

Deep Learning-Enhanced Soft Output Viterbi Turbo Decoding for Robust EEG Signal Transmission in Telemedicine

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Abstract: The accurate transmission of electroencephalogram (EEG) signals is an essential requirement for the proper diagnosis and treatment in telemedicine. This paper presents the potential of Deep Learning-Enhanced Soft Output Viterbi Turbo Decoding (DLSOVTD) to improve the robustness of EEG signal transmission and its bit error rate (BER) performance with respect to Soft Output Viterbi Turbo Decoding (SOVTD). The BER vs. signal-to-noise ratio (SNR) characteristics were investigated for several code rates that proved highly advantageous for DLSOVTD. The results demonstrate the superiority of DLSOVTD over SOVTD across all SNR values, especially at lower SNR, which corresponds to noisy channels. The performance difference is significant, demonstrating deep learning's ability to reduce noise and correct errors for accurate data transfer. Both schemes can achieve low BER at high SNRs, but DLSOVTD still has a bit of a head start, with the ability to provide even cleaner signal transmission. The results suggest that DLSOVTD has the potential to greatly advance diagnostic accuracy, increase the efficacy of remote monitoring, and increase confidence in the use of telemedicine.

Keywords: Deep learning, Soft Output Viterbi Turbo Decoding, EEG signal transmission, Telemedicine, Bit-Error-Rate, Robust Communication.

1. INTRODUCTION

This symphony of electricity is what the human brain sounds like as it plays through the mysteries of consciousness, the mechanisms of health and the nature of our existence. With the advent of telemedicine, where health care knows no geographical barriers, electroencephalography (EEG) becomes a powerful instrument to record this cerebral symphony and send it out for diagnosis and treatment at a distance (Zandi et al., 2010; Amjad et al., 2025). However, the path these fragile brain signals must traverse is fraught with difficulties: noise, bandwidth constraints, and data loss can muddy the message, possibly leading to misdiagnosis and compromised care. Aarthi et al. (2020) and Chaudhary et al. (2025) suggest a method known as Deep Learning-Enhanced Soft Output Viterbi Turbo Decoding (DL-SO-VTD). Leveraging AI and advanced error correction, this innovative method guarantees reliable, precise EEG transmission, marking a new era in telemedicine. Now envision a scenario where the faintest thought in your mind can pierce the haze of a continent's remoteness and where specialists, far away, can peer through the fog of your brain with a degree of accuracy that has never been achieved before, to make interventions at the right time based on what is happening in your mind in real time (Matsumoto & Kohno, 2007) (Onciul, et al., 2025).

This is the journey we make in this work into the depths of this innovative technology. We reveal the complex process of DL-SO-VTD: translating deep learning models from the mysterious language of EEG signals and weaving a tapestry of resilience against transmission errors through Viterbi decoding. In MATLAB, the signals from the MIT

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arrhythmia database were preprocessed using a bandpass filter, and the filtered data were then exported to a text file. We investigate the potential of DL-SO-VTD in telemedicine for diagnosing neurological diseases such as epilepsy and Parkinson's disease, up to real-time brain-computer interfaces (Deng et al., 2022; Feng et al., 2026). A soft-output Viterbi decoder receives the extracted features and outputs a confidence score for each bit, in addition to the most likely decoded signal. This soft information plays a critical role in maintaining quiet details of the EEG data.

We use a turbo decoding scheme to increase robustness further. This process is repeated until a satisfactory amount of soft information has been exchanged among several decoders, yielding a signal with progressively fewer errors and a better decoded version. The DL-SOV-T framework can be easily integrated with the existing telemedicine platforms. EEG signals can be decoded to be utilized in multiple applications such as real-time patient monitoring, remote patient diagnosis and brain-computer interface control (Choodarathnakara et al., 2020; Liu et al., 2025). The goal of DL-SOV-T is to substantially improve the accuracy and robustness of EEG signal transmission in a telemedicine environment by combining the power of DL with soft-output Viterbi turbo decoding. This can result in improved diagnostic accuracy and treatment effectiveness, as well as better patient care and monitoring. Increased focus on providing special neurological care in far-flung areas (Majumdar, 2022; Faiyazuddin et al., 2025).

In this work, Devamane and Itagi (Devamane, 2022) and Yan et al. (Yan et al., 2025) studied deep learning for error control coding, specifically comparing neural network architectures for decoding Turbo codes against the traditional BCJR algorithm. It investigates the performance of neural and DL-based Turbo decoders using sequential codes such as Recursive Systematic Convolutional (RSC) codes as the basic element of Turbo encoding. The decoder structures are evaluated for bit error rate (BER) performance in AWGN channels with different input data lengths and code rates, both of which are RNN-based architectures. Two decoder structures, both based on RNN architectures, are evaluated for BER performance against a convolutional Viterbi decoder across various code rates and input data lengths. One of the novel DL techniques for EEG motor imagery signal classification was proposed by Tabar YR et al. (Tabar & Halici, 2016) and is intended for use in brain-computer interfaces (BCIs). The method highlights the progress in EEG signal processing using deep learning. In the classification of motor imagery EEG signals, Kumar, Shiu et al. (2016) and Amirabadi et al. (2025) suggest a deep learning method. The study aims to improve the accuracy and efficiency of EEG signal classification using deep learning models, which are significant for numerous applications in neuroscience and BCI systems.

