Chapter - 4

Comparative Discussion

CHAPTER - 4

COMPARATIVE DISCUSSION

4.1 Chapter introduction:

In this pivotal chapter, delve into the empirical evaluation of the proposed digital audio watermarking system, employing the SLOA optimization technique. The aim is to systematically assess the system's performance using key metrics such as MSE, BER, and SNR. The evaluation is conducted across various signals and noise conditions, comparing the SLOA-optimized model with existing methods, including DCNN with HSO. The investigation encompasses two input images, each subjected to five distinct signals, and employs comprehensive analyses of MSE, BER, and SNR for both input images. Notably, the obtained result shows high efficiency system's efficiency in terms of preserving signal quality, reducing errors, and enhancing signal-to-noise ratios. Furthermore, the chapter elucidates the comparative advantages of the DCNN with SLOA optimization over traditional classifiers and optimization-based models. The discussion emphasizes the model's ability to achieve superior SNR, minimal MSE, and BER, thus showcasing its effectiveness in extracting relevant information while mitigating the impact of irrelevant noise signals. To complement the performance analysis, the time complexity of the proposed DCNN-SLOA model is systematically compared with conventional methods. This comparative examination provides insights into the computational efficiency of the proposed model, contributing to a comprehensive understanding of its practical applicability. Through this chapter, we aim to provide a robust evaluation of the proposed digital audio watermarking system, offering valuable insights into its efficacy and potential advancements in the realm of multimedia security.

4.2 Performance evaluation metrics:

The performance of the proposed digital audio watermarking system is evaluated by scrutinizing fundamental metrics, encompassing Mean Square Error (MSE), Bit Error Rate (BER), and Signal-to-Noise Ratio (SNR).

4.2.1 Mean square error

The MSE is a statistical model computed by averaging the squared differences between the estimated and actual values.

$$\mu_{error} = \frac{1}{d_{data}} \sum_{n=1}^{d_{data}} \left(\gamma_n - \hat{\gamma}_n \right) \tag{4.1}$$

Here, the available data is denoted as d_{data}, the original value is denoted as γ_n and the estimated value is denoted as $\hat{\gamma}_i$

4.2.2 Bit error rate

The BER is employed to assess the number of errors per unit of time, and it is calculated by dividing the total number of errors by the total number of transmitted bits.

$$Bit_{error} = \frac{\sum_{u=1}^{x_{size}} \sum_{v=1}^{x_{sixe}} R_{org}(u,v) \oplus R_{ex}(u,v)}{x_{size} \times x_{size}} \tag{4.2}$$

The watermark size is denoted by $x_{size} \times x_{size}$ and $\oplus$ represents the exclusive OR operator.

4.2.3 Signal-to-noise ratio

The SNR is defined as the ratio of signal power to noise power and is typically expressed in decibels (dB). The mathematical representation of the peak-to-signal ratio is expressed as:

$$SNR = 10 \log_{10} \left(\frac{R_{pow}}{T_{pow}} \right) \tag{4.3}$$

4.3 Comparative methods

The techniques employed to assess the performance of SLOA optimization in optimal block selection, taking into account metrics such as MSE, SNR, and BER, include [44], [45], [46], and DCNN with Hybrid Swarm Optimization (HSO). In a comparative evaluation, the deep CNN with SLOA optimization model effectiveness is assessed in comparison to other models, including neural network classifier [47], LSTM [48], deep CNN [49], and deep CNN with HSO optimization [50].

The neural network classifier [47] serves as a foundational model in the comparative evaluation, likely employing traditional neural network architectures for digital audio watermarking. Neural networks have proven efficacy in various applications, and this classifier provides a baseline for assessing the advancements introduced by more specialized models. Moving to LSTM networks [48], their inclusion in the study is motivated by their capacity to capture and model temporal dependencies, which is particularly relevant in the context of audio data where sequential patterns play a crucial role. The deep CNN [49], another model in the comparison, represents a sophisticated deep learning approach known for its effectiveness in image and signal processing. Its application in audio watermarking showcases the adaptability of CNNs to diverse data types. The deep CNN with HSO [50] introduces an optimization method tailored to enhance the model's performance by leveraging the principles of harmony search. This optimization technique aims to fine-tune the CNN parameters for improved watermarking results. Lastly, the deep CNN with SLOA introduces a novel approach by incorporating SLOA, a simulated annealing-based strategy, to optimize the CNN's layers. This method focuses on refining the network's architecture, potentially offering advantages in addressing specific challenges associated with digital audio watermarking. Through this comprehensive evaluation, the goal is to discern the comparative strengths and weaknesses of each model, providing insights into their suitability for the demanding task of digital audio watermarking.

