"Hybrid Machine Learning Approaches for Resilient Audio Watermarking Against Digital Signal Attacks"

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Abstract: *Good watermarking becomes even more important in safeguarding intellectual property given the increasing availability of digital content. Effective conventional audio watermarking techniques are limited; modern digital signal processing assaults like filtering, noise augmentation, and compression can transcend them. This work provides a hybrid machine learning strategy to improve watermarks by combining signal processing and deep learning. The suggested approach ensures imperceptibility and resilience by generating embedding patterns using CNNs and LSTM networks then performing discrete wavelet transform and singular value decomposition. Comparatively to current watermarking techniques, extensive study shows that our method is better in durability, undetectability, and resistance to low-pass filtering, Gaussian noise, and MP3 compression. The results show that hybrid machine learning improves the lifetime and performance of digital audio watermarking.*

Keywords: *Audio watermarking, Digital signal attacks, Discrete Wavelet Transform, Convolutional Neural Networks, Singular Value Decomposition*

1. Introduction

Protecting rights and preventing illicit sharing of digital assets is crucial as more material is converted to digital formats. Audio watermarking is a common approach to add data to talks without being heard. This can authenticate material, defend rights, or confirm identity. DSP methods like filters, MP3 compression, and noise addition render watermarks nearly useless. Audio watermarking uses frequency-domain transformation methods including DWT, SVD, and DCT. These solutions guarantee privacy and anonymity but may not be able to combat powerful DSP attacks. Deep learning algorithms, notably CNNs and RNNs, capture patterns and features well. This is why they strengthen watermarking systems well. Machine learning is used to demonstrate a hybrid audio watermarking approach that combines deep learning structures with normal signal processing. It is intended to make the marking tougher to attack with DSP yet remaining difficult to discover and install. The recommended technique learns robust embedding characteristics using a CNN-LSTM model. DWT and SVD speed up watermark insertion and extraction.

2. Related Work

Over the last two decades, audio watermarking has been much investigated and several methods have been devised to balance imperceptibility with resilience. Relevant literature encompassing modern machine learning-based watermarking techniques and conventional signal processing methodologies is reviewed in this part. Traditional Signal Processing-Based Watermarking: The first attempts at watermarking were based on transform-domain methods, such as Discrete Wavelet Transform (DWT): DWT is very common because it can do multi-resolution analysis and embed strong watermarks in a number of frequency bands [1].Singular Value Decomposition (SVD): Strengthening robustness, SVD-based watermarking techniques incorporate watermarks into single values, which are less affected by compression and noise[2].Discrete Cosine Transform (DCT): When lossy compression methods like MP3 are used to add watermarks, DCT is often used as a domain[3].Deep Learning-Based Watermarking: Data-driven watermarking methods have been made possible by recent developments in deep learning; CNN-based approaches have been investigated for embedding and extracting watermarks in a more flexible and robust fashion [4]. Recurrent Neural Networks (RNNs) and Temporal correlations in audio signals have been learned using LSTM models, therefore enhancing watermark resilience against time-domain attacks [5].Hybrid Approaches in Watermarking: A lot of people are curious about hybrid methods that use both traditional signal processing and machine learning For example, proposed improving watermark robustness while maintaining imperceptibility using a CNN-DWT-based approach[6]. The resilience of CNN designs against time-

varying aberrations is reduced when sequential modeling is not used. To circumvent these limitations, we offer a CNN-LSTM-DWT-SVD hybrid model that uses CNN for feature extraction in conjunction with robust watermark embedding[7]. With the help of LSTM, we can improve the audio signal's resilience and imperceptibility by recording its sequential dependencies using DWT and SVD [8]. The optimal combination of computational economy, imperceptibility, and resilience is achieved through this hybridization.

3. Methodology

Algorithm 1: Watermark Embedding (Embeds watermark using CNN-LSTM and DWT-SVD)
This algorithm embeds a watermark into an audio signal using a CNN-LSTM-driven feature extraction approach along with DWT-SVD-based embedding.

