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Article title

MATLAB-Simulated Dataset for Automatic Modulation Classification in Wireless Fading Channels

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Keywords

Adaptive communication; Spectrogram; Feature extraction; Machine Learning; Signal processing; Image processing.

Abstract

Accurate modulation classification is a core challenge in cognitive radio, adaptive communications, spectrum analysis and related domains especially under dynamic channels without transmitter knowledge. To address this need, the article presents a labeled synthetic dataset designed for wireless modulation classification under realistic propagation scenarios. The signals were generated in MATLAB by modulating randomly generated bitstreams using five digital modulation schemes—BPSK, QPSK, 16-QAM, 64-QAM, and 256-QAM. These signals were then transmitted through Rayleigh and Rician fading channels with standardized parameters, along with additional impairments to enhance realism and diversity. Each modulated signal contains 1000 symbols. A comprehensive set of features was extracted from the signals, encompassing statistical, time-domain, frequency-domain, spectrogram-based, spectral correlation-based and image processing-based descriptors such as BRISK, MSER, and GLCM. The dataset is organized into 10 CSV files covering two channel types (Rayleigh and Rician) across five sampling frequencies: 1 MHz, 10 MHz, 100 MHz, 500 MHz, and 1 GHz. To facilitate reproducibility and encourage further experimentation, the MATLAB scripts used for signal generation and feature extraction, are also provided. This dataset serves as a valuable benchmark for developing and evaluating machine learning models in modulation classification, signal identification, and wireless communication research.

SPECIFICATIONS TABLE

Subject	Electrical Engineering
Specific subject area	Wireless Networks, Modulation Classification, Signal Processing, Machine Learning, Deep Learning.

Type of data	Comma Separated Values files (.csv), MATLAB scripts(.m)
Data collection	This dataset was generated using MATLAB simulations. Wireless signal data from five modulation schemes were simulated under two different fading channels (Rayleigh and Rician). After computing traditional signal-domain features, additional features are extracted using spectrogram analysis and advanced techniques such as BRISK, MSER, and GLCM. Setting different sampling frequencies (1 MHz, 10 MHz, 100 MHz, 500 MHz and 1 GHz), a total of 10 datasets (5 under each fading channel) were created.
Data source location	Islamic University of Technology, Board Bazar, Gazipur 1704, Bangladesh
Data accessibility	Repository name: Mendeley Data Data identification number: 10.17632/kfzyp9hnzb.1 Direct URL to data: https://data.mendeley.com/datasets/kfzyp9hnzb/1
Related research article	None

VALUE OF THE DATA

- **Modulation classification under blind scenario:** The dataset consists of signal data from five broadly used digital communication schemes (BPSK, QPSK, 16-QAM, 64-QAM, 256-QAM) with 202 extracted features. The features were extracted for two different fading channels (Rayleigh and Rician). These data will be useful to develop machine learning models for modulation classification in wireless communication systems.
- **Understanding the effect of frequency variation:** As the dataset features signal data from a wide sampling frequency range (1 MHz, 10 MHz, 100 MHz, 500 MHz, and 1 GHz), it will help researchers observe the impact of variability in bandwidth on modulation scheme and classification model performances.
- **Diversity of features:** Apart from the conventional signal domain features, extracting features using spectrogram-based and image-processing techniques (BRISK, MSER, and GLCM) has diversified the dataset which will facilitate feature selection, evaluation of traditional classifiers and deep learning methods.
- **Mimics real-world wireless environments:** By providing signal distortions due to different types of noise and fading channels, the dataset simulates practical wireless systems and aids research in cognitive radio, LTE/5G networks and adaptive communication systems.
- **Aiding regeneration of the dataset by including MATLAB scripts:** The MATLAB scripts added in the dataset folder will guide the interested individuals to reproduce the dataset under modified conditions. They will be able to extract their desired features and use it for varied purposes. Altogether it will extend the scope for further research in this field.

