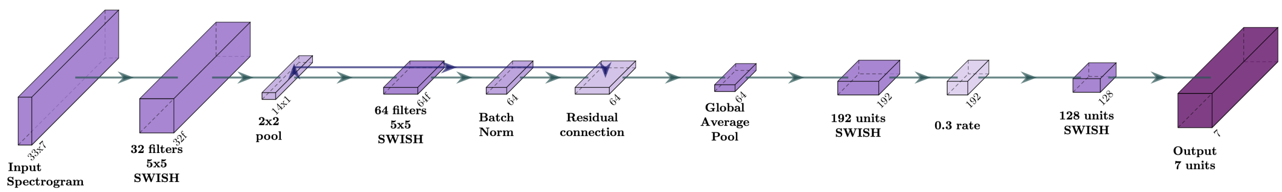

Fig. 1. NAS Optimal CNN Architecture for Signal Classification featuring residual connections, average pooling strategies, and progressive filter expansion with uniform 5×5 kernels throughout convolutional layers.

TABLE II
NAS MODEL PERFORMANCE ANALYSIS

Metric	NAS Model	Search Statistics
Test Accuracy	96.29%	Best in trial 17/20
Test Loss	0.0800	Final achieved
Trainable Parameters	91,367	Efficient design
Total Parameters	182,864	Including batch norm
Convergence	30 epochs	Stable training
Search Time	1h 21m 28s	20 trials total
Best Trial Discovery	Trial 17	Progressive improvement
Optimizer	RMSprop	Outperformed Adam
Learning Rate	1.48×10^{-4}	Optimized value

TABLE III
ABLATION STUDY OF ARCHITECTURAL COMPONENTS

Component Removed	Accuracy (%)	Performance 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 kernels → 3×3 kernels	94.68	-1.61%
Dropout Removal	93.49	-2.80%

explicit consideration of inference latency and energy consumption.

V. CONCLUSION AND FUTURE WORK

This work demonstrates the effectiveness of NAS for telecommunication signal classification. We developed a comprehensive NAS framework exploring 63M configurations using Bayesian optimization. Results show that convolutional spectrogram processing with optimized architectural components achieves competitive performance with superior computational efficiency. The discovered architecture offers significant advantages for resource-constrained environments, making it well-suited for real-time spectrum monitoring, embedded cognitive radio applications, and edge computing deployments.

Future research should focus on: cross-dataset validation, advanced attention mechanisms, multi-objective optimization balancing accuracy with energy efficiency, hardware-specific optimizations, and extended search spaces with transfer learning techniques.

ACKNOWLEDGMENT

The funding for these actions/grants and contracts comes from the European Union's Recovery and Resilience Facility-Next Generation, in the framework of the General Invitation of the Spanish Government's public business entity Red.es to participate in talent attraction and retention programmes within Investment 4 of Component 19 of the Recovery, Transformation and Resilience Plan. This work was also

TABLE IV
PERFORMANCE COMPARISON ACROSS DIFFERENT APPROACHES

Approach	NAS CNN	Multi-Domain DNN	Spectrogram Only DNN
Accuracy (%)	96.29	97.72	95.84
Loss	0.0800	0.0681	0.1242
Trainable Parameters	91,367	166,151	145,231
Total Parameters	182,864	166,919	166,845
Input Features	Spectrogram (33×7)	Multi-domain (513D)	Spectrogram (449D)
Architecture Type	CNN with residuals	Dense DNN	Dense DNN
Processing Pipeline	Direct spectrogram	Feature extraction + DNN	Flattened spectrogram + DNN
Search Method	Bayesian NAS	Manual design	Manual design
Activation Function	Swish	ReLU	ReLU
Optimizer	RMSprop	Adam	Adam

supported in part by PID2022-138078OB-I00, and PDC2023-145808-I00, funded by MICIU/AEI/10.13039/501100011033, by grant USECHIP (TSI-069100-2023-001), project funded by the Secretary of State for Telecommunications and Digital Infrastructure, Ministry for Digital Transformation and Civil Service and by the European Union–NextGenerationEU, by ERDF A way of making Europe.

REFERENCES

[1] T. Elsken, J. H. Metzen, and F. Hutter, "Neural architecture search: A survey," *Journal of Machine Learning Research*, vol. 20, no. 55, pp. 1–21, 2019. [Online]. Available: http://jmlr.org/papers/v20/18-598.html

[2] B. Zoph and Q. V. Le, "Neural architecture search with reinforcement learning," in *Proceedings of the International Conference on Learning Representations (ICLR)*, Toulon, France, April 2017.

[3] T. J. O'Shea, T. Roy, and T. C. Clancy, "Over-the-air deep learning based radio signal classification," *IEEE Journal of Selected Topics in Signal Processing*, vol. 12, no. 1, pp. 168–179, 2018.

[4] C. Wang, J. Wang, and X. Zhang, "Automatic radar waveform recognition based on time-frequency analysis and convolutional neural network," *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 2437–2441, 2017.

[5] A. Shankar, Y. Shen, A. Kumar *et al.*, "Bayesian optimization based neural architecture search for classification of gases/odors mixtures," *IEEE Sensors Journal*, vol. 24, no. 4, pp. 4721–4730, 2024.

