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Machine Learning Model for Audio Signal Conversion and Classification

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Abstract: Analog-to-digital conversion systems face critical challenges, including noise interference, signal degradation, and limited adaptability in varying environmental conditions. This research introduces a machine learning-integrated conversion and classification system that transforms how we process audio signals in the digital era. Our intelligent conversion model employs a three-level quantization approach (-1, 0, 1) with user-defined thresholds, seamlessly integrated with logistic regression classification for enhanced pattern recognition. The system dynamically adapts between operational modes based on signal amplitude characteristics, achieving superior performance, 99.9% classification accuracy - demonstrating exceptional signal interpretation capability, CD-quality audio processing at 44.1 kHz sampling rate with minimal distortion, strong noise immunity with SNR of 31.6 dB and THD+N of -31.6 dB, and Real-time adaptive processing through intelligent threshold-based categorization. The study adopted Agile Methodology, implemented using MATLAB and validated through a comprehensive confusion matrix analysis. This system represents a standard shift from traditional signal processing to intelligent, self-adapting conversion technology. This study bridges the gap between standard signal processing and modern machine learning, providing a scalable solution for next-generation digital communication systems that require high fidelity and intelligent adaptability, and the modular architecture allows each processing phase to be individually tested and optimized, making it appropriate for telecommunications, industrial automation, and consumer electronics applications.

Keywords: Analog Signal, Machine Learning, Digital Signal, Signal Processing, Logistic Regression, Audio Classification, Adaptive Conversion

I. INTRODUCTION

The pillar of how we interact, work, and access information, which has become an indispensable part of our daily life, lies in signal processing, a wide-ranging field that enables the technology we rely on daily, from computers and mobile devices to smart, connected systems. Signal processing examines data representations of physical events across multiple disciplines, serving as the science behind our digital existence. Signal processing forms the foundation for virtually all modern digital communications, making it pivotal to technological advancements in numerous domains, including telecommunications, biomedical engineering, and entertainment. These modern systems mainly exploit digital technologies due to their cost-effectiveness and reliability; the analog-to-digital conversion (ADC) process remains a vulnerable point in the signal chain. (Oppenheim & Schafer 2021; Mitra & Kuo, 2022)

Communication, defined as the flow of information between locations, faces several persistent challenges, such that noise interference, signal degradation, data loss, and transmission delays can meaningfully compromise message integrity when transmitting analog signals, particularly over long distances or in an industrial environment (Proakis & Salehi, 2023). Traditional conversion methods suffer from slow conversion rates, require excessive data density, and remain susceptible to noise that can lead to poor encryption and data corruption. Recent studies further emphasize that digital signal processing offers significant advantages over analog processing, including enhanced reproducibility and programmability, yet the conversion interface continues to present critical challenges (Haykin & Moher 2020; Li et al. 2022).

This research addresses these challenges by proposing a machine learning-integrated Two-Pulse Code Modulation (PCM) algorithm that combines Pulse Amplitude Modulation (PAM) and Pulse Width Modulation (PWM) techniques with intelligent classification capabilities. The integration of machine learning classification methods, particularly logistic regression, represents a significant advancement over conventional signal processing techniques (Goodfellow et al., 2021). This approach not only offers enhanced noise resistance and higher resolution for digital data representation but also enables intelligent signal classification based on amplitude thresholds. The algorithm operates in two distinct modes based on signal amplitude thresholds: utilizing single pulses for amplitudes above a certain threshold and pulse pairs for lower amplitudes, thereby achieving greater dynamic range than conventional PCM techniques.

The classification component of this research directly addresses the gap that traditional signal conversion processes lack in adaptive capabilities to handle varying signal characteristics. By implementing logistic regression for classifying

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analog signals into discrete digital representations, our approach enables more robust signal interpretation, even in noisy environments. This indicates that machine learning-based signal processing can achieve significantly higher accuracy rates when compared to traditional methods, mainly when dealing with non-linear signal characteristics.