BACKGROUND

Classifying the modulation scheme is a principal challenge in the field of cognitive radio, interference management, adaptive communication systems and spectrum monitoring. In practical scenarios, for dynamic and unpredictable conditions, receivers have to perform modulation classification without prior information about transmitter parameters. This dataset features an extensive compilation of digitally modulated signals across five modulation schemes (BPSK, QPSK, 16-QAM, 64-QAM, 256-QAM) captured under Rayleigh and Rician fading channels, at five distinct sampling frequencies (ranging from 1 MHz to 1 GHz), effectively mimicking real-world noise and multipath effects. The incorporation of enhanced signal processing techniques like spectrogram analysis, BRISK, MSER, and GLCM-based feature extraction makes this dataset stand out from others. It will facilitate analysts to study novel machine learning and deep learning algorithms for blind modulation categorization. [1–4] The inclusion of MATLAB scripts encourages regeneration of the dataset under modified conditions. This resource will be of great help to develop advanced techniques and approaches to meet the challenge of modulation classification under blind scenarios.

DATA DESCRIPTION

The dataset is organized within a primary directory that contains three distinct sub-folders: Rayleigh Channel, Rician Channel, and MATLAB Codes. The Rayleigh Channel and Rician Channel folders include simulation data stored in CSV format, representing modulated signal features generated under their respective wireless fading channel conditions across five different sampling frequency, ranging from 1 MHz to 1 GHz. The MATLAB Codes sub-folder includes all simulation codes in .m format, corresponding to each dataset configuration. The structure of the dataset is shown in **Fig. 1.**

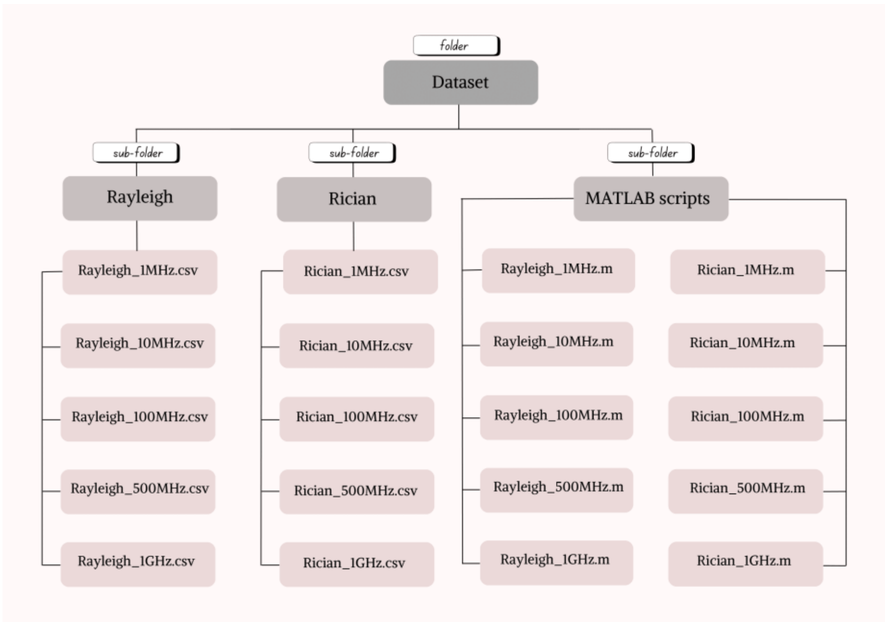

Fig. 1. Structure of the dataset.

Each dataset comprises 202 extracted features, systematically categorized into six groups: Statistical Moments, Time-Domain Features, Frequency-Domain Features, Spectrogram-Based Features, Spectral Correlation Features and Image Processing based Features. Among these, the first five categories—

encompassing a total of 58 features—are presented in **Table 1**, which includes the exact feature names used in the dataset along with concise descriptions. These features represent various signal characteristics across time, frequency, and time–frequency domains. The remaining features are derived using image processing techniques applied to spectrogram representations, providing additional high-dimensional descriptors for signal classification and analysis.

Using image processing techniques, we extracted an additional **144 features** from the spectrogram images, including **64 BRISK features**, **64 MSER features**, and **16 GLCM features**—to effectively capture local structures, stable regions, and texture-based patterns essential for signal classification.

Table 1
Feature Categorization and Contextual Descriptions.