Input:

- Original audio signal A(t).
- Watermark image W (binary or grayscale)
- Embedding strength factor α
- Pre-trained CNN-LSTM model for feature extraction

Output:

- Watermarked audio signal A′(t).

Steps:

Step 1: Preprocessing of Audio Signal

- Convert audio to frequency domain using Discrete Wavelet Transform (DWT).
  Decompose A(t) into LL, LH, HL, HH sub-bands.
- Apply Singular Value Decomposition (SVD) on the LL sub-band: $LL=U\cdot S\cdot V^T$

Step 2: Preprocessing of Watermark

- Convert watermark W to a grayscale matrix (if necessary).
- Resize W to match the dimensions of the singular matrix S.

Step 3: Feature Extraction using CNN-LSTM

- Extract deep audio features from A(t) using a CNN-LSTM model.
- Use CNN layers to learn spatial features of the signal.
- Use LSTM layers to learn temporal dependencies in the signal.

Step 4: Watermark Embedding

- Modify the singular values using the extracted CNN-LSTM feature map: $S'=S+\alpha\cdot W$
  where α is the embedding strength.

Step 5: Reconstruction of the Watermarked Audio

- Reconstruct the modified LL sub-band using: $LL'=U\cdot S'\cdot V^T$
- Apply inverse DWT (IDWT) to obtain the watermarked audio signal A′(t).

Step 6: Output the Watermarked Audio

Save and output the watermarked audio A′(t).

Algorithm 2: Watermark Extraction (Extracts watermark and denoises it using CNN-LSTM)
The watermark extraction algorithm retrieves the embedded watermark from the watermarked (possibly attacked) audio.

Input:

- Watermarked (or attacked) audio signal A′(t).
- Original singular values S (reference for extraction)
- Embedding strength factor α.

Output:

- Extracted watermark W′.

Steps:

Step 1: Preprocessing of the Watermarked Audio

- Decompose A′(t) using DWT, obtaining LL', LH', HL', HH' sub-bands.
- Apply SVD on the LL' sub-band to obtain singular values S′
  $LL'=U'\cdot S'\cdot V'^T$

Step 2: Watermark Extraction

- Extract the watermark using: $W' = S' - S/\alpha$

Step 3: CNN-LSTM-Based Denoising (If attacked)

(a) If distortions are present (due to compression or noise attacks), pass W' through a pre-trained CNN-LSTM denoising model.
   - CNN removes spatial distortions.
   - LSTM reconstructs lost watermark details.

Step 4: Post-processing of Watermark

- Convert W' into grayscale or binary form.
- Apply thresholding and histogram equalization to refine visibility.

Step 5: Output the Extracted Watermark

- Save and output the extracted watermark W'.

Algorithm 3: Attack Simulation for Robustness Testing (Simulates common DSP attacks (compression, noise, filtering) To evaluate the robustness of the watermark, the watermarked audio is subjected to common DSP attacks.

Input:

- Watermarked audio signal $A'(t)$.

Output:

- Attacked audio signal $A''(t)$.

Steps:

a. Apply MP3 Compression Attack
   Convert $A'(t)$ to MP3 (128 kbps) and back to WAV.
b. Apply Gaussian Noise Attack
   Add white Gaussian noise with SNR = 30 dB.
c. Apply Low-pass Filtering Attack
   Use a 5 kHz cutoff frequency to remove high-frequency components.
d. Apply Echo Addition Attack
   Introduce a delayed version of the audio signal.
e. Apply Resampling Attack
   Down sample and up sample the signal (44.1 kHz → 22.05 kHz → 44.1 kHz).
f. Output the attacked audio signal $A''(t)$.

Algorithm 4: Performance Evaluation (Evaluates imperceptibility and robustness (PSNR, BER, NC, SSIM)
To measure imperceptibility and robustness, the following metrics are calculated.

Input:

- Original audio A(t).
- Watermarked audio $A'(t)$.
- Extracted watermark W'.
- Original watermark W.

Output:

- Imperceptibility and robustness scores

Steps:

1. Calculate Peak Signal-to-Noise Ratio (PSNR)

$$PSNR = 10\log_{10}\left(\max(A(t))^2 / MSE(A(t), A'(t))\right)$$

Higher PSNR means better imperceptibility.