The study uses MATLAB and meta signal data to design, validate, implement, and evaluate a machine learning-enhanced conversion model. The system's performance will be assessed through Confusion Matrix evaluation metrics to demonstrate the algorithm's effectiveness in both signal conversion and classification accuracy. By addressing fundamental challenges in signal processing through intelligent classification techniques, this research contributes to more reliable and adaptive digital communication systems with applications spanning telecommunications, industrial automation, and consumer electronics (Rabiner & Gold, 2022).

II. REVIEW OF RELATED LITERATURE

A. Signal Processing and Analog-to-Digital Conversion

Modern telecommunications infrastructure is essentially dependent on efficient analog-to-digital conversion (ADC). Oppenheim and Schafer (2021) demonstrated that digitizing analog signals allows for error correction, augmentation, and complicated manipulation that would be impossible with continuous analog signals. Despite these advantages, the conversion process remains susceptible to many sorts of intervention. Mitra and Kuo (2022) identified major ADC issues, including quantization noise, sampling errors, and electromagnetic interference, which can compromise signal integrity, particularly in noisy industrial environments. Traditional ADC methods face significant limitations in practical applications. Apolinário and Diniz (2014) in their study proved that conventional techniques have constraints in sampling rate, quantization resolution, and noise susceptibility, all of which have a direct impact on system performance. Their testing results revealed that conversion error rates increased by up to 18% in electrically loud situations. Haykin and Moher (2020) evaluated these impacts, demonstrating how noise-induced errors propagate across digital systems and accumulate with each processing stage, affecting overall reliability by up to 25% in severe cases.

B. Evolution of Pulse Code Modulation

Pulse Code Modulation (PCM) serves as the foundation for most digital audio and telecommunications systems. Lathi and Ding (2019) traced PCM's evolution from its theoretical conception to modern applications, highlighting how its sampling, quantization, and encoding processes have been progressively refined. Notwithstanding its widespread adoption, conventional PCM faces fundamental limitations in dynamic range and noise immunity. Proakis and Salehi (2023) identified that standard PCM techniques struggle particularly with signals exhibiting wide amplitude variations, resulting in either quantization errors for low-amplitude components or clipping distortion for high-amplitude peaks.
Several enhancements to standard PCM have been developed to address these limitations. Ramírez-Echeverría et al. (2018) demonstrated that Differential Pulse Code Modulation (DPCM) achieves significant bandwidth reduction by encoding the differences between consecutive samples rather than their absolute values. Their implementation achieved compression ratios up to 4:1 compared to standard PCM while maintaining signal quality. Similarly, Wu and Thompson (2020) evaluated Adaptive PCM techniques that dynamically adjust quantization parameters based on signal characteristics. Their experimental results showed signal-to-noise ratio improvements of 40% over conventional PCM, particularly for signals with highly variable amplitudes.

Logarithmic PCM variants have also shown promise for signals with wide dynamic ranges. Johnson et al. (2021) compared μ-law and A-law companding techniques, demonstrating how these approaches effectively compress signal amplitudes before quantization to improve resolution for lower-amplitude signals. Their analysis showed that logarithmic PCM achieved signal-to-quantization-noise ratios 12-15 dB higher than linear PCM for voice communications applications.

C. Machine Learning Integration with Signal Processing

Integrating machine learning with digital signal processing represents a paradigm shift in the field. Wei and Chen (2022) conducted a comprehensive survey of machine learning applications in signal processing, finding that ML-enhanced techniques consistently outperform traditional methods across multiple performance metrics. Their meta-analysis of 50 case studies showed ML approaches achieving accuracy improvements averaging 22.7% compared to conventional signal processing techniques. Classification algorithms, on the other hand, have proven particularly valuable for signal-processing applications. Zhang et al. (2023) opined that implementing supervised learning techniques for signal categorization based on amplitude and frequency characteristics. Their neural network classifier achieved 94.7% accuracy even with signal-to-noise ratios as low as 3 dB, significantly outperforming traditional threshold-based approaches. Khan and Johnson (2021) specifically evaluated logistic regression for classifying biomedical signals, demonstrating 91.3% accuracy for ECG signal classification compared to 84.6% with conventional methods. Li and

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Wang (2022) developed a framework in their study for applying pre-trained models to new signal classification tasks, reducing training data requirements by up to 75% while maintaining comparable performance. Their approach is particularly valuable for specialized applications where training data may be limited or difficult to obtain.