Category	Feature Name	Description
Statistical Moments	MeanAmplitude	Average strength of the signal
	AmplitudeVariance	Fluctuation in signal amplitude
	AmplitudeSkewness	Asymmetry in amplitude distribution
	Kurtosis	Sharpness of amplitude distribution of signal
	SignalPower	Average energy per sample
	MedianAmplitude	Middle value of amplitude distribution
	RMSAmplitude	Effective signal magnitude
	StdAmplitude	Spread of amplitude values
	MeanDiffAmplitude	Average change between consecutive amplitudes
	MeanPhase	Average phase angle of the signal
	PhaseVariance	Spread of phase angle values
	EnvelopeMean	Average magnitude of the analytic signal
	EnvelopeStd	Spread of envelope magnitudes
	SpectrogramVariance	Spread of amplitude values
	SpectrogramSkewness	Asymmetry of amplitude distribution
	SpectrogramKurtosis	Sharpness of amplitude distribution of spectrogram
	MeanInstantaneousFreq	Central tendency of frequency variations over time
	InstantaneousFreqVariance	Degree of fluctuation in frequency changes
	InstantaneousFreqSkewness	Asymmetry in the distribution of frequency shifts
	InstantaneousFreqKurtosis	Sharpness or flatness of frequency distribution compared to a normal curve
Time-Domain Features	RSCR	Signal quality relative to noise
	ZeroCrossingRate	Rate of polarity changes in the signal
	MaxAmplitude	Highest signal magnitude
	MinAmplitude	Lowest signal magnitude
	TotalAmplitude	Sum of all amplitude values
	AmplitudeArea	Total accumulated amplitude
	AmplitudeEntropy	Uncertainty in amplitude distribution
	DynamicRange	Difference between maximum and minimum amplitude

	TotalAmpChange	Sum of all amplitude variations
	PAPR	Ratio of peak signal power to its average power, expressed in dB
Frequency-Domain Features	SignalEnergy	Total power contained in the signal
	SpectralCentroid	Center of mass in the frequency spectrum
	SpectralFlatness	Tonality measure of the spectrum
	SpectralPAR	Ratio of highest spectral component to mean
	SpectralEnergy	Total power in the frequency domain
	SpectralBandwidth	Width of significant spectral components
	LowFreqEnergy	Energy in the lower half of the spectrum
	HighFreqEnergy	Energy in the upper half of the spectrum
Spectrogram-Based Features	SpectrogramEntropy	SpectrogramEntropy
	SpectrogramEnergy	SpectrogramEnergy
	SpectrogramContrast	SpectrogramContrast
	SpectrogramHomogeneity	SpectrogramHomogeneity
	MaxSpectrogramAmplitude	MaxSpectrogramAmplitude
	MinSpectrogramAmplitude	Lowest intensity value in spectrogram
	MeanSpectrogramAmplitude	Average intensity across the spectrogram
	SpectralCentroidFrom-Spectrogram	Frequency center of energy distribution
	SpectralSpread	Dispersion of spectral energy around centroid
	LogAmplitudeSummation	Sum of log-transformed amplitude values
	SpectralFlatnessRatio	Ratio of geometric mean to arithmetic mean of spectrum
	MeanMaxSpectrogram-Amplitude	Average peak intensity per time step
	MeanMinSpectrogram-Amplitude	Average lowest intensity per time step
	AmplitudeCountAboveMean	Number of spectrogram values above average
	MeanSpectrogramRow-Range	Average difference between max and min per row
	MeanSpectrogramColumn-Range	Average difference between max and min per column
	NormalizedSpectrogram-Energy	Average power per spectrogram element
Spectral Correlation Features	SCFmax	Highest spectral correlation function magnitude.
	AVGscfPeakFreqOffset	Mean shift in frequency where SCF reaches peak values.
	VARscfPeakFreqOffset	Spread of frequency shifts at SCF peak points.

The correlation between input features and the target variable plays a critical role in the performance of machine learning classification models, as it influences both feature selection and model generalization. **Fig. 2** presents the top 30 features exhibiting the highest correlation with the target variable for one representative dataset, highlighting the most informative attributes for classification.