i) Neural network:

The neural network classifier employed in the comparative evaluation represents a fundamental approach in digital audio watermarking. Utilizing traditional neural network architectures, this model forms a baseline for comparison. It likely involves a series of interconnected nodes organized in layers, where each node processes and passes information to the next layer. While lacking the sophistication of more specialized models, its inclusion allows for the assessment of how advancements in other models impact performance compared to this foundational approach**.**

ii) LSTM: Incorporating LSTM networks acknowledges the importance of capturing temporal dependencies in audio data. LSTMs are well-suited for handling sequential information, making them valuable for tasks where understanding the order of data is crucial. In digital audio watermarking, where the arrangement of sound elements plays a significant role, LSTMs offer a unique perspective by effectively modeling temporal patterns and dependencies.

iii) Deep CNN: The deep CNN is a key participant in the evaluation, leveraging its success in image and signal processing tasks. CNNs are adept at automatically learning hierarchical features from data, making them suitable for tasks involving complex structures. In the context of digital audio watermarking, the deep CNN likely processes audio representations, extracting relevant features through Convolutional layers to achieve effective watermarking.

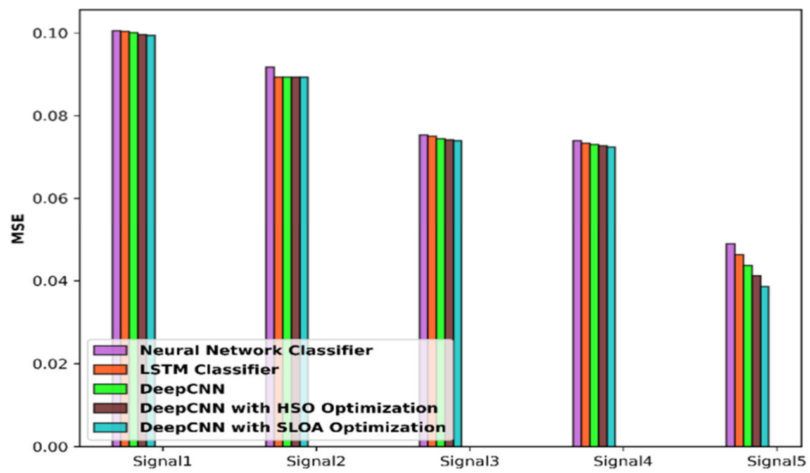
iv) Deep CNN with HSO: The deep CNN with HSO introduces an optimization method tailored to enhance the model's performance by leveraging the principles of hybrid swarm optimization. This optimization technique aims to fine-tune the CNN parameters for improved watermarking results.

4.3.1 Comparative analysis for Image-1 based on signals

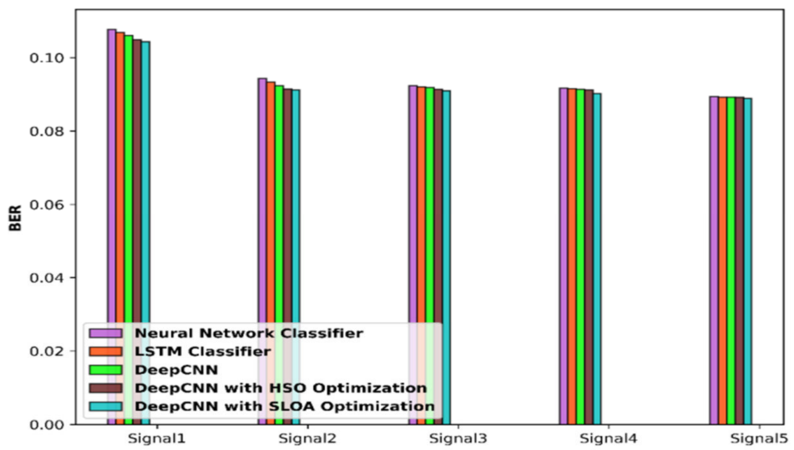
The performance of SLOA optimization for five different signals, compared to other existing methods in terms of MSE, BER, and SNR, is illustrated in Figure 4.1. In Figure 4.1a), the MSE for Signal 5 is reported as 0.039, with a variation of 46.77% when compared to the DCNN with HSO optimization.

