Date of publication DEC-31, 2025, date of current version OCT-22, 2025.
www.computingonline.net / computing@computingonline.net

Print ISSN 1727-6209
Online ISSN 2312-5381
DOI 10.47839/ijc.24.4.4343

Deep Learning for Classifying Chaotic Signals Transformed by Advanced Techniques

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ABSTRACT The rapid evolution of stealthy signals has introduced significant challenges in signal classification, necessitating advanced methodologies for accurate identification and characterization. This study investigates the classification of chaotic signals transformed into Analytic Chaotic Sequences. We utilized a ResNet34 architecture, adapted for one-dimensional signal data, to assess how varying network depths influence classification performance. The dataset comprised sequences with frequency- dependent variations, and the model's robustness was evaluated under varying noise levels. Results indicate that while the full ResNet34 model maintains high accuracy at elevated signal-to-noise ratios, its performance deteriorates with increased noise. In contrast, models with reduced depths (1, 2, and 3 layers) exhibit improved adaptability and noise resilience. Notably, the 2-layer and 3-layer ResNet34 variants show greater robustness in noisy conditions, suggesting practical benefits for real-world applications. This research highlights the importance of network depth and frequency adaptation in chaotic signal classification, emphasizing that simplified models can provide efficient performance and competitive accuracy, particularly in environments with fluctuating noise levels. Future work will optimize the ResNet34 architecture and expand the dataset to enhance generalization and robustness.

KEYWORDS analytic chaotic sequences; Chebyshev polynomials; ResNet34; signal classification; deep learning.

I. INTRODUCTION

The rapid evolution of signals with high levels of stealth has precipitated significant challenges in signal classification, driven by escalating requirements for enhanced security and reliability in communication networks. Recent advancements have yielded highly stealthy signals capable of evading conventional classification methodologies, thereby complicating accurate identification and characterization efforts [1]. Integrating sophisticated algorithms and state-of-the- art technologies has substantially augmented these signals' stealth characteristics, initiating an ongoing technological arms race between developers of highly stealthy signals and classification experts.

Within this context, chaotic signals have emerged as a powerful tool for ensuring high stealth levels in various practical applications. These signals possess inherent properties that make them difficult to detect and intercept, providing a natural advantage in scenarios where concealment is crucial. In radar systems, chaotic waveforms enhance target detection and tracking capabilities, particularly in complex and noisy signal environments or against sophisticated jamming techniques, while maintaining a low probability of intercept [2].

The application of chaotic signals extends beyond traditional radar systems [3]. In wireless communication networks, these signals increase channel capacity and spectral efficiency, addressing the growing demand for higher data rates and more efficient spectrum utilization. This is particularly crucial for information transfer through radio channels, where the transmitted data volume continues growing exponentially [4, 5]. The stealth properties of chaotic signals make them especially valuable in this context, allowing for secure and covert communications. This progression necessitates continuous adaptation and innovation in classification techniques, as the primary challenge now encompasses not only the detection of these elusive signals but also their precise characterization within an increasingly complex and congested electromagnetic spectrum. Enhanced classification techniques enable better detection, identification, and utilization of these stealthy signals across various fields, ultimately improving system performance and security while mitigating potential misuse or interference. As the complexity of these signals continues to grow, so does the need for advanced classification methods to ensure their practical use and management across diverse technological domains [6, 7].

Beyond theoretical contributions, the proposed framework has potential applications in secure military communications, radar systems, and IoT networks operating in challenging environments. Its ability to classify chaotic signals under noisy conditions makes it particularly relevant for real-time systems where stealth and reliability are critical. To position our contribution, we first review related studies on stealth properties and signal classification approaches.

II. RELATED WORKS

Several intrinsic properties of signals can influence their stealth characteristics to varying degrees [8, 9]. For example, in [10], the concept of IID-stealth was introduced. This concept refers to Independent and Identically Distributed stealth signals, which statistically resemble white noise and are characterized by their ability to remain masked within the noise. As demonstrated in [11], the numerical assessment of IID-stealth is based on calculating nonparametric BDS-statistics, which measure the closeness of the signal's "shape" in pseudo-phase space (a reconstructed state space derived from time series using delay embedding) to that of "white" noise. For independent and identically distributed random variables ("white" noise), the BDS statistics values lie within the range of (-1.96, 1.96). On the other hand, structural stealth depends on the complexity and variability of the signal's structure, making it harder for enemy to detect and decode the signal. By optimizing the parameters of the communication system, structural stealth can be maximized, thereby significantly increasing the enemy's time and effort required for successful interception [12, 13].