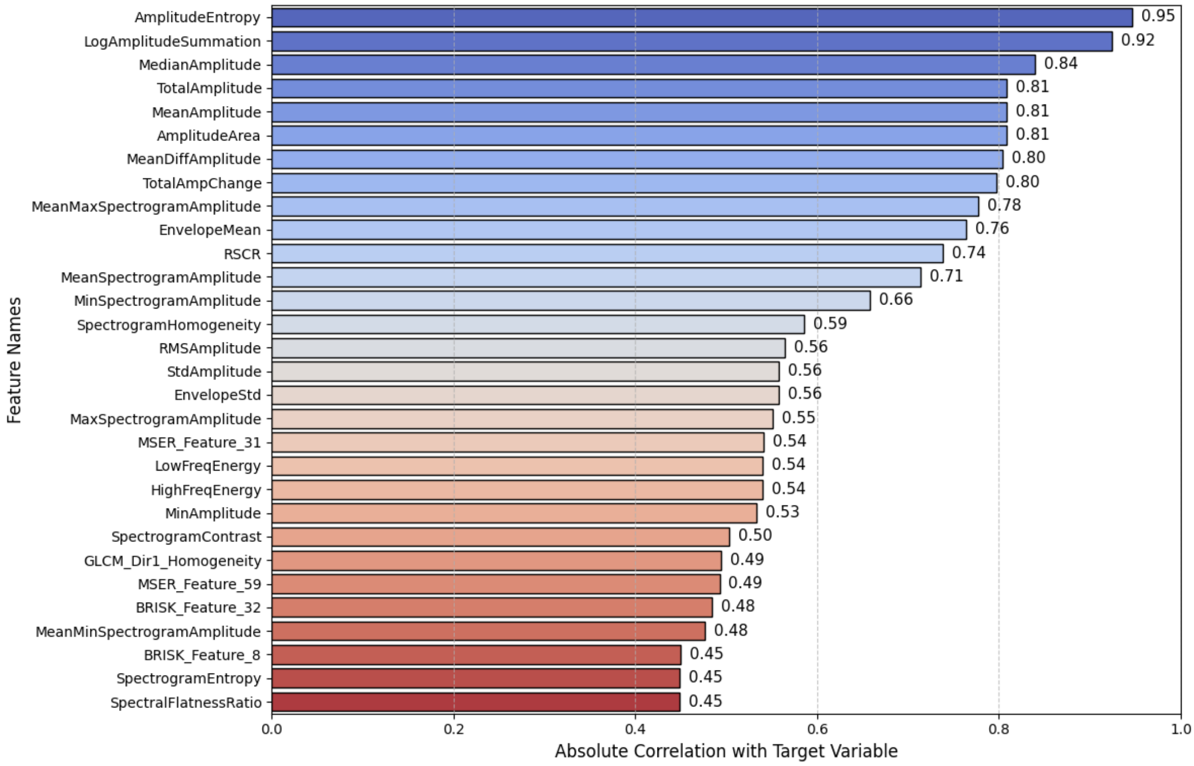

Fig. 2. Absolute feature correlation with target variable.

A separate folder contains the MATLAB scripts (*.m* files) corresponding to each of the 10 datasets, ensuring reproducibility and facilitating further experimentation.

EXPERIMENTAL DESIGN, MATERIALS AND METHODS

In this portion, the detailed methodology of generating the dataset containing modulated signals with diverse features using MATLAB R2021a has been explained. The corresponding flowchart of this methodology is presented in **Fig. 3.**

3.1 Signal Generation and Channel Simulation

This section outlines the end-to-end process of wireless signal generation, modulation, channel modelling, and noise incorporation for building a realistic synthetic dataset suitable for classification tasks.

3.1.1 Bitstream Generation and Modulation Schemes

To simulate diverse wireless communication signals, random bitstreams were first generated to emulate digital transmission. These bitstreams were modulated using five commonly used modulation schemes: **BPSK, QPSK, 16-QAM, 64-QAM**, and **256-QAM**. The MATLAB functions pskmod and qammod were used for phase-shift keying (PSK) and quadrature amplitude modulation (QAM), respectively.

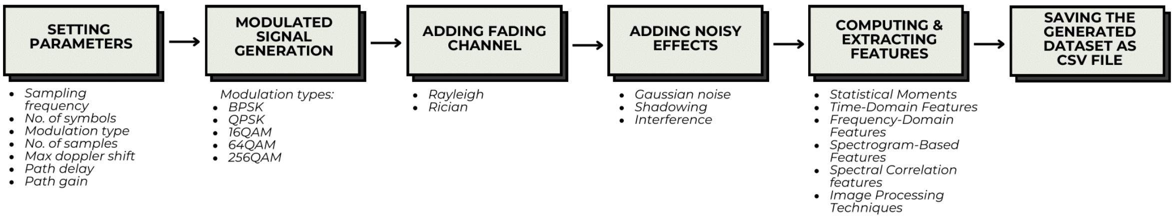

Fig. 3. Methodology flowchart illustrating the steps taken to construct the dataset.