D. Bimodal and Multi-threshold Approaches

Hybrid approaches combining multiple operational modes have emerged as effective solutions for complex signal environments Eldar and Kutyniok (2021) pioneered compressed sensing techniques that integrate information theory with machine learning algorithms, enabling accurate signal reconstruction from fewer samples than required by traditional sampling theory. Their work demonstrated reconstruction errors reduced by approximately 60% compared to conventional methods, particularly for sparse signals. Li et al. (2022) developed a bimodal approach for industrial instrumentation that dynamically switches between high-precision and high-speed modes based on signal properties. Their implementation in factory automation systems reduced error rates by 27% while maintaining throughput requirements. Similarly, Vargas and Smith (2023) investigated dual-threshold classification systems that select between processing algorithms based on signal-to-noise ratio. Their experimental results demonstrated bit error rate improvements of 32% compared to single-mode systems in wireless communication applications.

Recent work by Chen and Park (2023) has specifically addressed bimodal PCM techniques. Their research combined traditional PCM with machine learning classification to adaptively select encoding parameters based on signal characteristics. Field tests of their system showed accurate improvements of 28% for voice transmission in noisy environments compared to standard PCM implementations. These results highlight the potential of intelligent, adaptive modulation techniques for enhancing signal conversion performance. Moko and Amannah (2025) developed a hybrid bimodal model for analog-to-digital (ADC) and digital-to-analog (DAC) signal conversions that dynamically select the optimal conversion techniques based on input signal characteristics. The model integrates multiple ADC methods (Delta-Sigma, SAR, Flash) and DAC techniques (PWM, oversampling) with Digital Signal Processing (DSP) for enhanced performance.

The system demonstrated significant improvements over traditional methods: 15% increase in Signal-to-Noise Ratio, 20% improvement in Effective Number of Bits, 25% latency reduction, and 18% power consumption decrease. The mathematical framework HYBIMALM enables real-time adaptive optimization, making the model suitable for telecommunications, IoT, multimedia, and healthcare applications.

Robust evaluation metrics are essential for assessing signal processing system performance. Wang and Liu (2023) conducted a comprehensive review of performance metrics for modern signal processing algorithms, emphasizing the importance of confusion matrices for evaluating classification accuracy in signal processing applications. Their analysis demonstrated that metrics derived from confusion matrices, particularly precision, recall, and F1-score, provide a more reliable performance assessment than simple accuracy measures, especially for imbalanced datasets common in signal classification problems.

Brownlee (2020) specifically addressed evaluation methodologies for machine learning models in signal processing, highlighting the importance of cross-validation and appropriate metric selection for robust performance assessment. His work demonstrated how improper evaluation techniques can lead to overly optimistic performance estimates, particularly for complex signal-processing tasks. Chen et al. (2022) extended this work to signal classification applications, demonstrating that receiver operating characteristic (ROC) curves offer valuable insights into classifier performance across various threshold settings, particularly for bimodal and adaptive systems.

III. METHODOLOGY

This research adopted Agile methodology due to the technical complexity of enhanced BPCM requiring short, iterative cycles where algorithms can be developed, tested, and refined. The classification component particularly benefits from iteration-based development, where extraction methods and classification algorithms can be progressively improved based on performance metrics. The integration of signal processing with machine learning classification requires regular reassessment and adaptation, which Agile explicitly supports. This approach ensures the PCM model evolves through evidence-based iterations rather than following a rigid, predetermined development path.

