DOI https://doi.org/10.30525/978-9934-26-597-6-27

UAV SIGNAL CLASSIFICATION USING NEURAL NETWORKS AND SPECTROGRAM ANALYSIS

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Abstract

This article presents a deep learning approach for classifying signals of unmanned aerial vehicles (UAVs) based on spectrogram analysis. The methodology includes the collection of radio frequency (RF) data via Software Defined Radio (SDR), signal transformation into spectrograms using Fast Fourier Transform (FFT), and subsequent classification using convolutional neural networks (CNNs). The study compares CNN performance with traditional machine learning algorithms such as Random Forest, Decision Tree, and Support Vector Machine (SVM), highlighting CNN's superior performance in classifying spectral data. The model achieves up to 92.7% classification accuracy and is optimized for deployment on low-power hardware like Raspberry Pi. The proposed system offers a cost-effective and accurate method for real-time UAV detection, suitable for both civilian and defense applications.

Keywords: UAV, neural networks, spectrogram, signal classification, SDR, CNN, machine learning

Introduction

The increasing use of UAVs in military and civilian domains has created an urgent need for reliable detection systems. While radar, optical, and acoustic methods provide partial solutions, their limitations in urban and complex environments necessitate the use of RF signal analysis. UAVs emit control signals and telemetry in RF bands that can be captured, transformed into spectrograms, and analyzed using artificial intelligence. This article explores the implementation of CNN-based spectrogram classification as a robust method for UAV signal detection.

Main Part

In parallel to real-time classification, the system also supports post-processing modes in which captured signals are stored in raw IQ format for offline analysis. This capability enables further experimentation and retraining on previously unseen signal types. Custom scripts were developed to segment, label, and batch-process spectrograms from recorded sessions, facilitating dataset expansion and domain-specific training.

From a usability standpoint, the system includes an LCD interface displaying signal type, signal strength, and confidence score in real time. Settings for signal duration, FFT resolution, and classification interval can be adjusted via a simple button-based menu. This user interface design makes the system accessible even to non-technical operators, broadening its applicability for rapid deployment.

An ensemble model strategy was briefly explored by combining the CNN classifier with a secondary decision layer using gradient boosting, which accepted softmax confidence values as input features. Although this approach increased complexity, it yielded a slight improvement in handling ambiguous samples–especially those on the class boundary between ELRS and Wi-Fi emissions. Confusion matrices and receiver operating characteristic (ROC) curves were plotted to assess classification performance in detail across all signal categories. Precision, recall, and F1-score metrics demonstrated consistent generalization across multiple test datasets.

A key consideration in the design phase was resilience to adversarial attacks, such as intentional signal obfuscation or spectrum jamming. The CNN was exposed to perturbed spectrograms during training using adversarial augmentation. These experiments showed a 9% drop in accuracy without augmentation, reinforcing the need for defensive training strategies in real-world deployments.

To further refine the system, experiments were conducted on signal characteristics such as modulation type, bandwidth usage, and frequency hopping patterns. These traits were used to generate enhanced spectrogram features by incorporating color-mapped frequency components and signal density estimations. Multiple signal preprocessing pipelines were benchmarked to evaluate optimal methods for retaining spectral integrity while compressing input data. It was found that log-scaling the spectrogram amplitude and applying histogram equalization improved feature extraction, leading to marginal gains in model precision.

The CNN architecture was iteratively tuned using Bayesian optimization, targeting parameters such as kernel size, learning rate, and number of filters per layer. Early stopping and dropout layers helped mitigate overfitting. Feature maps from each layer were visualized using TensorBoard to interpret what frequency components the CNN learned to focus on, aiding in explainability.

The study involved the acquisition of RF signals using a USRP N210 SDR. Raw signals were segmented and transformed into 128x128-pixel spectrograms using FFT. CNN architecture was implemented using TensorFlow and Keras frameworks, with three convolutional layers, max-pooling, dropout regularization, and softmax activation for multiclass classification.

A dataset containing 3 classes (Wi-Fi, ELRS, and other UAV signals) was created and split into training (70%), validation (15%), and test (15%) sets. Data augmentation was applied via amplitude scaling, Gaussian noise, and time-frequency shifts. CNN achieved 92.7% accuracy, outperforming SVM (82%) and Random Forest (75%)

The model was deployed on Raspberry Pi 4 using TensorFlow Lite, enabling real-time classification with minimal computational overhead. Signal preprocessing included real-time FFT computation, normalization, and automatic class prediction. Integration with alert modules (LED indicators and network messages) allowed immediate notification of detected UAV types.