- **Binary Phase Shift Keying (BPSK)**: Each bit was directly mapped to one of two distinct phases.
- **Quadrature Phase Shift Keying (QPSK)**: Bit pairs were mapped to four equidistant phase angles.
- **Quadrature Amplitude Modulation (QAM)**: Groups of 4, 6, and 8 bits were mapped to constellation points in 16-QAM, 64-QAM, and 256-QAM respectively, varying both amplitude and phase.

Each modulated signal contained 1000 symbols to maintain consistency across samples for training machine learning models.

3.1.2 Propagation Effects via Channel Models

To reflect real-world transmission conditions, the modulated signals were passed through either a **Rayleigh** or **Rician** fading channel using MATLAB's comm.RayleighChannel and comm.RicianChannel objects.

- **Rayleigh Fading Channel:** Simulates non-line-of-sight (NLOS) scenarios common in urban and indoor environments.
- **Rician Fading Channel:** Models environments with a strong line-of-sight (LOS) component such as rural or suburban settings, with a K-factor of 6. [5]

Both models shared the following configuration parameters:

- *Maximum Doppler Shift:* 100 Hz
- *Path Delays:* [0, 1e-6, 3e-6] seconds
- *Path Gains:* [0, -3, -6] dB

These fading effects were applied to distort the transmitted signals based on multi-path propagation and mobility.

3.1.3 Incorporation of Noise and Interference

To mimic the imperfections encountered in real-world wireless communication systems, various sources of noise and interference were incorporated into the signal generation pipeline. These distortions were applied cumulatively to increase the diversity and realism of the dataset.

a) Additive White Gaussian Noise (AWGN): To model thermal noise and background interference, AWGN was added to the signals. The noise level was dynamically adjusted using randomly selected

Signal-to-Noise Ratio (SNR) values ranging from 5 dB to 30 dB, thereby simulating a wide range of channel conditions.

b) Shadowing (Large-Scale Fading): Large-scale variations in signal strength due to physical obstructions were emulated using a log-normal fading model. The signal power was attenuated following a log-normal distribution with a standard deviation of 2 dB, representing shadow fading caused by terrain or structural obstacles.

c) Adjacent Channel Interference: To represent interference from neighbouring frequency bands, an additional QPSK-modulated interfering signal was introduced with a frequency offset of 10 kHz relative to the main carrier. This mimics interference scenarios in congested wireless environments.

By combining these effects—AWGN, shadowing, and adjacent channel interference—each signal in the dataset was subjected to a realistic and challenging propagation environment, enhancing its applicability for machine learning-based classification and analysis.

3.2 Feature Extraction

To comprehensively characterize the modulated signals, feature extraction was performed across six categories: **Statistical Moments**, **Time-Domain Features**, **Frequency-Domain Features**, **Spectrogram-Based Features**, **Spectral Correlation Features** and **Image Processing based Features**. These features capture both structural and spectral variations in the signal, serving as the foundation for accurate classification and analysis.

3.2.1 Statistical Moments

Statistical descriptors were applied to various signal transformations to summarize the distribution and variability of signal characteristics. [6] The following moments were calculated:

- **Mean:** Represents the central tendency of the signal, providing an estimate of its average amplitude level over time. It serves as a baseline for analyzing variations in signal behavior.
- **Variance:** Measures the degree to which amplitude values deviate from the mean, reflecting the spread or power variability within the signal. Higher variance indicates greater fluctuation in signal strength.
- **Skewness:** Quantifies the asymmetry of the amplitude distribution. A positive skew indicates a longer right tail (more high-amplitude events), while a negative skew indicates a longer left tail (more low-amplitude events).
- **Kurtosis:** Describes the sharpness of the amplitude distribution and the presence of extreme values in the tails. High kurtosis implies the presence of sharp peaks and outliers, while low kurtosis suggests a flatter, more uniform distribution.

These moments were computed not only in the time and frequency domains but also for derived features such as the instantaneous frequency and spectrogram matrix, ensuring consistent statistical profiling across domains.