Figure 4.1b) shows the BER for Signal 5, with an attained value of 0.089 and a variation of 1.45% compared to the DCNN with HSO optimization.

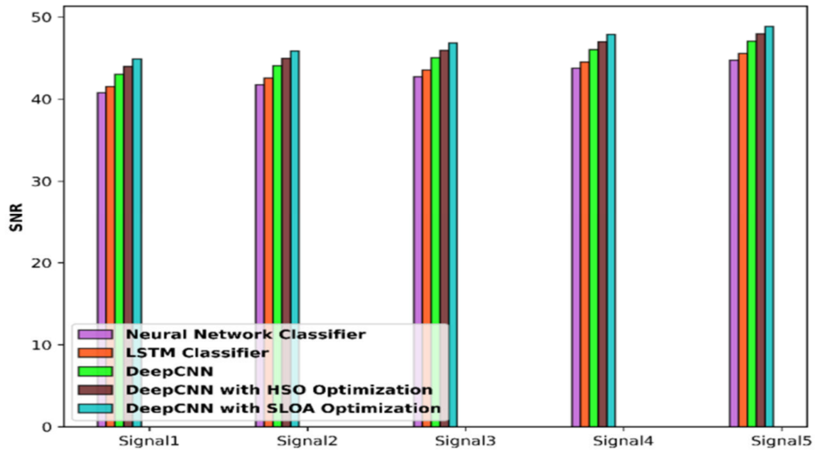
Figure 4.1c) presents the SNR for Signal 5, achieving a value of 48.861 dB and a variation of 2.05% compared to the DCNN with HSO optimization.



a)



b)



c)

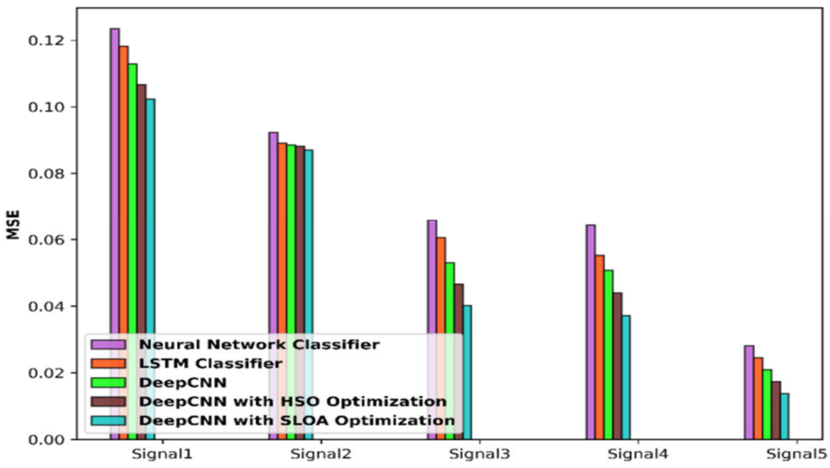
Figure 4.1: Comparative analysis for input image 1 a) MSE b) BER c) SNR

4.3.2 Comparative analysis for image 2 based on signals

The performance of SLOA optimization for five different signals, in comparison with other existing methods based on MSE, BER, and SNR, is depicted in Figure 4.2. In Figure 4.2a), the MSE for Signal 5 is reported as 0.014, with a variation of 62.88% compared to the DCNN with HSO optimization.