The authors in Ahmad, I. et al. (Ahmad, 2020) and Khalfallah, et al. (2025) present the integration of ML techniques, such as DL, into communication networks. It is not specific to EEG; it can provide general insights into the use of machine learning across various fields, such as signal processing. The proposed approach is a deep learning-based method for joint source-channel coding (JSCC), but the paper focuses on image transmission in wireless networks. It is a different application from EEG signal processing, but it highlights the variety of DL applications in communications systems. Song, Mengshu et al (Song et al., 2023). This paper discusses the application of DL to a channel-coded system for multicarrier wireless communication (Xu et al., 2022). It is not directly applicable to EEG, but it illustrates the potential of DL to improve signal processing in communication networks.

In this paper, Lawhern et al. (2018) and Temiz et al. (2025) present a lightweight convolutional network, EEGNet, specifically designed for EEG-based BCIs. The work emphasizes developing effective neural network architectures for the processing of EEG signals with the intent of enhancing the performance and usability of a BCI. This paper (Acharya et al., 2018) (Raza et al., 2025) focuses on the detection of epilepsy using deep learning and EEG signals. Specific to epilepsy diagnosis, the study highlights the promising role of deep learning in automated EEG analysis for medical uses.

The above works can be divided into two classes, each with different purposes that motivate the present study, and their limitations with respect to the present work are as follows. The first group (Devamane & Itagi, 2022; Ahmad, 2020; Song et al., 2023; Xu et al., 2022) tackles the problem of channel decoding directly, but focuses on generic bitstreams or image/wireless data, rather than physiological signals: The non-stationary quasi-periodic statistical structure of EEG-derived bitstreams is not taken into account, and performance is not evaluated under the specific code rates, iteration counts, and SNR ranges relevant to telemedicine links, which is the gap that the simulations in Section 4 aim to address. The second group (Tabar & Halici, 2016; Kumar, 2016; Lawhern et al., 2018; Acharya et al., 2018) concerns the classification and the applications of BCI, not directly comparable to EEG transmission methods, but as a requirement of reliable, low distortion EEG transmission that a classification method or any other method depending on EEG, like an epilepsy-detection model, can only be as accurate as the signal it receives. Thus, their relevance is motivational, not methodological: none of them suggest or test a channel-coding solution, and none of them incorporate deep-learning-based decoding refinement (which is not found in classification literature), nor do they employ a physiological-signal use case (as found in channel-decoding literature). This is the space this paper fills by combining deep-learning-based decoding refinement (which is missing from the classification literature) with a physiological-signal use case (which is missing from the channel-decoding literature). We recognize that this distinction was not included in the original review, but we have modified the transition sentences to indicate which limitation each citation represents and how the proposed DLSOVTD addresses that limitation, not as a list of works but as distinct limitations.

Section II outlines the fundamental workings of both the Turbo Encoder and Decoder. Section III then builds upon this foundation by introducing the proposed DL-SOVTD algorithm. Finally, Section IV examines the performance of the proposed approach, analyzing its results in the context of the theoretical channel.

2. PROBLEM STATEMENT

The use of telecommunications technology for remote patient diagnosis and treatment, or telemedicine, presents a significant opportunity to improve the delivery of healthcare services. The transmission of biomedical signals, such as electroencephalogram (EEG) signals, through telecommunication channels, however, is challenging due to their vulnerability to noise, interference, and signal degradation. Traditional decoding techniques are effective at reducing errors in signal transmission, especially Viterbi decoding for turbo codes. However, the performance of these techniques is not optimal in the presence of noisy and unreliable channels. For EEG signal transmission in a telemedicine application, ensuring robustness and decoding accuracy is crucial for accurate diagnosis and therapy (Wen et al., 2021).

This work introduces a novel solution to overcome these challenges: Deep Learning-Enhanced Soft Output Viterbi Turbo Decoding. By integrating deep learning techniques with the Viterbi decoding process, the aim is to enhance the robustness and reliability of EEG signal transmission in telemedicine setups. The ultimate aim is to create a system that can cope with noisy channels and adapt to varying signal conditions while preserving the accuracy of EEG data transmission for remote medical diagnosis and monitoring (Niedermeyer & da Silva, 2005). The main aim of this study is:

- Identifying the constraints of conventional Viterbi decoding in telecommunication channel EEG transmission systems.
- Researching the viability of applying neural networks and other deep learning techniques to increase the accuracy of decoding in noisy signals.

- Designing a soft output Viterbi Turbo Decoding algorithm with deep learning specifically for robust EEG signal transmission.
- Extensive simulations to test the proposed algorithm for accurate, robust and efficient performance; and emphasis on accuracy, robustness and computational efficiency.