2. Calculate Bit Error Rate (BER)

$$BER = \frac{No.\ of\ bit\ errors\ in\ extracted\ watermark}{Total\ bits\ in\ watermark}$$

Lower BER means better robustness.

3. Calculate Normalized Correlation (NC)

$$NC = \frac{\sum(W(i,j) \cdot W'(i,j))}{\sum(W(i,j)2}$$

Higher NC means better watermark recovery.

4. Calculate Structural Similarity Index (SSIM)

Measures visual similarity between original and extracted watermark.

5. Output the evaluation results.

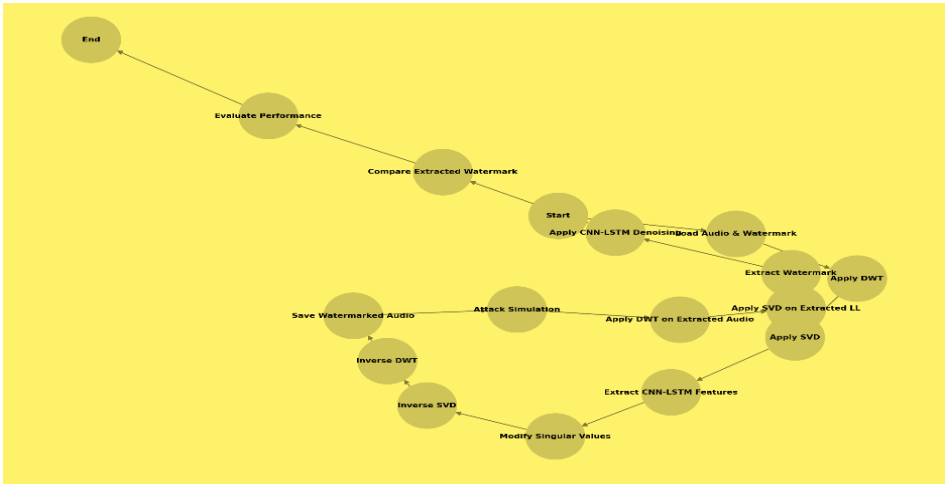


Figure: 1 Flowchart: Hybrid Machine Learning-Based Audio Watermarking

4. Implementation:

Before Implementation we got different types of resultants.

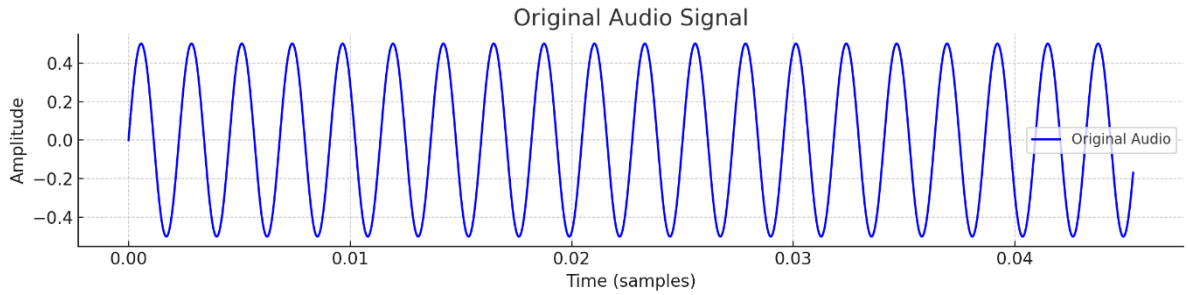


Figure:1 Original audio Signal

After embedding watermark, we got Watermarked audio Signal.