It has recently been posited that effectively ensuring the stealth of transmitted data requires achieving high levels of both structural and IID-stealth in signals [14]. To this end, the authors in [15] propose utilizing dynamic (deterministic) chaos in forming the information sequence. The inherent unpredictability and complex dynamics of chaotic signals make them ideal for applications requiring high levels of security and low detectability [16, 17]. Here are some key reasons why chaotic signals are advantageous for stealth [16, 17]:

- the random-like nature of chaotic signals makes them difficult to predict and intercept. This unpredictability ensures that conventional methods do not easily detect the signals;
- chaotic signals typically exhibit wideband characteristics, spreading their energy over a broad frequency range. This reduces the chance of detection and interception by narrowband receivers;
- despite their complex nature, chaotic signals can be synchronized, allowing for coherent detection and secure communication between transmitter and receiver.

However, classifying chaotic signals presents significant challenges due to their inherent characteristics:

- traditional classification methods often rely on energy-based criteria, which may not adequately capture the unique "shape" or dynamics of chaotic signals in pseudo-phase space;
- chaotic signals are susceptible to initial conditions, leading to unpredictable long-term behavior that is difficult to model accurately;
- chaotic signals often exhibit irregular patterns that can resemble noise, posing challenges in distinguishing accurate chaotic signals from random noise;
- in practical scenarios, chaotic signals may be obscured by background noise, making their detection and classification more challenging;
- the non-stationary nature of chaotic signals means their statistical properties change over time, requiring adaptive classification methods for consistent detection;
- achieving accurate classification and analysis of chaotic signals often necessitates computationally intensive algorithms, which can pose challenges for real-time applications.

Researchers have proposed various methods to address these challenges to classify chaotic signals. In [18], the authors present a classification method for chaotic codes using higher-order statistics features extracted via wavelet transforms and several clustering techniques. They tested four clustering methods: k-means, hierarchical clustering, fuzzy c-means, and subtractive clustering. The study found that features extracted from non-decimated wavelet transforms generally outperformed other methods, except when using subtractive clustering, where stationary wavelet transforms performed better. However, the reliance on higher-order statistics and wavelet transforms suggests a need for more robust and generalized feature extraction methods that can adapt to various types of chaotic signals. Also, in [19], the authors explore further the classification of chaotic signals generated by low-dimensional deterministic models. They introduce statistical concepts such as the "best predictor" of a signal and apply them through the ergodic theory lens. This theoretical framework allows them to develop a "bootstrapping" estimator to assess the statistical properties of these signals. Their approach is validated through comprehensive numerical simulations, demonstrating its efficacy in handling deterministic chaotic signals.

Despite the effectiveness of these statistical methods [18], [19], the inherent complexities and uncertainties present in real-world chaotic signals often necessitate more advanced approaches. Therefore, leveraging novel classification algorithms based on neural networks is increasingly advocated. Neural networks offer adaptive learning capabilities that significantly enhance classification accuracy and robustness across diverse and challenging chaotic signal datasets. Integrating these advanced algorithms with statistical insights could pave the way for more comprehensive and effective chaotic signal classification and analysis solutions.

Building on this idea, the article [20] focuses on employing standard deep neural networks to classify univariate time series from dynamical systems like the logistic map and the Lorenz system. The study underscores the effectiveness of a convolutional neural network (CNN) architecture without batch normalization layers in distinguishing chaotic from non-chaotic behaviour. However, a significant limitation identified in this work is its narrow exploration of the neural network's performance in real-world, high-dimensional chaotic systems. The study also acknowledges the impact of training dataset size on model performance, highlighting the need for broader validation across more complex and diverse chaotic datasets to enhance generalizability and applicability in practical settings. In contrast, the article [21] introduces the Triad State Space Construction (TSSC) as a novel image encoding method for chaotic time series. By transforming time series data into TSSC images, the authors utilize Convolutional Neural Networks (ConvNet) for classification. The TSSC approach enhances classification accuracy and robustness by capturing higher-order temporal patterns and new forbidden regions beyond traditional methods like permutation entropy. However, the paper needs to address the computational complexity and potential limitations of TSSC when applied to large datasets or its generalization capability across different types of chaotic systems. This approach highlights ongoing efforts to innovate deep learning techniques for chaotic signal analysis, aiming to overcome existing methodological limitations and expand applications in diverse and challenging real-world scenarios.

The work [22] also focuses on classifying chaotic signals using recurrence plots and CNNs, validated through the Lyapunov exponent. The method effectively differentiates between smooth and nonsmooth chaotic systems. However, the paper could further investigate the scalability of this approach and its application to more complex chaotic systems with varying parameters. Moreover, [23] proposes a method for classifying chaotic time series data by embedding at- tractor images with time information and using residual networks (ResNet). Their results demonstrate that incorporating time information into the attractors improves classification accuracy, particularly with Lorenz data. The study achieves high test accuracy and effectively distinguishes between different chaotic states, showcasing advancements in leveraging deep learning for chaotic signal classification.