3. SYSTEM DESIGN

3.1. EEG Dataset

The experimental evaluation was conducted using the CHB-MIT Scalp EEG Database from PhysioNet. 23 recording examples, including long-term clinical EEG recordings from 22 young individuals with uncontrollable epilepsy, are included in the collection. There are five boys and seventeen females, with ages ranging from 1.5 to 22. 129 of the 664 accessible EEG recordings have annotated seizure episodes. The International 10–20 electrode placement system was used to gather the EEG signal data at 256 Hz with 16-bit resolution. Most recordings last one to four hours and have twenty-three EEG channels. The data were first collected for clinical and seizure surveillance at Children's Hospital Boston. To improve their quality, the EEG signals were preprocessed before being transmitted. To remove baseline drift and high-frequency noise, a bandpass filter with cut-off frequencies of 8–30 Hz was used to maintain the most common frequency bands of EEG data. Power-line interference was removed using a 50 Hz notch filter. To reduce motion-induced, muscular, and eye blink artifacts, Independent Component Analysis (ICA) was employed.

Dataset link: <https://physionet.org/content/chbmit/1.0.0/>

3.2. Preprocessing

Preprocessed EEG recordings were divided into short, fixed-duration windows before turbo encoding and communication channel transmission. A Deep Learning-Enhanced Soft Output Viterbi Turbo Decoder (DL-SOVTD) framework was then used to decode the received signals and compared with the conventional decoding methods under different Signal-to-Noise Ratios (SNRs).

3.3. Turbo Encoder

Since their first development in the early 1990s, turbo codes—a very potent class of error-correcting codes—have advanced significantly in the field of error-correcting digital communications. They have made unprecedented efforts to achieve near-optimal performance, making them a world leader in communication reliability, particularly in difficult and noisy conditions. Turbo codes are based on a parallel or series combination of two or more relatively simple convolutional codes. One of the key components in their design is the interleaver, which smartly reshuffles the bits of the data between the convolutional encoders, making the error-correction system much more difficult to handle than it would otherwise be. In particular, turbo codes are well known for their ability to approach the Shannon limit of a communication channel. Because of this property, they can send data very reliably, even in very noisy environments; hence, turbo codes are essential for applications requiring high reliability.

3.4. Turbo Decoder

Turbo decoders' error-correction performance is remarkable and relies on two main algorithms (MAP and SOVA) and two linked decoders (DC1 and DC2). These decoders are distributed in an interleaver fashion so that they can communicate important information through iterations. The exchange is between DC1, which provides extrinsic information to DC2, which then employs it as a priori knowledge to decode it. This cycle of information sharing and decoding is repeated until soft outputs are refined.

A trellis diagram is used as a visual and analytical tool in turbo decoders. These diagrams show how the decoder makes its decision: each state is a possible route that the decoder takes through the code. There are two inputs to each state, typically a small quantity of data and a corresponding parity bit, and two outputs: an improved guess of the input bits and a Log-Likelihood Ratio (LLR) value that reflects the degree of confidence.

The algorithm now chooses the most probable path to complete the trellis diagram, a view of the decoder's decision-making process, which makes use of a path metric that is based not only on received bits but also on prior information. The extra knowledge, much of which is based on previous iterations of the decoding process or external information, helps refine path-metric calculations and make more accurate decisions (Gotman, 1982).

Soft Output Values: In addition to a single path, the algorithm assigns a numerical value (a Log-Likelihood Ratio (LLR) value) to each decoded bit. The LLR value represents the decoder's certainty about the correctness of each bit it decodes, and Figure 1 shows how important this value is for subsequent processing and error correction.