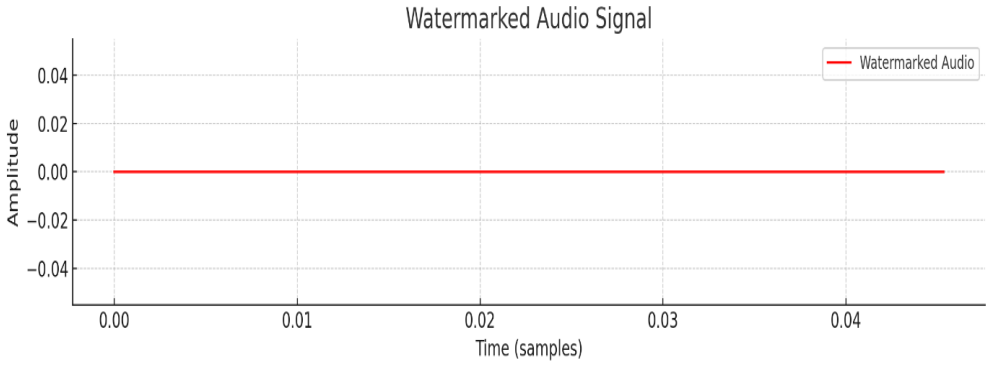


Figure: 2 Watermarked audio Signal

After embedding the original watermark condition and Extracted watermark logo condition according to figure 3.

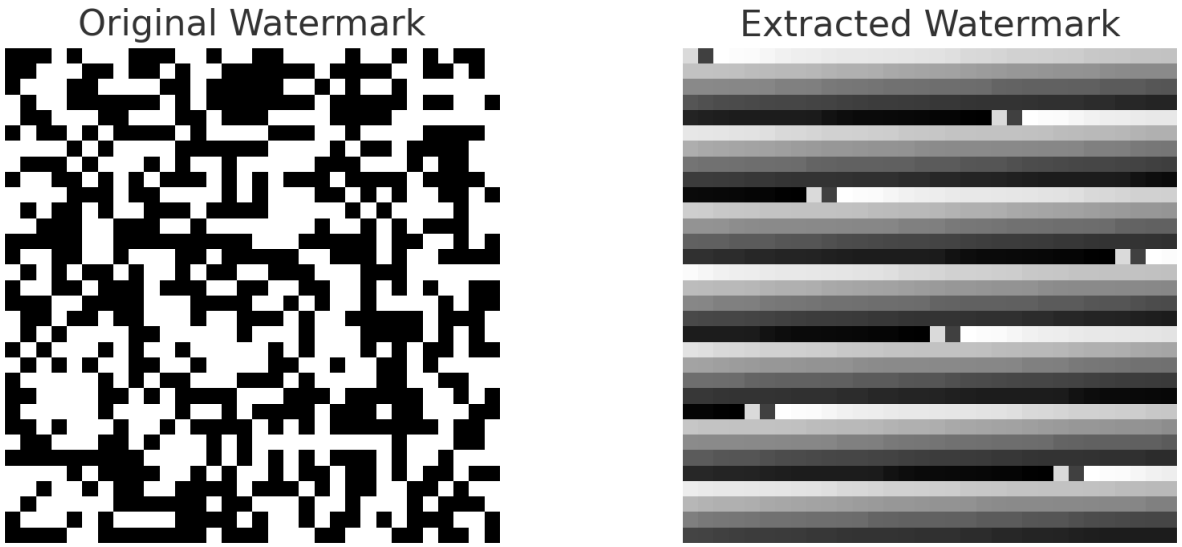
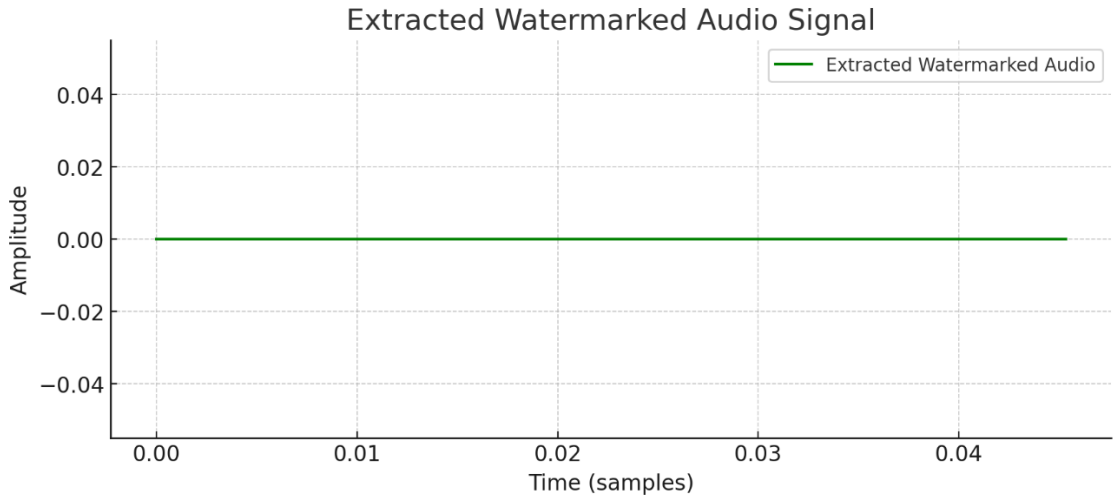