Recently, new works have emerged focusing on con-structing novel chaotic signals. The subject of the re- search involves the processes of formation and processing of analytical chaotic signals to ensure the stealthiness of data transmission [14]. The research synthesizes a method for increasing the stealthiness of information transmission systems based on signals formed by chaotic mapping using Chebyshev polynomials. This method aims to ensure reliable information protection in radio transmission systems, achieving a high level of the signals' structural and IID (independent and identically distributed) stealthiness. The tasks include investigating the effectiveness of the developed method by numerical assessment of the level of structural and IID-stealthiness and the quality of recovery of the masked information on the receiving side. Also, in [24], authors propose an innovative approach to enhancing the robustness of chaotic signal construction by utilizing Mandelbrot kernel values. These values serve as weight coefficients during the transformation of white Gaussian noise into fractal (colored) noise, thereby dynamically altering the distribution density of the generated chaotic sequence. The study demonstrates how this transformation complicates the attractors within the sequence, leading to a detailed analysis of its dynamic and static characteristics. Furthermore, a comprehensive numerical security assessment is conducted to evaluate the influence of transformation kernel parameters on the sequence's resilience and reliability in practical applications.

As advancements in chaotic signal construction continue to evolve, there is a critical need for corresponding advancements in signal classification methodologies. The complex and unpredictable nature of chaotic signals necessitates innovative approaches to discern and analyze their unique characteristics effectively. By harnessing the adaptive learning capabilities and deep learning architectures of neural networks, researchers aim to achieve superior classification accuracy and robustness across a wide range of chaotic signal types and scenarios. This research aims to develop new algorithms based on neural networks tailored explicitly for classifying these emerging chaotic signals.

In recent years, hybrid architectures combining transformer/attention modules with other techniques have begun to show promising results in signal and time-series tasks. For example, in [28] authors present a CNN-Transformer hybrid for automatic modulation classification in radio frequency signals, comparing multi-head, causal, and sparse attention mechanisms and demonstrating significant reductions in inference time while maintaining classification performance. Moreover, in [29] has been proposed a hybrid transformer + XGBoost ensemble model optimized via wavelet decomposition and chaotic billiards optimization for forecasting chaotic systems, achieving robust performance across frequency bands. Another recent work develops a dynamic adaptive graph convolutional transformer for time-series modeling, combining graph convolution and attention-based modules to capture temporal dependencies and relational structure in the data [30]. These recent studies highlight the growing role of hybrid and attention-based architectures in time-series and chaotic signal analysis, but further research is required to address the challenges of efficiency and adaptability in real-time applications.

III. MATERIAL AND METHODS

A. DATASET FORMATION

In this work, we plan to classify chaotic signals proposed in [14]. Thus, to create the dataset, we use the Chebyshev polynomial of the first kind, third order:

$$x_{n+1} = 4x_n^3 - 3x_n , \qquad (1)$$

where $n = 0 \cdots N-1$ is the number of samples in the sequence and x_0 is the initial value of the sequence.

We will use an analytic signal to "destroy" the structured image in the pseudophase space, as proposed in [14]. The analytic signal corresponding to expression (1) is defined as:

$$\dot{x}_n = x_n + jy_n, \tag{2}$$

where $y_n = \{y_0, y_1, \cdots, y_{N-1}\}$ is the imaginary part of the analytic signal given by the Hilbert transform of the input sequence $x_n = \{x_0, x_1, \cdots, x_{N-1}\}$:

$$y(n) = \sum_{k=0}^{N-1} \frac{x(n)}{\pi(n-k)}, \tag{3}$$

This representation provides direct access to the instantaneous envelope A_n and phase ψ_n, calculated as:

$$A_n = |\dot{A}| = \sqrt{x_n^2 + y_n^2}, \tag{4}$$

and

$$\psi_n = \arctan\left(\frac{x_n}{y_n}\right), \tag{5}$$

After transferring the complex amplitude to the harmonic modulation frequency ω, we obtain the Analytic Chaotic Sequence (ACS) in the form:

$$s_n = \mathrm{Re}\left(A_n e^{j\omega n}\right) = A_n \cos\left(\psi_n + \omega n\right), \tag{6}$$

Fig. 1 shows the transformation of the Chebyshev polynomial of the first kind, third order, to the ACS with $\omega = 1.0$.