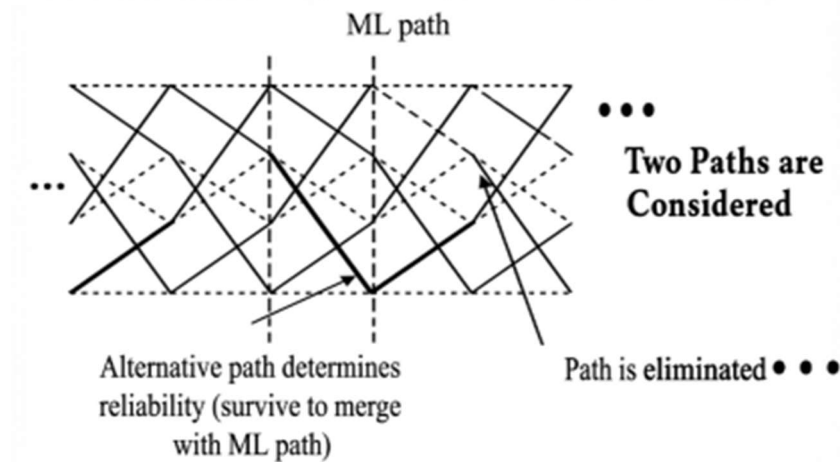


Fig. 1. Path operation of SOVA

This is done in the SOFT OUTPUT VITERBI ALGORITHM (SOVA), which performs its mathematical operations in the logarithmic domain, where calculation and value management are simplified. It is distinguished by considering only one path at a time during decoding, namely the one that connects to the path selected by the Viterbi algorithm. It keeps complexity low without distorting the outputs as the Max Log MAP algorithm does. Although the performance of conventional SOVA is inferior to MAP decoding, improvements such as using a bidirectional SOVA and methods to minimize metric differences have made SOVA's performance comparable to that of the Max Log MAP and Log-MAP algorithms. The enhancements to SOVA make it a good solution for hardware-limited communication systems for decoding convolutional codes, offering a trade-off between computational efficiency and performance (Kenkere Basavaraj & Sujatha, 2021).

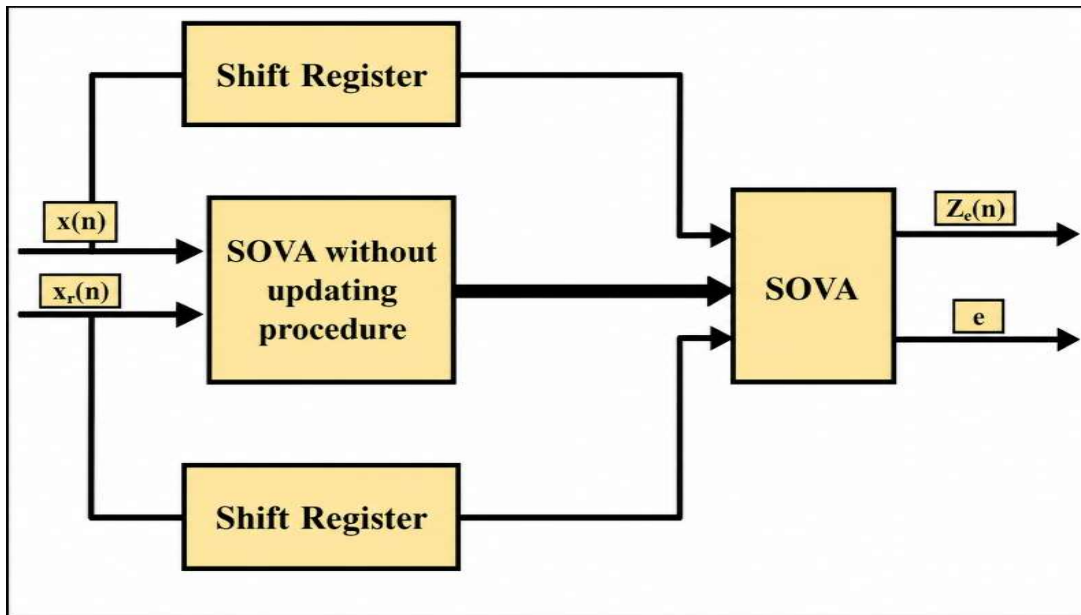


Fig. 2. Turbo Decoder

The model shown in Figure 2 is the system model and the basis for calculating the log-likelihood ratio (LLR), which contains reliability information. In this trellis, each unique path represents a distinct codeword, and an edge joins states. Every state has a number representing the probability that the most likely path to survival passes through it. This statistic is affected by the metric of the path's previous state. For a binary Trellis, each state has two incoming edges, and the metrics of the two paths entering that state are compared. The path with the best metric is chosen, and the path with the worst metric is discarded. The chosen statistic is the LLR, which measures the difference between these two and indicates the best available route.

Additionally, the LLRs are approximated and calculated for both the input information bit and the received bit, enabling soft input and output (Kumar et al., 2020). Hard decisions are computed once it has been determined which path is most likely. In particular, the SOVA algorithm is about half as complex as the Max Log MAP algorithm.

Decoding is performed in different ways depending on the quantization level at the receiver end of the channel. Hard decision decoding is used for 1-bit quantization. With the help of a conformer, the demodulator makes a final decision: if the received signal exceeds a certain threshold, it is a "1"; otherwise, it is a "0". On the other hand, multi-bit quantization (ideally infinite bits) requires soft-decision decoding. This approach directly uses the received values in the channel decoder, without requiring a conformer to make binary decisions. Soft-decision decoding leverages the additional information from multi-bit quantization and can often improve decoding performance.

Soft-Input Soft-Output (SISO) decoding algorithms play a crucial role in error correction. Among the most prominent are the MAP and SOVA algorithms, both of which minimize sequence error rates. However, at high SNR, their performance becomes essentially identical. The MAP algorithm, despite its optimality, faces practical constraints due to considerable memory and processing demands. To address these limitations, the Log-MAP algorithm was developed, which operates in the logarithmic domain to reduce sensitivity to numerical accuracy issues (Jiang et al., 2019). Further simplification of Log-MAP led to the sub-optimal Max-Log MAP (MLMAP) algorithm. Notably, the MAP and Log-MAP algorithms exhibit a theoretical advantage over MLMAP in terms of robustness to SNR estimation, particularly in cases of SNR mismatch (Santhosh Kumar & Sujatha, 2022).