[6] X. Luo, Y. Liu, Z. Chen, and Y. Wang, "Lsbo-nas: Latent space bayesian optimization for neural architecture search," in *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023, pp. 10 053–10 062.

[7] J. Jagannath and A. Jagannath, "Multi-task learning approach for automatic modulation and wireless signal classification," *arXiv preprint arXiv:2101.10254*, 2021. [Online]. Available: https://arxiv.org/abs/2101.10254

[8] A. Jagannath and J. Jagannath, "Dataset for modulation classification and signal type classification for multi-task and single task learning," *Computer Networks*, vol. 199, p. 108441, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S138912862100400X

[9] C. Liu, B. Zoph, M. Neumann, J. Shlens, W. Hua, L.-J. Li, L. Fei-Fei, A. Yuille, J. Huang, and K. Murphy, "Progressive neural architecture search," in *Proceedings of the European Conference on Computer Vision (ECCV)*, Munich, Germany, September 2018, pp. 19–34.

[10] H. Liu, K. Simonyan, and Y. Yang, "DARTS: differentiable architecture search," *CoRR*, vol. abs/1806.09055, 2018. [Online]. Available: http://arxiv.org/abs/1806.09055

[11] H. Wang, R. Yang, D. Huang, and Y. Wang, "idarts: Improving darts by node normalization and decorrelation discretization," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 34, no. 4, pp. 1945–1957, 2023.

[12] L. Zhang, Y. Wang, H. Liu, and J. Zhang, "Deep learning methods for automatic modulation classification of communication signals," *IEEE Transactions on Signal Processing*, vol. 71, no. 3, pp. 482–497, 2023.

[13] D. Martinez, P. Rodriguez, and C. Lopez, "Automatic classification of telecommunication signals using convolutional neural networks," *Journal of Signal Processing Systems*, vol. 96, no. 1, pp. 23–41, 2024.

[14] X. Cao, B. Zhang, N. Liu, J. Li, and Z. Feng, "Robust and fast automatic modulation classification with cnn under multipath fading channels," in *2020 IEEE International Conference on Communications (ICC)*, 2020, pp. 1–6.

[15] A. P. Hermawan, R. R. Ginanjar, D. Kim, and J. Lee, "Cnn-based automatic modulation classification for beyond 5g communications," *IEEE Communications Letters*, vol. 24, no. 5, pp. 1038–1041, 2020.

[16] D.-Y. Kwon, J.-M. Kim, J.-H. Ra, J.-S. Yoon, J.-S. Lee, and J.-H. Lee, "Mcnet: An efficient cnn architecture for robust automatic modulation classification," *IEEE Communications Letters*, vol. 25, no. 2, pp. 427–431, 2021.

[17] S. Chen, S. Zheng, L. Yang, and X. Yang, "A data preprocessing method for automatic modulation classification based on cnn," *IEEE Communications Letters*, vol. 24, no. 12, pp. 2755–2758, 2020.

[18] A. Bashar, G. Ding, Y. Xiao, and J. Zhang, "Automatic modulation classification for cognitive radio systems using cnn with probabilistic attention mechanism," in *2022 IEEE International Conference on Communications (ICC)*, 2022, pp. 4742–4747.

[19] A. Ren, T. Zhang, S. Ye, J. Li, W. Xu, Q. Qiu, Y. Wang, and S. Yu, "Bayesft: Bayesian optimization for fault tolerant neural network architecture," in *2021 Design, Automation Test in Europe Conference Exhibition (DATE)*, 2021, pp. 1078–1083.

[20] S. Peng, H. Jiang, H. Wang, H. Alwageed, Y. Zhou, M. M. Sebdani, and Y. Yao, "Modulation classification based on signal constellation diagrams and deep learning," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 3, pp. 718–727, 2019.

[21] R. Li, L. Li, S. Yang, and S. Li, "Robust automated vhf modulation recognition based on deep convolutional neural networks," *IEEE Communications Letters*, vol. 22, no. 5, pp. 946–949, 2018.

[22] N. Bitar, S. Muhammad, and H. H. Refai, "Wireless technology identification using deep convolutional neural networks," in *Proc. of International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, 2017, pp. 1–6.

[23] M. Schmidt, D. Block, and U. Meier, "Wireless interference identification with convolutional neural networks," in *Proc. of the IEEE International Conference on Industrial Informatics (INDIN)*, 2017, pp. 180–185.

[24] A. Jagannath and J. Jagannath, "Multi-task learning approach for modulation and wireless signal classification for 5g and beyond: Edge deployment via model compression," *Physical Communication*, vol. 54, p. 101793, 2022.

[25] J. Jagannath, N. Polosky, D. O'Connor, L. Theagarajan, B. Sheaffer, S. Foulke, and P. Varshney, "Artificial neural network based automatic modulation classifier for software defined radios," in *Proc. of IEEE International Conference on Communications (ICC)*, Kansas City, USA, 2018.

[26] O. S. Mossad, M. ElNainay, and M. Torki, "Deep convolutional neural network with multi-task learning scheme for modulations recognition," in *Proc. of International Wireless Communications Mobile Computing Conference (IWCMC)*, 2019, pp. 1644–1649.