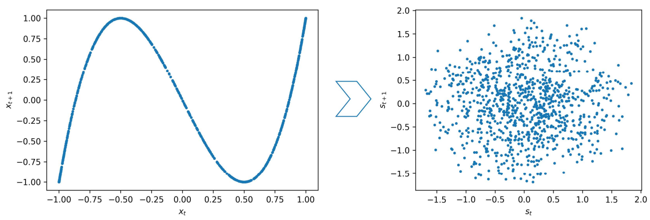

Figure 1. Transformation of the Chebyshev Polynomial to ACS.

The analysis of Fig. 1 demonstrates the effectiveness of the ACS transformation in disrupting the structured shape of the original Chebyshev polynomial sequence. The resulting sequences exhibit a more random behavior, potentially displaying a high level of stealth. We should create a dataset that accurately captures these frequency-dependent variations to distinguish sequences transformed with different frequencies in ACS.

Each class in the dataset represents a unique frequency setting, enabling the model to discern and classify sequences based on their frequency-transformed characteristics. This approach enhances our understanding of the chaotic behaviors introduced by ACS and prepares the dataset for sophisticated pattern recognition tasks, essential for applications requiring robust signal analysis and classification. The dataset consists of 10 classes, with nine classes showcasing sequences transformed using ACS at varying frequencies (ω) from 0.5 to 5 with step 0.5, alongside one class featuring original Chebyshev polynomial of the first kind, third order (cp31). Each class contains 10,000 sequences, each 1024 units in length, with initial values for the Chebyshev polynomial sequences spanning from 0.28 to 0.98. To ensure sequence diversity, the initial values of the Chebyshev polynomials were systematically varied across a predefined range. This approach generated a wide spectrum of chaotic sequences with distinct frequency-dependent characteristics. The range was chosen to include both stable and unstable regions of the polynomial dynamics, thereby preventing repetitive or degenerate sequences. While this construction ensures high variability, potential biases may still arise from focusing only on Chebyshev-based chaotic sequences.

B. NEURAL NETWORK ARCHITECTURE AND TRAININGMETHODOLOGY

For this classification problem, we choose a ResNet34 architecture (Fig. 2) due to its proven efficacy in handling complex image and signal classification tasks [25].

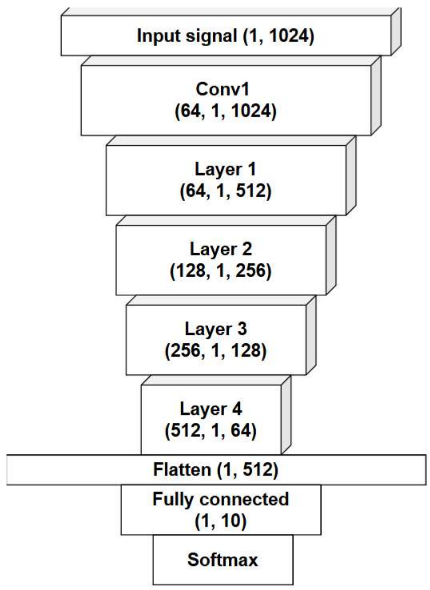

Figure 2. The architecture of ResNet 34 [25].

ResNet34, a deep residual network, leverages skip connections to mitigate the vanishing gradient problem, allowing for practical training of intense networks. This architecture is particularly suitable for capturing the intricate patterns in our frequency-transformed sequences. ResNet34 is typically used for image classification, where the input consists of RGB images with three channels. However, we adapt the network for signal classification to accept input sequences with a single channel, as our data represents one-dimensional signals rather than three-dimensional image data. This adaptation involves modifying the first convolutional layer to accommodate an input shape with one channel instead of three. By doing so, the network can effectively process and learn from the one-dimensional signal data while retaining the powerful feature extraction capabilities of the ResNet34 architecture.

To train the model, we use the cross-entropy loss function and the Adam optimizer. The cross-entropy loss function is defined as [26]:

$$Loss = -\sum_{i=1}^{N} y_i \log\left(\hat{y}_i\right), \tag{7}$$

where y_i is the true label and $\hat{y}_i$ is the predicted probability for class i, N – number of classes.

The Adam optimizer updates the model parameters using the following steps [26]:

1. Update biased first moment estimate:

$$m_t = \beta_1 m_{t-1} + \left(1-\beta_1\right) g_t, \tag{8}$$

where m_t is the exponentially moving average of the gradients, β_1 is the decay rate for the first moment, and g_t is the gradient at time step t.

2. Update biased second raw moment estimate:

$$v_t = \beta_2 v_{t-1} + \left(1-\beta_2\right) g_t^2, \tag{9}$$

where v_t is the exponentially moving average of the squared gradients, and β_2 is the decay rate for the second moment.