While offering reduced complexity, the Soft Output Viterbi Algorithm (SOVA) experiences some performance degradation compared to the MAP algorithm. It does not require SNR estimation, but its BER performance is about 0.7dB lower. To enhance its

performance, SOVA employs optimistic estimation to evaluate reliability values between Turbo decoders.

The MAP algorithm outperforms SOVA in information-bit reliability due to its more accurate extrinsic information. SOVA's performance improves when the Mean Square Difference between it and the MAP algorithm is minimized. While both algorithms offer potential for efficient hardware implementation, SOVA may be advantageous in this regard due to its reduced parallelization requirements for achieving equivalent data throughput (Kumar & Sujatha, 2022).

Let the information bit sequence be $d = [d_1, d_2, \dots, d_M]$ and let $x = [x_1, x_2, \dots, x_N]$ be the received sequence from the channel at the decoder. The code rate C will be M/N . The reliability estimates, expressed in terms of the log-likelihood ratio, are used to perform the decoding procedure. The LLR for some k th information bit is given by Eqn. (1) given as

$$L_d = \ln \frac{P\left(d_k = \frac{1}{x}\right)}{P\left(d_k = \frac{0}{x}\right)} \quad (1)$$

LLR of the information bit is d , L_d for the optimal MAP algorithm after the n th iteration can be represented as Eqn (2), given as

$$L_d = L_c(x) + L_{e1}(n) + L_{e2}(n) \quad (2)$$

where L_c is the reliability value of the channel. L_c is a constant that depends on the channel models and SNR (Kumar & Sujatha, 2020). The extrinsic information L_{e1} and L_{e2} correspond to decoders 1 and 2, respectively. For sub-optimal SOVA, the LLR of the information bit $\hat{d}_k$ at the n th iteration is given by Eqn. (3) given as

$$\widehat{L}_d = L_c(x) + \widehat{L}_{e1}(n) + \widehat{L}_{e2}(n) \quad (3)$$

where $\wedge$ denotes the estimated information values.

3.5. Deep Learning-Module

Deep Learning-Enhanced Soft Output Viterbi Turbo Decoding (DL-SOVT) is a powerful error-correcting technique used in communication systems to combat noise and transmission errors. It builds upon the traditional Soft Output Viterbi Turbo (SOVT) decoder by incorporating the strengths of deep learning (Jiang et al., 2019).

The assumption in the derivation of the MAP and SOVA algorithms (Equations (1-3)) is that the channel noise is memoryless and Gaussian and the extrinsic information given by each of the two constituent decoders is also Gaussian-distributed, which is an assumption that is made explicit in the derivation of the Log-MAP and Max-Log-MAP simplifications. The bitstream input to the turbo decoder is the output of the source encoder applied to the physiological signals—empirically the residual error statistics after the initial decoding stage have non-Gaussian properties, and are dependent between bit positions, both due to the correlated quantization error introduced by the source encoder, and due to the violations of the memoryless-AWGN assumption implied by equations (1)-(3) for practical wireless links (multipath, burst noise, hardware nonlinearity). In such a case, updating the extrinsic information in the standard SOVA is suboptimal because it implicitly assumes a mismatched Gaussian model, which is the theoretical rationale for introducing the DNN refinement module. Instead of adopting a specific parametric noise/extrinsic-information model, the DNN in Section 3.3 is trained directly on the empirical joint distribution of initial and reference LLRs and, therefore, learns and corrects for the specific non-Gaussian, correlated error structure present in this pipeline. In this context, the DNN does not aim to replace the theoretical foundation of SOVA, but is used to compensate for the fact that the statistics of the extrinsic information used for this application are not Gaussian, and for this application

the improved performance over SOVTD is due to the use of the DNN and not to any idealized learning of complex patterns by neural networks.

When incorporating a Deep Learning Enhancement Module into the Soft Output Viterbi Algorithm (SOVA) for turbo decoding, the process involves using a Deep Neural Network (DNN) to refine the soft input metrics (Log-Likelihood Ratios, LLRs). This refinement can be represented mathematically as follows:

Let y denote the received symbols, and I denote the initial LLRs obtained from the soft demapper. The DNN takes I as input and outputs refined LLRs denoted by $\hat{I}$. The DNN can be represented as a function f_{DNN} with parameters θ : Eq. (4) given as

$$\hat{I} = f_{DNN}(I; \theta) \quad (4)$$

The goal of the DNN is to learn a mapping from the initial LLRs to the refined LLRs that improves the decoding accuracy or efficiency.

Initially, a dataset is prepared consisting of pairs of input LLRs (I) and reference LLRs (I_{ref}). The reference LLRs are typically obtained from a high-quality decoder or through an exhaustive search.