3.2.2 Time-Domain Features

Time-domain features were extracted directly from the raw signal amplitude to characterize its temporal behavior and modulation-specific variations. These features fall into the following categories:

- **Signal Strength and Extremes:** Features such as MaxAmplitude, MinAmplitude, TotalAmplitude, DynamicRange, TotalAmpChange, and AmplitudeArea capture both the overall magnitude and the variability of the signal. Together, they reflect the signal's peak limits, accumulated energy, and the extent of amplitude fluctuations over time—key indicators of modulation-induced behavior.
- **Complexity and Uncertainty Measures:** ZeroCrossingRate and AmplitudeEntropy quantify the rate of sign changes and randomness in the amplitude distribution, indicating the complexity and unpredictability of the waveform.
- **Power and Clarity Indicators:** PAPR (Peak-to-Average Power Ratio) evaluates power efficiency, while RSCR (Received Signal Clarity Ratio) measures signal clarity in relation to background noise—both are critical for assessing transmission quality.

3.2.3 Frequency-Domain Features

Extracted from the signal's Fourier spectrum, these features provide compact representations of power distribution across frequencies and aid in distinguishing modulation characteristics:

- **Energy Distribution:** Includes SignalEnergy, SpectralEnergy, LowFreqEnergy, and HighFreqEnergy, which quantify total signal power and its allocation across lower and higher frequency bands.
- **Center and Spread:** Centroid measures the center of mass of the frequency components, while bandwidth describes the range over which significant frequencies are spread.
- **Texture and Dominance:** Flatness evaluates the noisiness versus tonal quality of the frequency content, and Peak-to-Average Ratio (PAR) highlights dominant frequency components relative to the average level.

3.2.4 Spectrogram-Based Features

Computed from the signal's time-frequency representation, these features capture nonstationary behavior and evolving spectral patterns characteristic of the modulation schemes using the Short-Time Fourier Transform (STFT):

STFT parameters: window size of 128, overlap of 120 samples, and FFT size of 128.

Extracted from the spectrogram matrix:

- **Spectrogram Energy Patterns:** Features such as SpectrogramEnergy, MeanSpectrogramAmplitude, NormalizedSpectrogram-Energy, etc., quantify power distribution and intensity variation across time-frequency bins, reflecting modulation-specific energy characteristics.
- **Spectrogram Texture and Complexity:** Measures like SpectrogramEntropy, SpectrogramContrast, SpectrogramHomogeneity, etc., describe the statistical texture of the spectrogram, capturing contrast, uniformity, and structural complexity.
- **Temporal-Spectral Variation Metrics:** Features such as SpectralCentroidFrom-Spectrogram, SpectralSpread, MeanSpectrogramRow-Range, AmplitudeCountAboveMean, etc., characterize frequency dispersion, dynamic range, and local intensity changes over time.

These features emphasize localized time-frequency patterns and complement traditional signal representations. [7]

3.2.5 Spectral Correlation Features (Cyclostationary Analysis)

To exploit the cyclostationary nature of modulated signals, spectral correlation was analyzed:

- **Spectral Correlation Function (SCF)**: computed by circularly shifting the signal and evaluating the frequency-domain correlation between shifted versions. [8,9]
- Derived features include:
    - **Maximum SCF value** – indicating the most prominent cyclic feature.
    - **Statistical measures of frequency offsets** – at which SCF peaks occur, reflecting modulation-induced periodicities.

These features are particularly effective in distinguishing signals with inherent periodic structures.

3.2.6 Image Processing Techniques

To complement statistical and spectral features, advanced image processing techniques were employed to extract robust descriptors from spectrogram representations of the modulated signals. [10][11] These techniques—**BRISK (Binary Robust Invariant Scalable Keypoints)**, **MSER (Maximally Stable Extremal Regions)**, and **GLCM (Gray-Level Co-occurrence Matrix)**—capture distinct structural and textural characteristics inherent in the time-frequency domain.