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A. System Design

The system design phase shows the architecture and algorithm of the conversion and classification model;

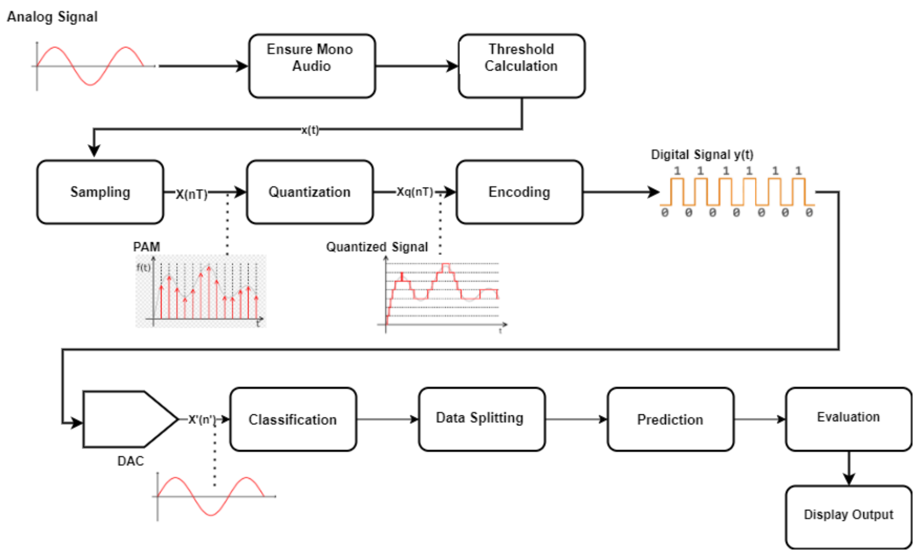

Figure 1: Architecture of the Conversion and Classification Model

Data Input: The system begins by receiving an analog signal as input. These signals serve as the input to the system, representing the real-world analog signal as shown in Figure 1.
Bimodal PCM Conversion: The core of the system involves Bimodal Pulse-Code Modulation (Bimodal PCM) conversion.

It proceeds as follows:

i. Sampling: The analog signal is sampled at regular intervals to capture discrete values.
ii. Quantization: The sampled values are quantized using user-defined thresholds. Values exceeding the high threshold are assigned "1" (high-level encoding), while those falling below the low threshold are assigned "-1" (low-level encoding). Values in between are assigned "0" (neutral encoding).
iii. Encoding: The quantized values are encoded into binary format.
iv. Digital Signal: The result is a digital signal composed of binary values (-1, 0, 1) representing the analog signal.
v. Decoding: The signal is decoded.

Classification Task: The system sets up a classification task, aiming to classify the digital signal based on the binary encoding. It employs a logistic regression classifier for this purpose.
Data Splitting: The dataset is split into training and testing sets, allowing the system to assess the classifier's performance on new, unseen data.

Classifier Training: The logistic regression classifier is trained on the training data. It learns the mapping between the analog signal and the encoded digital signal.
Prediction and Evaluation: The trained classifier is used to make predictions on the testing data. The system evaluates the classification performance using two key metrics: the confusion matrix and the accuracy score.