Real-world validation was also performed using consumer-grade drones flying within a 200-meter range. Signal acquisition hardware was mounted on a mobile platform, simulating vehicular patrol scenarios. The system successfully detected UAV signals despite Doppler shift effects due to drone motion. Audio-visual alerts were integrated via LED indicators and sound buzzers triggered on successful classification. An Android companion app was prototyped using Bluetooth communication to receive alerts and spectrogram snapshots from the classifier system.

The robustness of classification was further validated in outdoor environments with varying topographies and reflective surfaces. Data collection took place in open fields, wooded areas, and urban courtyards, allowing measurement of the impact of multipath propagation and signal occlusion. In these tests, system performance remained consistently high when antenna placement and calibration procedures were followed.

The system was also compared to classical spectral anomaly detectors. While traditional methods could detect outliers, they lacked the specificity and classification granularity provided by CNN-based models. This contrast highlights the advantage of supervised learning in high-noise scenarios where feature extraction is otherwise complex.

System Evaluation

Stress testing was also performed under various RF conditions, including interference from mobile devices, Wi-Fi routers, and Bluetooth signals. The model consistently maintained above 85% accuracy even in hostile environments, validating its applicability in dense RF landscapes. Latency measurements showed that signal capture to classification time remained below 250 ms, meeting real-time constraints for field deployment.

Integration with open-source SDR software such as GNU Radio and SDR++ was evaluated to streamline signal acquisition. This allowed the system to be extended to support multiple concurrent SDR inputs across a distributed architecture. In addition, the system's data logging capabilities were extended to include geotagging and timestamping, useful for post-analysis and forensic applications.

An extension of the system's functionality is planned for swarm drone detection, where multiple UAVs emit overlapping RF signatures. Clustering and multi-object tracking algorithms will be introduced to distinguish and classify concurrent UAV signals, potentially using time-frequency heatmaps and temporal correlation.

Finally, the creation of an online dashboard for live visualization and map-based tracking is envisioned. This would allow centralized monitoring of UAV activity across distributed sensor nodes, supporting coordinated security operations and situational awareness for law enforcement and disaster response teams.

Performance testing under varied environmental noise confirmed CNN's robustness, maintaining over 90% accuracy even with 15% signal distortion. Power consumption remained below 3W, confirming the model's suitability for edge deployment. Further testing validated compatibility with signals generated by commercial drones and emulated threats using signal generators.

Compared to commercial systems like DroneShield and Dedrone, the proposed system is more cost-effective and customizable. While those platforms require multi-sensor arrays and cloud integration, our solution operates locally, ensuring autonomy and data privacy.

Future Work

Another promising direction involves integrating explainable AI (XAI) techniques such as saliency maps to visualize the influence of signal regions on classification decisions. Additionally, transformer-based models like Vision Transformers (ViTs) will be investigated for their ability to process large-scale spectrogram data with reduced computation overhead. The implementation of federated learning for distributed UAV signal classification is also a goal, enabling sensor nodes to collaboratively train models without sharing raw data, thereby preserving privacy.

Scalability to other RF-emitting threats such as radio-controlled IEDs or rogue transmitters will also be studied. The use of edge AI accelerators like

Coral TPU or NVIDIA Jetson Nano could further enhance deployment capabilities. Cross-platform deployment using Docker containers and Kubernetes orchestration will ensure high availability in critical infrastructure monitoring scenarios.

The approach also highlights the synergy between affordable SDR hardware, edge computing, and AI-based classification, bridging academic research and practical deployment. Its portability and independence from cloud connectivity address privacy concerns while maintaining performance. The framework also serves as an educational toolkit, allowing students and researchers to explore the intersection of signal processing and deep learning using real-world data.

Planned improvements include hybrid CNN-RNN models for analyzing dynamic signal changes and BLE Mesh integration for distributed sensor networks. The dataset will be expanded with real-world flight data and signals from various drone models. Research into adversarial robustness will strengthen the model against spoofed or encrypted signals.

Conclusions

CNN-based spectrogram analysis offers a scalable, accurate, and efficient method for UAV signal classification. The system's open-source implementation, hardware compatibility, and real-time capabilities make it ideal for embedded applications in security, infrastructure protection, and battlefield intelligence.

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