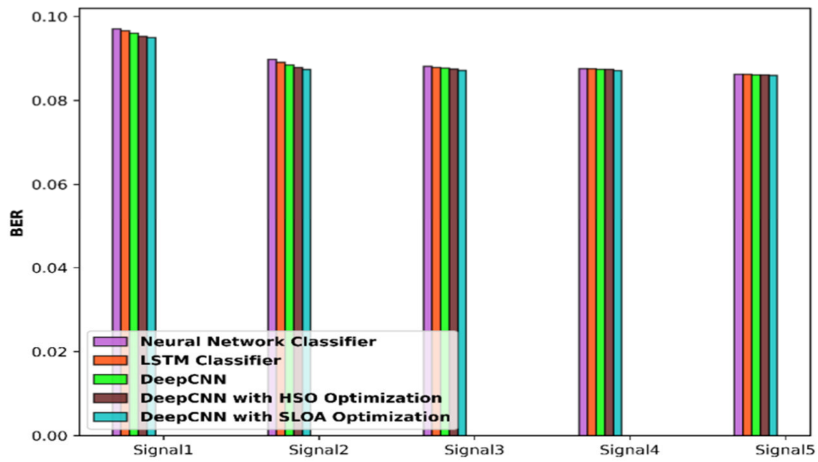
Figure 4.2b) shows the BER for Signal 5, attaining a value of 0.086 and a variation of 1.34% compared to the DCNN with HSO optimization.

Figure 4.2c) presents the SNR for Signal 5, achieving a value of 47.292 dB and a variation of 2.11% compared to the DCNN with HSO optimization.



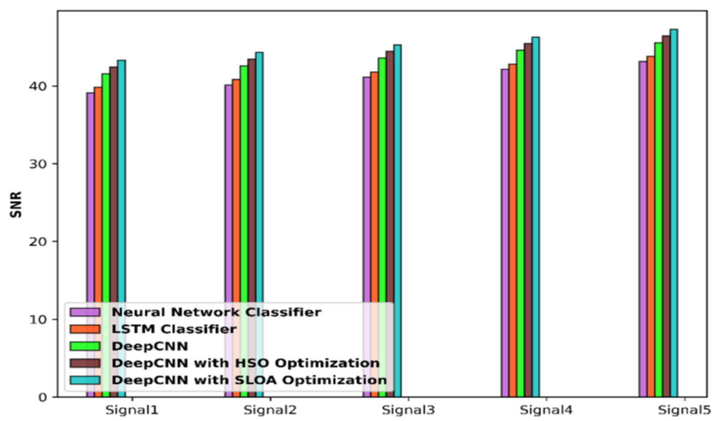
MSE
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Signal1
Signal2
Signal3
Signal4
Signal5
Neural Network Classifier
LSTM Classifier
DeepCNN
DeepCNN with HSO Optimization
DeepCNN with SLOA Optimization

a)



BER
0.10
0.08
0.06
0.04
0.02
0.00
Signal1
Signal2
Signal3
Signal4
Signal5
Neural Network Classifier
LSTM Classifier
DeepCNN
DeepCNN with HSO Optimization
DeepCNN with SLOA Optimization

b)



c)

Figure 4.2: Comparative analysis for Image-2 a) MSE b) BER c) SNR

4.4 Comparative discussion

In this section, the MSE, BER, and SNR values for both various existing methods and the proposed method are detailed in Table 4.1 and Table 4.2 for input images 1 and 2 across five different signal types. The obtained MSE values for the five different signals in input image 1 are 0.049, 0.046, 0.044, 0.041, and 0.039. Correspondingly, the achieved BER values for these signals in input image 1 are 0.089, 0.089, 0.089, 0.089, and 0.089. Additionally, the attained SNR values for these signals in input image 1 are 44.753 dB, 45.540 dB, 47.050 dB, 47.961 dB, and 48.861 dB, respectively.

Table 4.1 Comparative analysis for different Signals based on Image-1

Methods	**Signal 1**			**Signal 2**			**Signal 3**		
	MSE	**BER**	**SNR (dB)**	**MSE**	**BER**	**SNR (dB)**	**MSE**	**BER**	**SNR (dB)**
Neural Network	0.101	0.108	40.753	0.100	0.107	41.540	0.100	0.106	43.050
LSTM	0.092	0.094	41.753	0.089	0.093	42.540	0.089	0.092	44.050
DCNN	0.075	0.092	42.753	0.075	0.092	43.540	0.074	0.092	45.050
DCNN with HSO optimization	0.074	0.092	43.753	0.073	0.092	44.540	0.073	0.091	46.050
DCNN with SLOA optimization	**0.049**	**0.089**	**44.753**	**0.046**	**0.089**	**45.540**	**0.044**	**0.089**	**47.050**