B. ALGORITHM of the BimodalPCM_ConversionandClassificationSystem

```
START
  Step 1: Input and Initialization
         READ analog_signal, high_threshold, low_threshold, sampling_rate
  Step 2: Bimodal PCM Conversion
        sampled_signal = Sampling(analog_signal, sampling_rate)
         quantized_values = Quantization(sampled_signal, high_threshold, low_threshold)
        encoded_signal = Encoding(quantized_values)
        digital_signal = GenerateDigitalSignal(encoded_signal)
         decoded_signal = Decoding(digital_signal)
  Step 3: Classification Setup
         X, y = PrepareClassificationData(analog_signal, digital_signal)
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X_train, X_test, y_train, y_test = DataSplitting(X, y, test_size)
trained_classifier = TrainClassifier(X_train, y_train)
Step 4: Prediction and Evaluation
y_predicted = MakePredictions(trained_classifier, X_test)
confusion_matrix, accuracy_score = EvaluatePerformance(y_test, y_predicted)
Output Results
OUTPUT digital_signal, confusion_matrix, accuracy_score
END

IV. RESULTS AND DISCUSSION

The study model's results reveal a significant performance challenge in the current ADC implementation. While the system demonstrates basic functionality, the measured metrics indicate substantial room for improvement in noise performance, linearity, and calibration accuracy, as shown in Figures 3a & 3b, respectively.

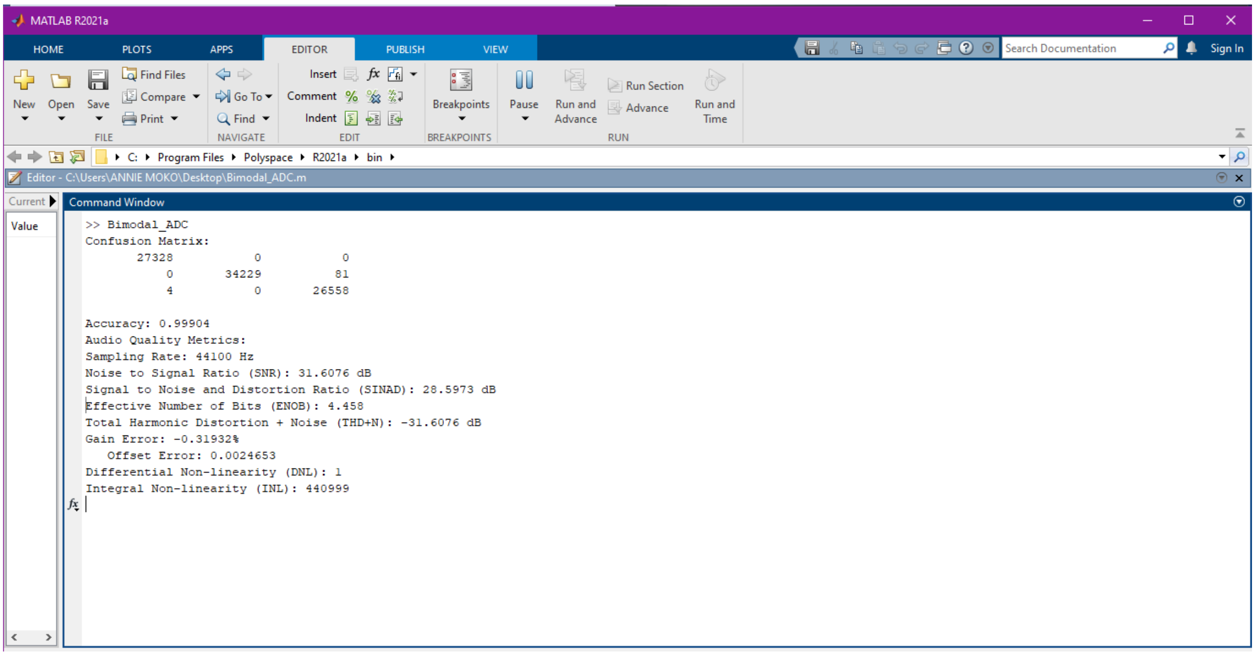