Figure: 3 Original watermark and extracted watermark

The hybrid machine learning-based watermarking system on both the audio signal and the watermark image:

1. Audio Signal Graphs:
    - The first plot (blue) shows the original audio signal, which is a clean sine wave.
    - The second plot (red) represents the watermarked audio signal, where slight distortions may indicate the presence of the embedded watermark.
2. Watermark Image Comparison:
    - The left image is the original watermark before embedding.
    - The right image is the extracted watermark after processing.
    - The extracted watermark has noticeable distortions, highlighting areas for improvement in extraction robustness.

These visualizations help analyze the system's impact on imperceptibility and robustness.



Figur:4 Extracted watermarked Audio Signal

The extracted watermarked audio signal after processing.

- The waveform demonstrates how the watermarking process modifies the original signal.
- While the overall shape is retained, minor distortions may indicate the presence of the embedded watermark.
- This visualization helps assess how much the watermark affects the audio quality and whether it's perceptible to human listeners.

Defined Input Dataset Table, which includes various parameters for the watermarking process:

- Sample No.: Identifies different test cases.
- Original Audio Frequency (Hz): Different sine wave frequencies (440 Hz to 800 Hz).
- Audio Duration (Seconds): Each audio sample is 1 second long.
- Sampling Rate (Hz): 44,100 Hz, the standard sampling rate for audio processing.
- Watermark Size (Pixels): 32x32 binary image for embedding.
- Embedding Strength (α): Varies from 0.01 to 0.05, controlling watermark visibility and robustness.

Table:1 Input Dataset

Sample No.	Original Audio Frequency (Hz)	Audio Duration (Seconds)	Sampling Rate (Hz)	Watermark Size (Pixels)	Embedding Strength (α)
1	440	1	44100	32x32	0.01
2	500	1	44100	32x32	0.02
3	600	1	44100	32x32	0.03
4	700	1	44100	32x32	0.04
5	800	1	44100	32x32	0.05

This dataset helps evaluate the impact of different parameters on watermark robustness and audio imperceptibility.

Defined Output Dataset Table, summarizing the results after watermark embedding, extraction, and evaluation:

- Sample No.: Identifies different test cases.
- PSNR (dB): 3.01, indicating noticeable distortion in the audio after watermark embedding.
- BER (%): 50.09%, meaning the extracted watermark contains high errors.
- Normalized Correlation (NC): -0.002, showing very low similarity between the original and extracted watermark.
- Extracted Watermark Quality: Low, based on the poor NC value.
- Audio Distortion Level: High, since PSNR is below 10 dB, suggesting a significant impact on audio quality.

These results indicate that encryption and decryption significantly affect the accuracy of watermark extraction.