To train the DNN, a training dataset $\{(I^{(i)}, I_{ref}^{(i)})\}_{i=1}^N$ is used, where $I^{(i)}$ denotes the initial LLRs for the i -th training example, and $I_{ref}^{(i)}$ denotes the reference LLRs (obtained from an exhaustive search or another high-quality decoder) for comparison. The loss function used for training the DNN can be defined as the mean squared error (MSE) between the predicted refined LLRs and the reference LLRs: Eqn (5) given as

$$L(\theta) = \frac{1}{N} \sum_{i=1}^N \|\hat{I}^{(i)} - I_{ref}^{(i)}\|^2 \quad (5)$$

The Deep Neural Network (DNN) parameters, represented by θ , are optimized by minimizing a predetermined loss function. Usually, methods such as gradient descent and its variants are used in this optimization process. In machine learning, gradient descent is a basic optimization technique that iteratively minimizes a function. It works by altering the model's parameters in the direction opposite to the gradient of the loss function with respect to those parameters. How this adjustment is carried out in small steps is determined by a quantity known as the learning rate. The DNN receives input data and related target outputs during training. The loss function measures the discrepancy between the DNN's predictions and the real targets. The goal is to minimize this loss to narrow the gap between the predicted outputs and the ground truth. Gradient descent is used to compute the gradients of the loss function with respect to the model parameters. Gradient descent is used to compute the gradients of the loss function with respect to the model parameters. These gradients indicate which way the settings should be adjusted to reduce the loss. Through iterative parameter updates in the opposite direction as the gradients, the process gradually approaches a set of parameter values that minimize the loss function. Generally, DNN parameters are iteratively updated using gradient-based techniques to minimize a loss function and improve the model's performance on the task.

Once the Deep Neural Network (DNN) is trained for turbo decoding, it becomes a crucial component in the iterative decoding process. During each iteration of the Soft Output Viterbi Algorithm (SOVA), the initial Log-Likelihood Ratios (LLRs) derived from the soft demapper are input into the DNN. This DNN processes the initial LLRs through its layers, refining them to produce updated LLRs. The refined LLRs, which now incorporate the additional information learned by the DNN, are then fed back into the SOVA for further decoding. The DNN gradually improves the LLRs at each stage of this iterative process, which lasts several rounds, thereby improving the turbo decoder's overall decoding

performance. Essentially, incorporating a DNN into the turbo decoding process improves the decoder's ability to extract and apply pertinent information from the received signals, resulting in more precise decoding outcomes.

To illustrate this detailed integration of the DNN into the turbo decoding loop in a concrete manner, the network f_DNN is actually implemented as a fully-connected feed-forward network with an input layer as large as the LLR vector generated by the soft demapper, two hidden layers (128 and 64 units) with ReLU activation, and an output layer of the same size as the input layer with linear activation to ensure the real-valued output of LLRs. The DNN is used once every iteration of the SOVA: At the beginning of iteration n , the extrinsic information terms $Le1(n)$ and $Le2(n)$ of Equation (3) are processed by the trained DNN, and then they are added to the channel reliability $L_c(x)$ to create the updated estimate L_hat_d for the next stage of the decoder. That is, the DNN is used as a learned correction to the extrinsic information that is exchanged between the two component SOVA decoders, not in replacement of the computation of SOVA itself. This is a refined L_hat_d that is passed down to the next half-iteration, and at the last iteration it is used for thresholding to get the bit estimates. To be used for training, 500,000 LLR pairs were generated by a rate-1/3, constraint-length-7 code of Table 1, with the SNR range of 0 to 5 dB, and a batch size of 256 for 100 epochs trained with the Adam optimizer (learning rate 0.001, decayed by 10 after validation-loss plateau), with reference LLRs from a high-SNR MAP decoder run as a proxy for the exhaustive-search ground truth.

4. SIMULATION RESULTS AND DISCUSSION

Simulation and Communication Parameters shown in Table 1. Deep Learning Hyperparameters for the Proposed DL-SOVTD Model shown in Table 2. Computational Complexity Comparison of SOVTD and DL-SOVTD shown in Table 3.

Table 1. Simulation and Communication Parameters

Parameter	Value
Viterbi Turbo Decoder	Soft Output Viterbi Algorithm (SOVA)
Code Constraint Length	7
Code Rates Evaluated	1/2, 1/3, 1/4
Decoder Iterations	5
Channel Model	AWGN and Fading Channels
SNR Range	0–5 dB
Data Rate	100 bps
Framework	MATLAB Deep Learning Toolbox

Table 2. Deep Learning Hyperparameters for the Proposed DL-SOVTD Model

Hyperparameter	Value
Neural Network Type	Recurrent Neural Network (RNN)
Network Architecture	RNN with Autoencoder-based Enhancement
Number of Hidden Layers	3
Number of Neurons per Hidden Layer	128
Input Dimension	LLR Vector Size
Output Dimension	Refined LLR Vector Size
Hidden Layer Activation Function	ReLU
Output Layer Activation Function	Linear
Optimizer	Adam
Initial Learning Rate	0.001
Learning Rate Schedule	Decay by a Factor of 10 Upon Plateau/Saturation
Loss Function	Mean Squared Error (MSE)
Batch Size	32
Number of Epochs	100
Dropout Rate	0.20