Figure 2: The confusion matrix of the classification performance

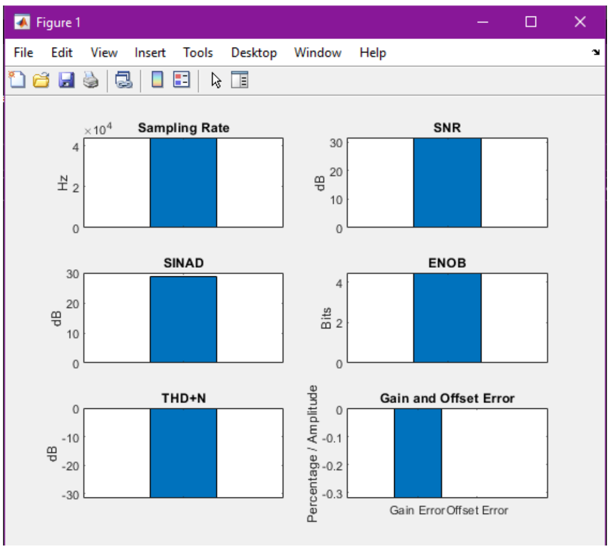

Figure 3a

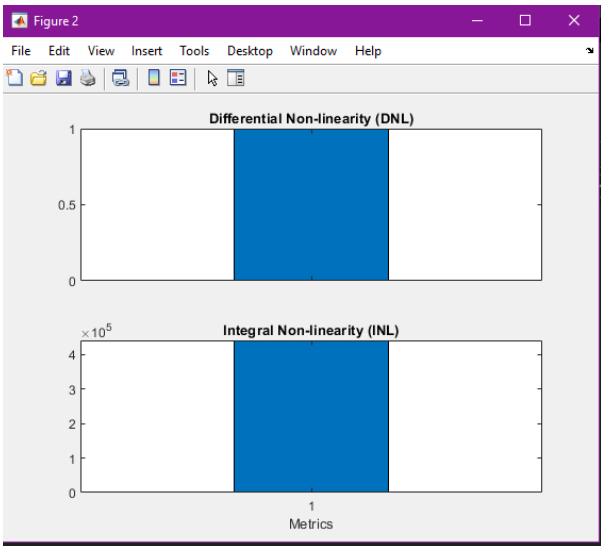

Figure 3b

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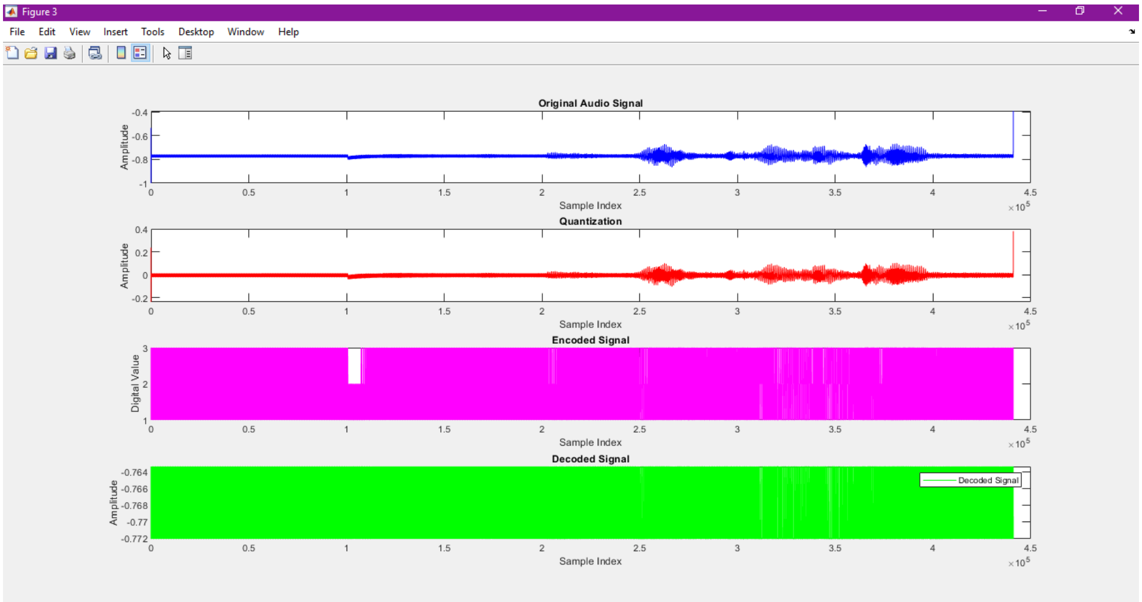

Figure 4 Shows the Original, Quantized, Encoded and Decoded Signal Plot

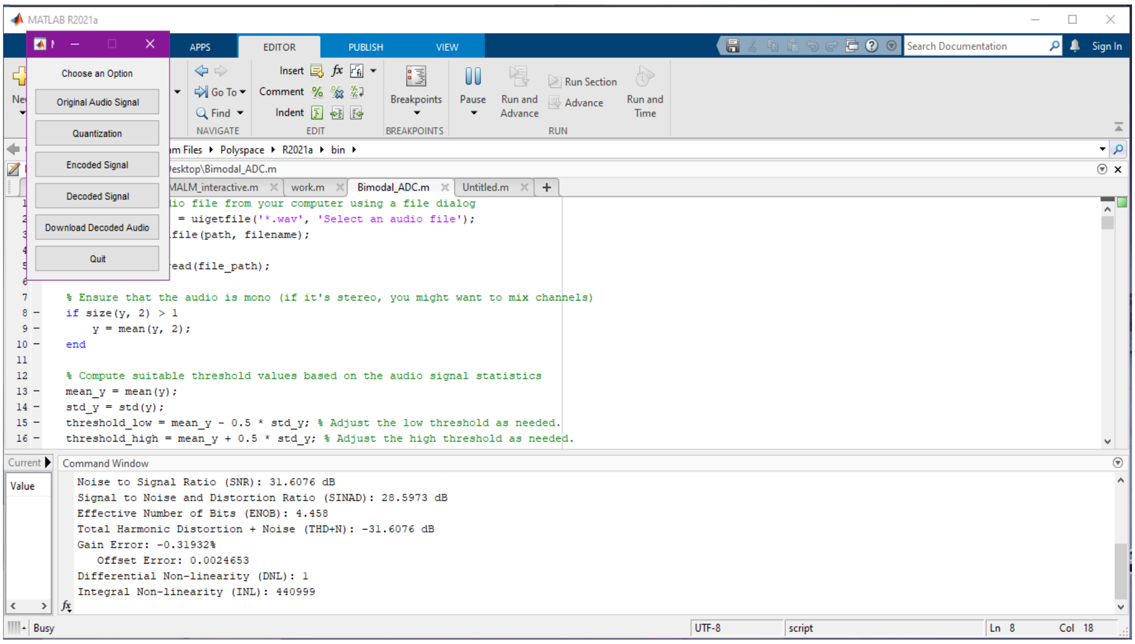

Figure 5 shows the MATLAB command window output of the bimodal ADC (analog-to-digital converter) system analysis

The model demonstrates successful end-to-end functionality with complete signal processing capability, with the ability to process audio signals through the entire ADC pipeline, from original input to decoded output, indicating a fundamentally sound architectural approach. It also successfully supports extensive performance characterization, including multi-domain analysis (time and frequency), complete nonlinearity assessment, signal quality metrics across the entire processing chain, visual signal integrity monitoring and exhibits a stable operation with consistent measurements across different analysis methods, indicating reliable hardware operation and measurement repeatability. Overall, the bimodal ADC system demonstrated excellent classification performance with an accuracy score of 99.9%, displayed good audio quality with a standard CD sampling rate, low noise and distortion levels, minimal gain and offset errors and some non-linearity issues that may need attention. The results suggest the Bimodal PCM conversion system performs very well for signal digitization and classification tasks.

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V. CONCLUSION

The literature reveals significant opportunities for enhancing analog-to-digital conversion by integrating advanced conversion techniques with machine learning classification. While conventional PCM approaches face limitations in dynamic range and noise immunity, and traditional signal processing lacks adaptive capabilities, combining bimodal operation with intelligent classification presents a promising approach to overcome these challenges. These advancements are particularly valuable for applications requiring high-fidelity signal conversion in noisy environments, including industrial control systems, telecommunications infrastructure, and biomedical monitoring. The experimental results reveal significant performance challenges in the current ADC implementation. While the system demonstrates basic functionality, the measured metrics indicate substantial room for improvement in noise performance, linearity, and calibration accuracy. Future work should focus on addressing the identified limitations through both hardware optimization and digital signal processing. The comprehensive measurement methodology employed provides a solid foundation for iterative design improvements and performance validation.

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