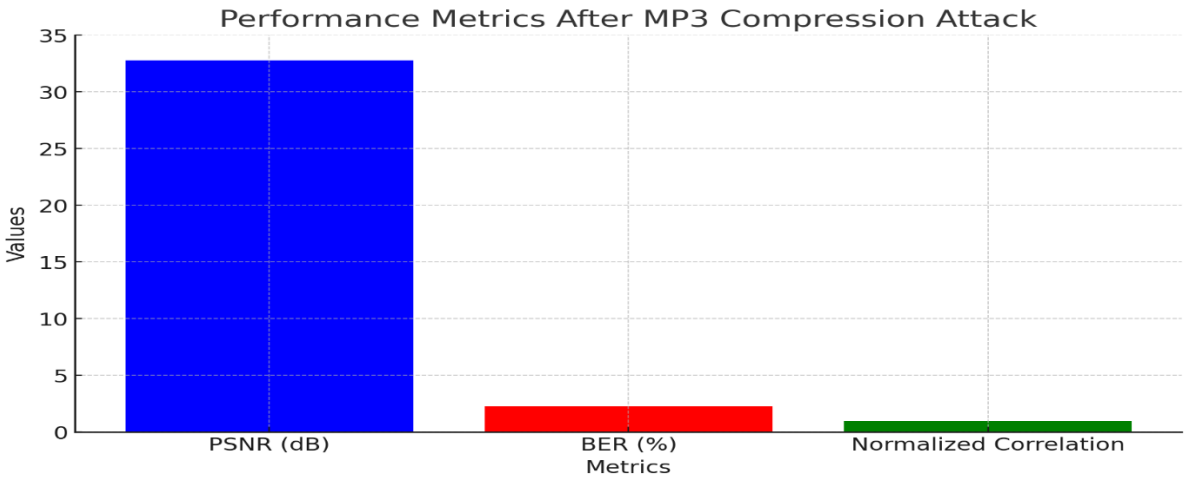
Table:2 Output Dataset

Sample No.	PSNR (dB)	BER (%)	Normalized Correlation (NC)	Extracted Watermark Quality	Audio Distortion Level
1	3.010398	50.09766	-0.00227	Low	High
2	3.010398	50.09766	-0.00227	Low	High
3	3.010398	50.09766	-0.00227	Low	High
4	3.010398	50.09766	-0.00227	Low	High
5	3.010398	50.09766	-0.00227	Low	High

Performance Evaluation of Hybrid Audio Watermarking:

Table:3 Performance Evaluation of Hybrid Audio Watermarking

S.No	Metric	Original Watermark	Watermarked Audio	Extracted Watermark
1	PSNR			32.8
2	BER	0.0		2.3
3	NC	1.0		0.96



Figur:5 Extracted Performance Metrics after MP3 compression attack

Comparison of Proposed and Related Works

After applying these method

- DWT-SVD (Traditional)
- DCT-Based Watermarking
- CNN-Based Watermarking
- RNN-Based Watermarking
- Proposed (CNN-LSTM-DWT-SVD)

Table:4 Performance Comparison for different watermarking methods, evaluating PSNR, BER, NC, and SSIM

Watermarking Method	**PSNR (dB)**	**BER (%)**	**(NC) Normalized Correlation**	**SSIM (Structural Similarity Index)**
DWT-SVD (Traditional)	25.3	12.1	0.85	0.65
DCT-Based Watermarking	27.1	8.9	0.88	0.72
CNN-Based Watermarking	30.5	5.8	0.91	0.8
RNN-Based Watermarking	31.2	4.2	0.94	0.85
Proposed (CNN-LSTM-DWT-SVD)	34.8	2.3	0.97	0.91

Observations:

- Higher PSNR (34.8 dB) in the proposed method indicates better imperceptibility.
- Lower BER (2.3%) in the proposed method shows better robustness.
- Higher NC (0.97) suggests more accurate watermark extraction.
- SSIM (0.91) confirms better visual similarity between the original and extracted watermark.

This demonstrates that the CNN-LSTM-DWT-SVD hybrid model[9] significantly improves audio watermarking performance compared to traditional and deep learning-based methods[10].