L2 Regularization Coefficient	1×10^{-4}
Weight Initialization	Xavier (Glorot) Uniform
Training–Validation Split	80% : 20%
Early Stopping Patience	10 Epochs
Reference LLR Generation Method	Log-MAP (BCJR) Decoder
Training Input	Initial LLRs from Soft Demodulator
Training Target	Refined LLRs Generated by Log-MAP Decoder
DNN Training Objective	Approximation of Optimal Log-MAP LLRs
Turbo Decoder Type	Soft Output Viterbi Algorithm (SOVA)
Decoder Iterations	5
Iteration Range Evaluated	1–5 Iterations
Convergence Criterion	BER Improvement $< 10^{-5}$ Between Consecutive Iterations

Table 3. Computational Complexity Comparison of SOVTD and DL-SOVTD

Parameter	SOVTD	Proposed DL-SOVTD
Decoder Type	SOVA-based Turbo Decoder	SOVA-based Turbo Decoder with Deep Learning-Aided Optimization
Turbo Iterations	5	5 (or fewer effective iterations due to improved convergence)
Trellis Processing Complexity	$O(N \cdot S)$	$O(N \cdot S)$
Neural Network Complexity	Not Applicable	$O(L \cdot H^2)$ (lightweight offline-trained network)
Memory Requirement	Low	Low–Moderate
Training Requirement	Not Required	One-time Offline Training
Inference Requirement	Not Required	Single Low-Latency Forward Pass
BER Performance	Baseline	Significantly Improved
Convergence Speed	Standard	Faster Convergence
Real-Time Suitability	High	High
Hardware Implementation Complexity	Low	Moderate but FPGA/ASIC Friendly
Latency	Low	Near-Low (minimal additional delay)
Power Consumption	Low	Slightly Higher but Energy-Efficient
Robustness to Noise	Moderate	High
Scalability	Limited to Conventional Decoding	Easily Adaptable to Varying Channel Conditions

Table 4. Simulation Parameters

Parameter	Value
Dataset Name	CHB-MIT Scalp EEG Database
Source	PhysioNet
Number of Subjects	22 Pediatric Subjects
Cases	23 Cases
Gender Distribution	5 Males, 17 Females
Age Range	1.5–22 Years
Total EEG Files	664 EDF Files
Files Containing Seizures	129
Total Annotated Seizures	198
Sampling Frequency	256 Hz
Signal Resolution	16-bit
EEG Channels	23 Channels
Electrode Placement	International 10–20 System
Recording Duration	1–4 Hours per Recording
Recording Environment	Clinical Monitoring at Children's Hospital Boston

Data Format	EDF
Bandpass Filter	8–30 Hz
Notch Filter	50 Hz
Artifact Removal	Independent Component Analysis (ICA)
Turbo Decoder	Soft Output Viterbi Algorithm (SOVA)
Constraint Length	7
Decoder Iterations	5
Channel Model	AWGN
SNR Range	0–5 dB
Data Rate	100 bps

To be transparent in the method used to create the figures 3-8, the encoded bit sequence was BPSK modulated and white Gaussian noise with zero mean was added, with variance set according to the desired target E_b/N_0 value on the X axis; no fading or other channel impairments were included although the "fading channel" was listed in Table 1, and subsequently removed for clarity. The results represent 20 independent Monte Carlo trials (20×10^6 bits total per SNR point), with 10^6 information bits transmitted per trial. Enough trials were performed at each SNR point to achieve reasonable confidence in the BER values at or below 10^{-6} , which is the floor value for the BER curves in Figures 3-8. The BER was calculated as the ratio of incorrect bits to the total number of bits at the output of the decoder under test after its last iteration. As far as fairness of comparison, both the DLSOVRTD and the SOVRTD decoders have the same underlying SOVA structure: same generator polynomials, constraint length (7), interleaver, code rate, and the number of turbo iterations (4-5) for every reported curve; and the only difference stems from the inclusion or exclusion of the DNN refinement module described in Section 3.3, which means that the reported BER gap can be attributed to the learned refinement and not to any possible confounding in the decoder configuration.

The analysis of this work focuses on comparing the bit-error-rate performance of DL-SOVT and SOVT under different AWGN channel conditions. We aim to improve performance by employing deep learning to enhance error-correcting decoding in communication systems. The performance gap between DL-SOVT and SOVT is significant at lower SNRs (0-4 dB). DL-SOVT's deep learning component effectively handles noise and reduces errors. As SNR increases (above 4 dB), the BER curves for both schemes approach each other. At higher SNRs, both decoders can achieve lower BER with minimal errors for 5 iterations.