3. Compute bias-corrected first moment estimate:

$$\hat{m}_t = \frac{m_t}{1-\beta_1^{t+1}}, \tag{10}$$

where $\hat{m}_t$ is the bias-corrected first moment estimate.

4. Compute bias-corrected second raw moment estimate:

$$\hat{v}_t = \frac{v_t}{1-\beta_2^{t+1}}, \tag{11}$$

where $\hat{v}_t$ is the bias-corrected second moment estimate.

5. Update parameters:

$$\theta_t = \theta_{t-1} - \frac{\alpha \hat{m}_t}{\sqrt{\hat{v}_t}} + \varepsilon, \tag{12}$$

where θ_t is the parameter being updated, α is the learning rate, and ε is a small constant to prevent division by zero.

The Adam optimizer combines the advantages of AdaGrad and RMSProp, making it well-suited for training deep learning models. It adapts the learning rate for each parameter individually by considering both the first and second moments of the gradient, and it corrects for bias in these moment estimates.

We plan to explore how the number of layers in ResNet34 influences model performance. Specifically, we aim to investigate whether deeper layers improve the model's ability to classify sequences with subtle frequency-dependent variations or if a shallower network suffices.

The dataset is divided into training, validation, and test sets to evaluate the model effectively. First, the data is split into two parts: 70% for training and 30% for testing. The 30% test data is then further divided equally to form validation and test sets. This ensures that the model is trained on 70% of the data, validated on 15%, and tested on the remaining 15%, allowing for a comprehensive evaluation of its performance.

This approach allows us to monitor the model's performance on unseen data during training, tuning hyper- parameters based on validation set performance, and ultimately assessing the final model accuracy on the test set. This structured division ensures that our model generalizes well to new, unseen sequences and effectively captures the frequency-dependent variations introduced by the ACS transformation.

IV. RESULTS

The initial step in analyzing the performance of our ResNet34 model on the signal classification task is to visualize the activation functions for each layer in the network. The activations demonstrate how the ResNet34 model processes and transforms the input signals through its deep network architecture. By examining these activations, we can gain insights into how the model extracts features at different levels of abstraction and how it distinguishes between different classes of frequency-transformed sequences.

To correctly visualize feature maps from ResNet34 layers, we use Uniform Manifold Approximation and Projection (UMAP) [27]. UMAP is a dimensionality reduction technique that helps in visualizing high-dimensional data in lower dimensions, making it easier to interpret the complex feature maps produced by the deep layers of the network.

The UMAP algorithm involves the following mathematical steps:

Step 1 – Constructing a fuzzy topological representation:

$$P_{ij} = e^{\frac{-d\left(x_i, x_j\right)}{\sigma_i}}, \tag{13}$$

where $d(x_i,x_j)$ is the distance between data points x_i and x_j, and σ_i is a local connectivity parameter hat adjusts the scale of distances for each data point.

Step 2 – Constructing a symmetrized graph representation:

$$A_{ij} = P_{ij} + P_{ji} - P_{ij} P_{ji}, \tag{14}$$

where A_{ij} represents the symmetrized weight between data points x_i and x_j, combining the influence of both P_{ij} and P_{ji}.

Step 3 – Optimizing the Low-dimensional Representation:

$$\min \sum_{i \neq j} A_{ij} \log\left(\frac{A_{ij}}{e^{-\|y_i - y_j\|}}\right) + \left(1 - A_{ij}\right)\log\left(\frac{1 - A_{ij}}{1 - e^{-\|y_i - y_j\|}}\right), \tag{15}$$

where y_i and y_j are the low-dimensional representations of the high-dimensional data points x_i and x_j.

Fig. 3 below displays these activation functions, illustrating how each layer responds to the input signal data.