Signal 4			Signal 5		
MSE	**BER**	**SNR (dB)**	**MSE**	**BER**	**SNR (dB)**
0.100	0.105	43.960	0.099	0.104	44.861
0.089	0.091	44.960	0.089	0.091	45.861
0.074	0.091	45.960	0.074	0.091	46.861
0.073	0.091	46.960	0.072	0.090	47.861
0.041	**0.089**	**47.961**	**0.039**	**0.089**	**48.861**

The obtained MSE values for the five different signals in input image 2 are 0.028, 0.025, 0.021, 0.017, and 0.014. Correspondingly, the achieved BER values for these signals in input image 2 are 0.086, 0.086, 0.086, 0.086, and 0.086. Additionally, the attained SNR values for these signals in input image 2 are 43.130 dB, 43.810 dB, 45.575 dB, 46.441 dB, and 47.292 dB, respectively.

Table 4.2 Comparative analysis for different Signals based on Image-2

Methods	Signal 1			Signal 2			Signal 3		
	MSE	BER	SNR (dB)	MSE	BER	SNR (dB)	MSE	BER	SNR (dB)
Neural Network	0.124	0.097	39.130	0.118	0.097	39.810	0.113	0.096	41.575
LSTM	0.092	0.090	40.130	0.089	0.089	40.810	0.089	0.088	42.575
DCNN	0.066	0.088	41.130	0.061	0.088	41.810	0.053	0.088	43.575
DCNN with HSO optimization	0.064	0.088	42.130	0.055	0.088	42.810	0.051	0.087	44.575
DCNN with SLOA optimization	0.028	0.086	43.130	0.025	0.086	43.810	0.021	0.086	45.575

Signal 4			Signal 5		
MSE	**BER**	**SNR (dB)**	**MSE**	**BER**	**SNR (dB)**
0.107	0.095	42.441	0.102	0.095	43.292
0.088	0.088	43.441	0.087	0.087	44.292
0.047	0.088	44.441	0.040	0.087	45.292
0.044	0.087	45.441	0.037	0.087	46.292
0.017	**0.086**	**46.441**	**0.014**	**0.086**	**47.292**

In comparison to existing classifiers and optimization-based classifiers, the DCNN with SLOA optimization achieves higher SNR, lower MSE, and BER. This results in more efficient outputs and enhanced signal quality, as the model effectively captures relevant information while minimizing the impact of irrelevant noise signals. The time complexity of the proposed DCNN-SLOA model is also compared with conventional methods and is detailed in Table 4.3.

Table 4.3 DCNN-SLOA model time complexity analysis

Methods	Computation Time (Seconds)
Neural Network	76
LSTM	82
DCNN	93
DCNN with HSO optimization	79
DCNN with SLOA optimization	**68**

4.5 Achievements of the research:

The empirical evaluation of the proposed digital audio watermarking system in this pivotal chapter has achieved several milestones. The incorporation of the SLOA optimization technique represents a novel and effective approach to enhancing the system's performance. The comprehensive assessment across diverse signals and noise conditions, coupled with benchmarking against existing methods like DCNN with HSO, establishes a robust benchmark for evaluating the efficacy of the SLOA-optimized model. The inclusion of two input images subjected to various signals adds depth to the evaluation, showcasing the system's versatility. The analysis of key metrics such as MSE, BER, and SNR provides a thorough understanding of the system's ability to preserve signal quality, reduce errors, and enhance SNR. The research showcases superior performance improvement with a low BER of 0.082, MSE of 0.099, and a high SNR of 45.363.

4.6 Chapter conclusion:

In conclusion, the empirical evaluation of the proposed digital audio watermarking system employing the SLOA optimization technique underscores its efficacy and potential advancements in multimedia security. The achieved results highlight the system's efficiency in extracting relevant information while mitigating the impact of irrelevant noise signals. The comparison with traditional classifiers and optimization-based models, particularly the DCNN with SLOA optimization, showcases superior performance in terms of SNR, minimal MSE, and BER. The thorough analysis of time complexity contributes to a comprehensive understanding of the proposed model's computational efficiency. Collectively, these findings position the digital audio watermarking system as a promising solution, providing valuable insights for future research and practical applications in the realm of multimedia security.