BRISK (Binary Robust Invariant Scalable Keypoints) is a keypoint-based descriptor that detects salient features invariant to scale and rotation. It employs a concentric sampling pattern around each keypoint and performs pairwise intensity comparisons to generate binary strings, yielding compact and discriminative descriptors. Applied to spectrograms, BRISK captures modulation-specific local structures in the time-frequency domain, enhancing robustness to noise, geometric distortions, and signal variability. [12]

To extract local structural features from the time-frequency domain, we applied the **BRISK** algorithm to the grayscale spectrogram images of the modulated signals. Using BRISK, distinctive keypoints were identified which represent unique local patterns within the spectrogram. **Fig. 4** displays the BRISK keypoints detected on the spectrogram of a generated 16-QAM signal. Following keypoint detection, BRISK descriptors were computed around each keypoint, encoding intensity variations within localized regions. To create a compact and uniform representation across samples, the mean of all BRISK descriptors per image was calculated, forming a fixed-length **briskFeatureVector**. This feature vector serves as a low-dimensional but discriminative summary of the spectrogram's content, facilitating efficient classification or clustering in downstream machine learning tasks. **Table 2** presents the key properties of the extracted BRISK features.

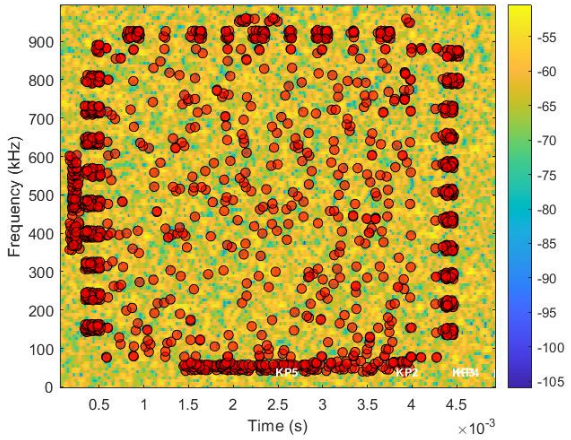

Fig. 4. Enhanced BRISK keypoints on spectrogram.

Table 2
Key properties of extracted BRISK features.

Parameter	Size	Description
briskPoints	1380 keypoints	Initially detected keypoints with scale, orientation, and metric values.
validPoints	1082 keypoints	Filtered keypoints used in actual feature extraction.
briskFeatures	1082 × 64 matrix	Binary descriptors capturing local image patterns around valid keypoints.
briskFeatureVector	64-dimensional vector	Mean descriptor representing overall BRISK features in compact form.

Maximally Stable Extremal Regions (MSER) is a region-based feature detection algorithm that identifies stable, blob-like structures in grayscale images. It operates by analyzing the intensity landscape of the image and consists of the following key steps:

I. **Pixel Intensity Sorting**: Pixels are first sorted based on their grayscale intensity values using efficient non-comparison-based algorithms such as counting sort or bin sort, achieving linear time complexity.
II. **Connected Component Tracking**: As the intensity threshold is varied, connected components are formed and merged using a disjoint-set data structure and union-find algorithm to efficiently manage region connectivity.
III. **Stability Evaluation**: For each connected component, the algorithm monitors changes in region area across varying thresholds. Regions exhibiting minimal area variation over a range of intensities are deemed **maximally stable** and are selected as key features. [13]

The MSER algorithm was employed using MATLAB's detectMSERFeatures() function to extract robust features from spectrogram images. These regions, defined by intensity stability, were extracted from grayscale spectrogram images. For each detected region, geometrical and spatial properties such as pixel locations, orientation, and region axes were computed and stored. Next, the valid MSER regions were refined using SURF keypoint detection to ensure that only robust and discriminative points were retained. The combination of MSER and SURF helped filter out unstable or irrelevant regions. After identifying valid regions, a 64-dimensional descriptor was generated for each MSER zone using histogram-based feature encoding. These descriptors were then aggregated and used to construct the final **MSER feature vector** for each signal sample. This process enabled the transformation of highresolution spectrogram images into fixed-length, compact vectors that encapsulate region-specific intensity distributions, suitable for classification or clustering. **Fig. 5** shows the MSER regions identified in a 16-QAM signal. The characteristics of MSER regions, SURF keypoints, and the feature vector are detailed in **Table 3**.

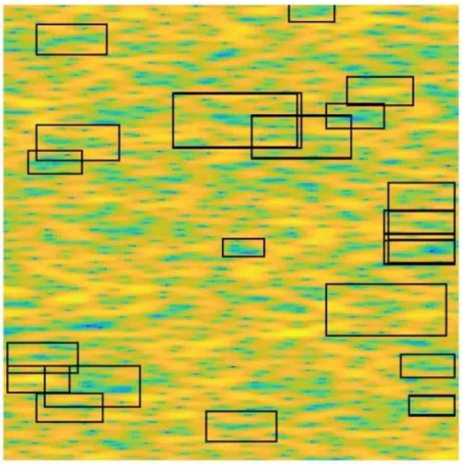

Fig. 5. MSER regions on spectrogram.