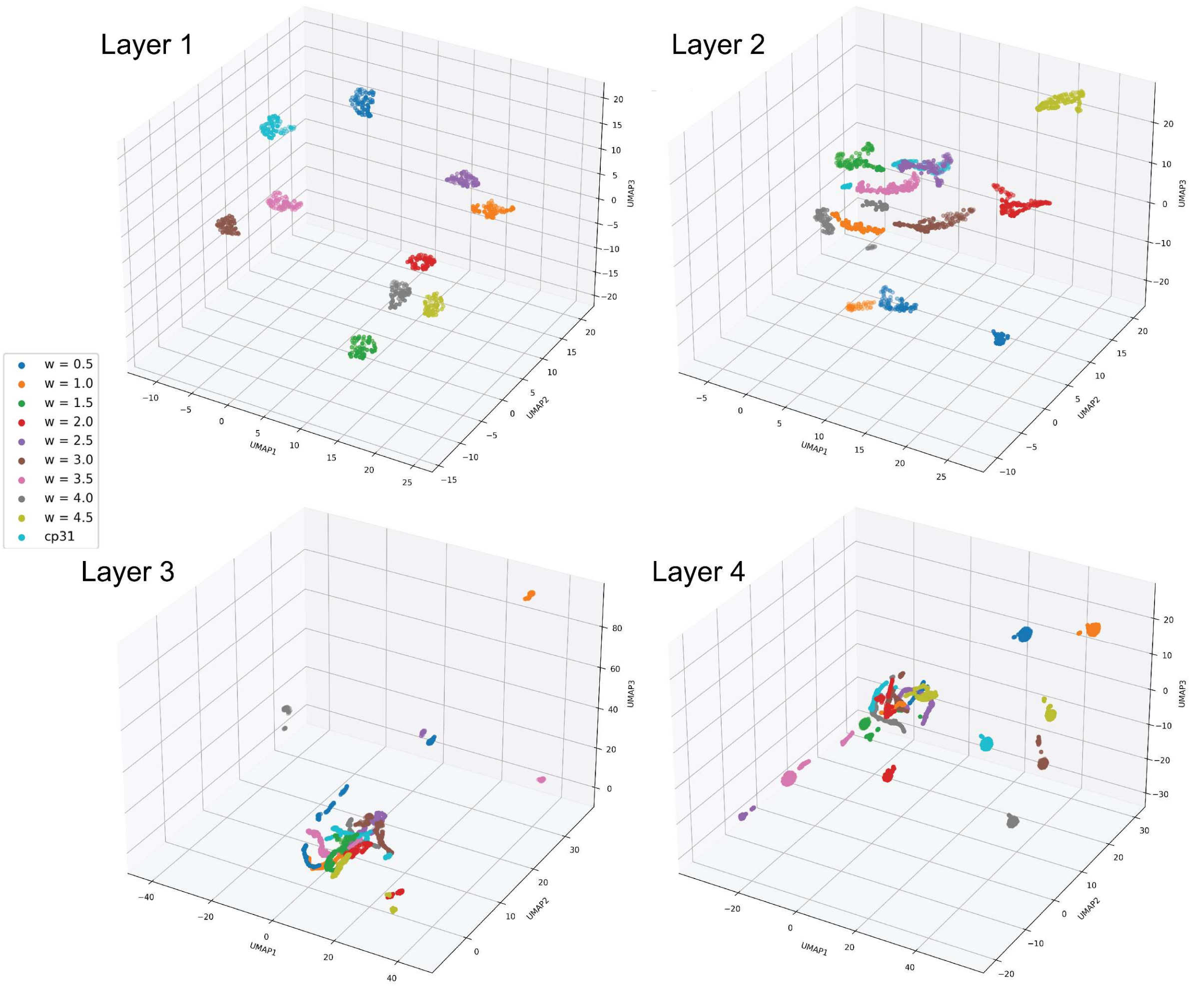

Figure 3. Activation Functions for Each Layer in ResNet34.

Upon examining the activations in Fig. 3, we found that layer 1 shows a relatively scattered distribution of activations, indicating that the first layer captures a broad range of features. In layer 2, the activations begin to cluster, reflecting the layer's focus on more specific features. By layer 3, the activations become more complex and overlap significantly, making it difficult to visually distinguish between different classes. Finally, in layer 4, although activations continue to show overlapping patterns, this indicates that the network is capturing more abstract, high-level features. While these deeper layers may not visually separate classes as clearly, they are likely integrating multiple complex features that contribute to the final decision-making in classification tasks. This observation implies that the intermediate layers might not effectively capture distinctive features for each class, underscoring the role of deeper layers in the ResNet34 architecture for differentiating between frequency-transformed sequences. To better understand the impact of network depth, we examine how varying the number of layers in the ResNet34 architecture affects classification performance, aiming to find the optimal balance between model complexity and accuracy. Each variant of the ResNet34 model was trained using a dataset of ACS. After evaluating each model on the test data, we observed that the confusion matrix for each ResNet34 variant showed 100% accuracy. Following this achievement, our next objective was to assess the robustness of these models in the presence of noise. To simulate this scenario, we generated 21 instances of white noise with varying standard deviations, altering the signal-to-noise ratio (SNR).

Fig. 4 presents four plots, each showing model accuracy as a function of SNR (in dB). This evaluation provides insights into how the classification performance of the models degrades as input signals become noisier. By analyzing these results, we assess the robustness of each ResNet34 variant to noise and identify which depth configuration maintains the highest accuracy across varying levels of noise interference.