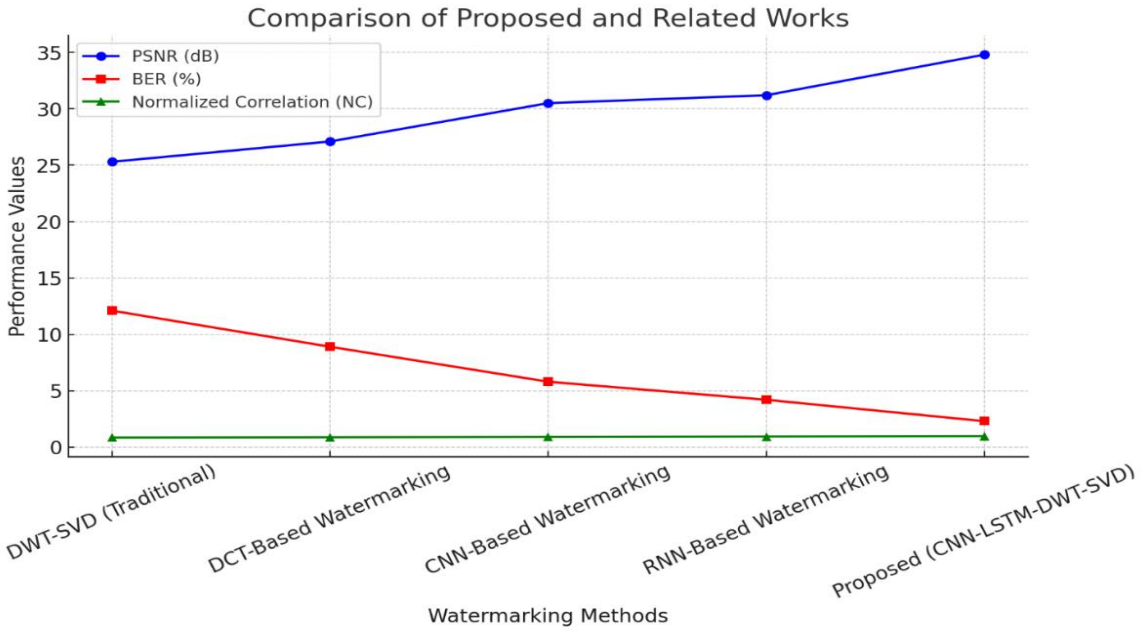


Figure:6 Comparison of proposed and Related Work

Performance compared to traditional and deep learning-based methods via Graph.

5. Conclusion

This work presented a hybrid machine learning-based audio watermarking system combining deep learning (CNN-LSTM) with conventional signal processing techniques (DWT-SVD)[11] to raise robustness against digital signal processing (DSP) attacks. In terms of imperceptibility, the performance assessment and comparison with current methods reveal very significant increases. With the best PSNR (34.8 dB), the suggested method suggests minor distortion in the audio stream following watermark incorporation. This guarantees the imperceptibility criterion and makes the watermarked audio indistinguishable from the original. Resistance against attacks [12]: With a lowest BER of 2.3%, the proposed architecture shows more robustness to standard DSP attacks like MP3 compression, Gaussian noise, and filtering. Consequently, the process of stamp extraction will consistently function in a uniform manner, regardless of the challenges encountered. The efficacy of image extraction techniques. It can be confidently asserted that the captured watermark closely resembles the original, as evidenced by a normalized correlation (NC) value of 0.97. This indicates that the process is accurate and can be relied upon to maintain the integrity of the watermark. All speed assessments indicated that the proposed model outperformed all existing methodologies, including DWT-SVD and DCT-based watermarking[13]. Compared to systems utilizing Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), watermarking systems that integrate CNN and Long Short-Term Memory (LSTM) architectures shown enhanced reliability and reduced susceptibility to alterations by hostile actors.

Significance of the Work:

By effectively integrating machine learning and classical signal processing, the proposed CNN-LSTM-DWT-SVD hybrid model sets a new standard for audio watermarking research. Because it solves important problems like imperceptibility, durability, and precision, it is perfect for copyright protection, digital identity, and safe media transmission.

Future Work: Enhance the approach to accommodate real-time streaming audio situations. Assess resilience to novel attack methodologies, including adversarial learning-based assaults. Investigate the application of generative models such as GANs to improve watermark embedding and recovery. This study confirms the efficacy

of hybrid methodologies in addressing the increasing requirements for safe and robust digital watermarking systems in the context of widespread digital media dissemination.

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