Table 3
MSER regions, SURF keypoints and feature vector properties.

Category	Property	Value
MSER Regions	Total Count	29
	Location	29×2 single
	Axes	29×2 single
	Orientation	29×1 single
	Pixel List	29×1 cell
Valid SURF Keypoints	Total Count	29
	Scale	29×1 single
	Sign of Laplacian	29×1 int8
	Orientation	29×1 single
	Location	29×2 single
	Metric	29×1 single
MSER Feature Vector	Feature Length	29×64 single matrix

GLCM is a texture analysis method that captures the spatial relationship of pixel intensities by computing co-occurrence matrices at defined offsets and directions. From these, second-order statistical features—such as contrast, correlation, energy, and homogeneity—are extracted. To improve discriminative power, features were calculated across multiple angles (0°, 45°, 90°, and 135°), capturing modulation-induced texture variations in the spectrogram.

In our approach, GLCM was applied to the grayscale spectrogram images to extract contrast, correlation, energy, and homogeneity. These features were computed using MATLAB's graycomatrix() and graycoprops() functions by analyzing multiple directional offsets to capture diverse spatial dependencies in the spectrogram. Initially, four primary directional offsets ([0,1], [-1,1], [-1,0], [-1,-1]) were selected to compute co-occurrence matrices, ensuring rotational and directional texture coverage. The feature values across these offsets, extracted from a generated 16 QAM are outlined in **Table 4**.

Each matrix captured pixel-pair statistics across a specific offset, and the derived features were averaged to form a robust descriptor set. This allowed us to quantify modulation-induced texture variations effectively. The contrast feature reflected local intensity changes; correlation measured pixel dependency; energy indicated spectral regularity; and homogeneity assessed local smoothness. These GLCM-derived descriptors were then appended to the overall feature vector, contributing to the classification and analysis of different modulation schemes with enhanced robustness and spatial sensitivity.

Table 4
GLCM Feature Values for Spectrogram Analysis.

Offset	Contrast	Correlation	Energy	Homogeneity
(0,1)	0.27774	0.8161	0.25053	0.88385
(-1,1)	0.7034	0.53423	0.16688	0.76937
(-1,0)	0.65162	0.56861	0.17365	0.78162
(-1,-1)	0.70448	0.53352	0.16616	0.76978

Together, the integration of BRISK, MSER, and GLCM enables a comprehensive image-based representation of the signals. These features capture both local and global structures within spectrograms, significantly enriching the feature space for downstream classification tasks. [14–16]

LIMITATIONS

Despite its diversity, the dataset has some inherent limitations. Limiting the dataset to five digital modulation schemes may reduce its applicability to broader communication scenarios involving diverse modulation types. The signals are synthetically generated, and while channel impairments (Rayleigh/Rician fading, AWGN, shadowing, adjacent channel interference) are modelled, hardware-specific artifacts (e.g., IQ imbalance, phase noise) and real-world spectral congestion are absent. The dataset size may be suboptimal for some deep learning architectures demanding large-scale data. Additionally, the use of fixed statistical models for noise and channel dynamics may not capture temporal or spatial variations in real environments. However, the included MATLAB scripts enhance reproducibility and flexibility, allowing users to customize modulation types, sampling rates, SNR ranges, and feature sets, partially offsetting the static nature of the dataset.

ETHICS STATEMENT

The authors confirm that they have adhered to the ethical requirements for publication in Data in Brief and the current work does not involve human subjects, animal experiments, or any data collected from social media platforms.

CRediT AUTHOR STATEMENT

M.M. Sadman Shafi: Conceptualization, Methodology, Software, Writing - Review and Editing, Project Administration.

Tasnia Siddiqua Ahona: Validation, Formal Analysis, Data Curation, Writing – Original Draft, Visualization.

Ashraful Islam Mridha: Resources, Supervision, Investigation.

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DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work the authors used ChatGPT to assist in improving the readability and language of the manuscript. After using this tool, the authors carefully reviewed and edited the content as needed and take full responsibility for the content of the published article.

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