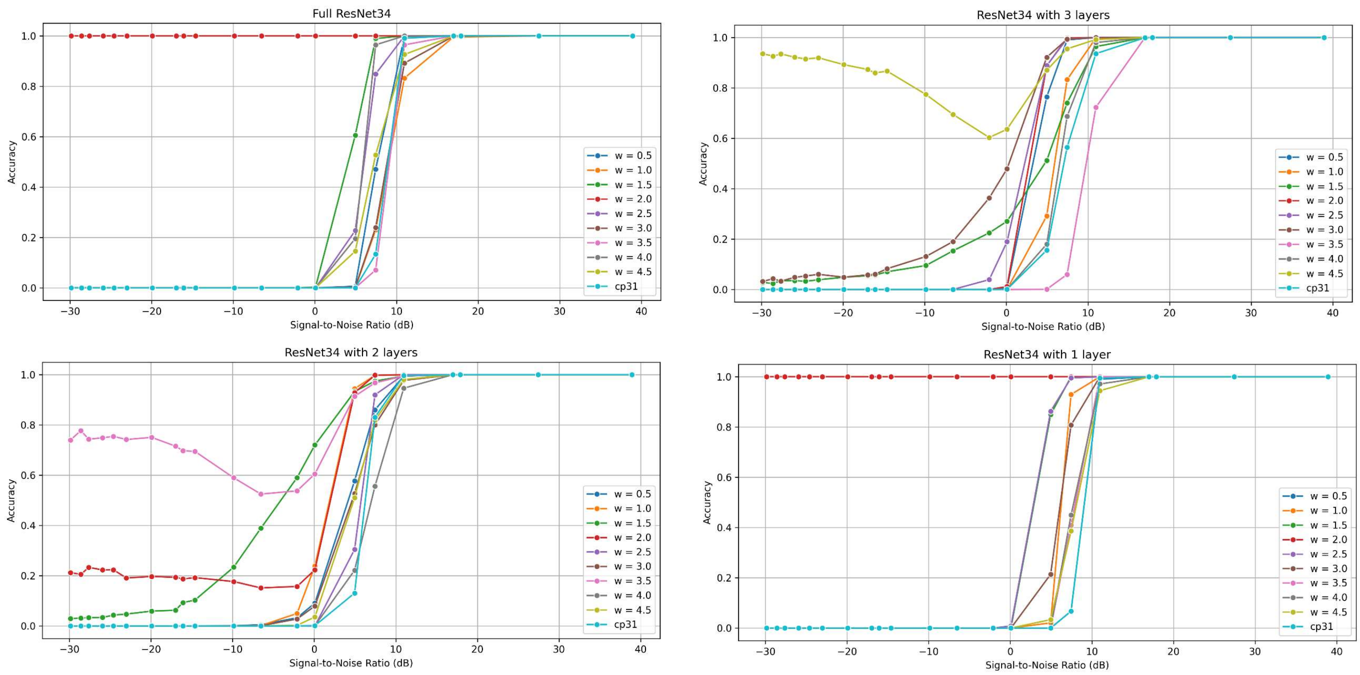

Figure 4. Performance comparison of ResNet34 variants under varying noise conditions.

The analysis of Fig. 4 reveals interesting patterns in how ResNet34 variants with different numbers of layers perform across varying SNR. The full ResNet34 model maintains almost perfect accuracy at high SNR values, above 10 dB, but its performance drops sharply as noise increases below this threshold. This behavior is consistent across different classes of ACS.

In contrast, the ResNet34 with 3 layers shows more varied performance depending on the class. Some configurations demonstrate impressive robustness to noise, maintaining high accuracy even at very low SNR levels. Others behave more like the full ResNet34, with sharp accuracy drops in noisy conditions. The 2-layer version of ResNet34 exhibits the most diverse behavior across classes. Certain classes maintain moderate accuracy even in very noisy conditions, while others show sharp transitions similar to the full model. This diversity suggests that the 2-layer model offers flexibility in tuning for specific noise environments.

Interestingly, the ResNet34 with just 1 layer behaves similarly to the full model, showing sharp transitions around 10 dB SNR for most classes. It maintains high accuracy in low-noise conditions but struggles in noisier environments.

These observations highlight how reducing the network depth allows for more diverse behavior and potentially better performance in noisy conditions for some ACS. The 3- layer and 2-layer models appear to offer a good balance between model complexity and noise robustness, making them potentially suitable for real-world applications with varying noise levels.

The impact of ACS becomes more pronounced in models with fewer layers, suggesting that careful tuning could optimize performance for specific noise conditions. While the full ResNet34 performs well in low-noise scenarios, the reduced-depth versions with appropriate ACS might be more suitable for applications where robustness to noise is crucial.

This analysis underscores the importance of considering both network depth and frequency in ACS when designing models for signal classification tasks, especially in environments with varying noise levels. It demonstrates that simpler models can sometimes offer advantages in terms of adaptability and robustness to noise, challenging the notion that deeper networks are always better.

To comprehensively assess the performance of each model, an examination of their accuracy across varying SNR is essential. Fig. 5 provides a comparative analysis of four ResNet34 variants under different SNR conditions. The graph illustrates a consistent trend across all models, depicting an S-shaped curve where accuracy increases as SNR improves.

At higher SNR levels, particularly above 10 dB, all models achieve near-perfect accuracy, converging closely to 1.0. Conversely, at lower SNR levels below -10 dB, performance notably declines, with accuracy hovering around 0.1, indicative of a challenge akin to random guessing in a 10-class classification scenario.

Distinctive differences between the models manifest within the 0-10 dB SNR range. The ResNet34 model with 1 layer demonstrates a slight advantage in performance, particularly noticeable between 5-10 dB. The 3-layer variant exhibits a marginal lag in the 5-10 dB range but shows comparable performance at higher SNR levels. Interestingly, the full ResNet34 and its 2-layer counterpart display remarkably similar accuracy profiles across all SNR levels.

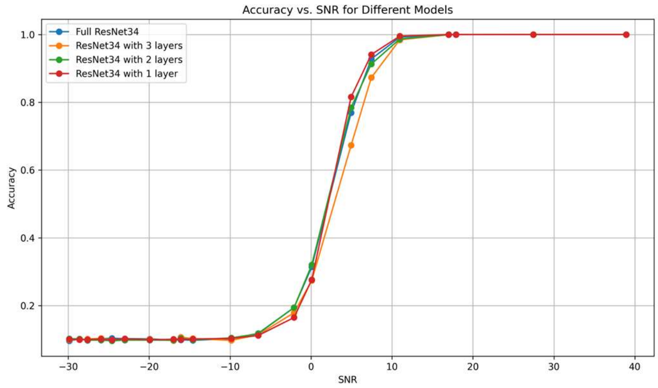

Figure 5. Accuracy vs. SNR for Different Models.

This consistency across models suggests comparable resilience to noise, with minimal variability observed in critical transition ranges. Notably, the performance parity between the 2-layers model and the full ResNet34 implies that, for this specific task, a simplified model could offer computational efficiency without substantial compromise in accuracy.

In summary, Fig. 5 underscores that while subtle performance distinctions exist among ResNet34 variants, their overall response across SNR levels remains largely analogous. The selection between these models may hinge on considerations such as computational resources and specific performance requirements, particularly within the 0-10 dB SNR range where nuanced differences are most pronounced. Regarding computational efficiency, the model was trained on an NVIDIA GeForce RTX 3050 GPU (4 GB) in approximately 30 minutes for the full dataset. Inference requires less than 1 ms per sequence, which demonstrates the suitability of the approach for near real-time applications.

VI. CONCLUSIONS

The development of signals with high stealthiness has significantly impacted the field of signal classification, driven by the increasing need for secure communication. This study applied ResNet34 to chaotic signals transformed by Analytic Chaotic Sequences from Chebyshev polynomials and evaluated robustness under varying SNR conditions.

Results show that while the full ResNet34 model achieves near-perfect accuracy at high SNR levels, its performance drops significantly with increased noise. In contrast, ResNet34 models with fewer layers (1, 2, and 3 layers) exhibit varying degrees of robustness to noise. The 2-layer and 3-layer models demonstrate better adaptability in noisy environments, indicating that reduced-depth architectures may offer practical advantages for real-world applications. In addition, the ACS transformation contributes to the stealthiness of chaotic signals by making them statistically resemble white noise, further strengthening their suitability for secure communication scenarios. This study underscores the importance of network depth and frequency adaptation in signal classification, with simplified models providing efficient performance and competitive accuracy, especially in noisy conditions.

Future research will focus on optimizing ResNet34 through alternative configurations, advanced regularization, and hybrid architectures to improve generalization. Extensions will also include scaling to other families of chaotic signals and testing in real-time scenarios such as military communications, radar-based detection, and low-power IoT. Limitations of the present study include reliance on Chebyshev-based sequences, evaluation restricted to white noise, and scalability to larger datasets, which we aim to address by expanding the dataset with diverse signal types and real-world noise.

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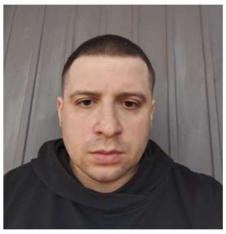

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