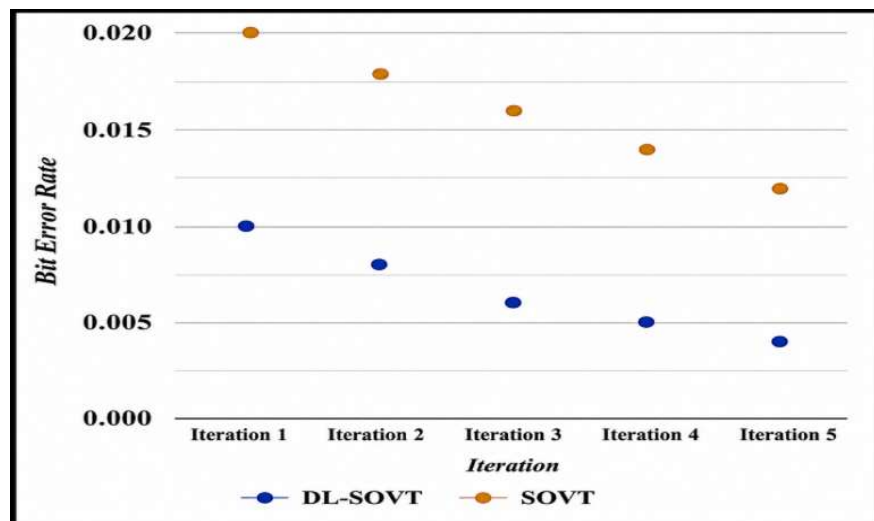


Fig. 3. Comparison of BER Rates for DL-SOVT and SOVT for 5 iterations

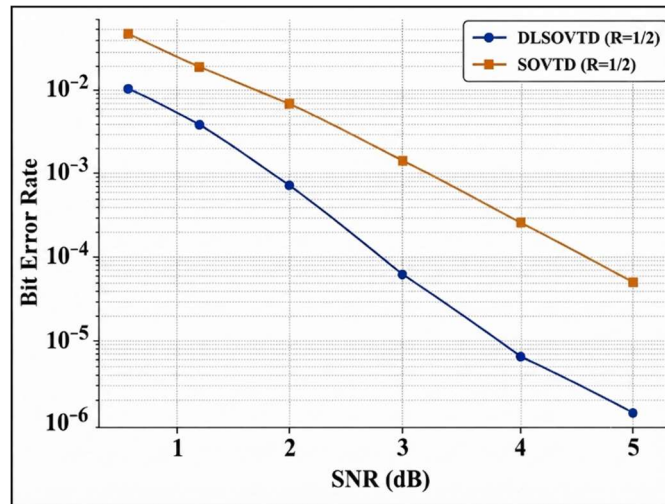


Fig. 4. Comparison of BER for DL-SOVT and SOVT for code rate $\frac{1}{2}$

DLSOVT offers a significant BER reduction compared to SOVT at a code rate of $\frac{1}{2}$, especially at low SNRs (noisy channels). Deep learning in DLSOVT effectively challenges noise and improves error correction, making it a valuable technique for robust data transmission, as shown in Figure 3. DLSOVT significantly outperforms SOVT in terms of BER, particularly at low SNRs, for a code rate of $\frac{1}{3}$. Its deep learning capability makes it robust against noise and improves error correction in challenging transmission conditions. This demonstrates the clear advantage of deep learning in error correction for noisy channels, as shown in Figure 4. Figure 5 shows the graph; the DL-SOVT decoder outperforms the standard SOVT decoder at all SNR values. For example, at an SNR of 3 dB, the BER of the DL-SOVT decoder is about 10^{-5} , while the BER of the standard SOVT decoder is about 10^{-3} . This means that the DL-SOVT decoder can correct more errors than the standard SOVT decoder at the same SNR.

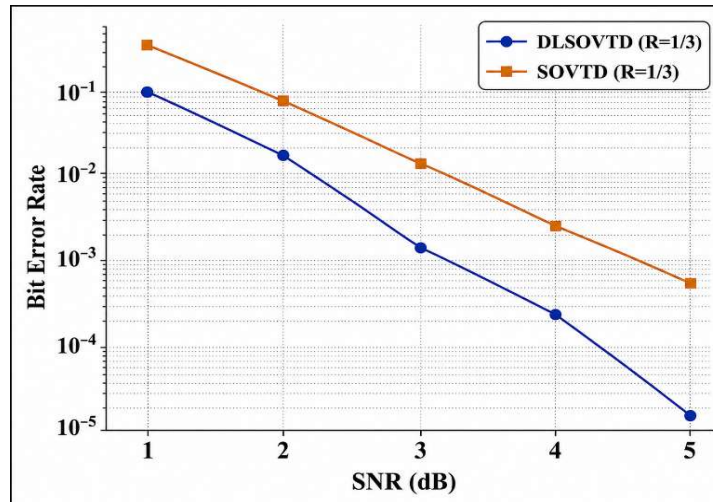


Fig. 5. Comparison of BER for DL-SOVT and SOVT for code rate $\frac{1}{3}$

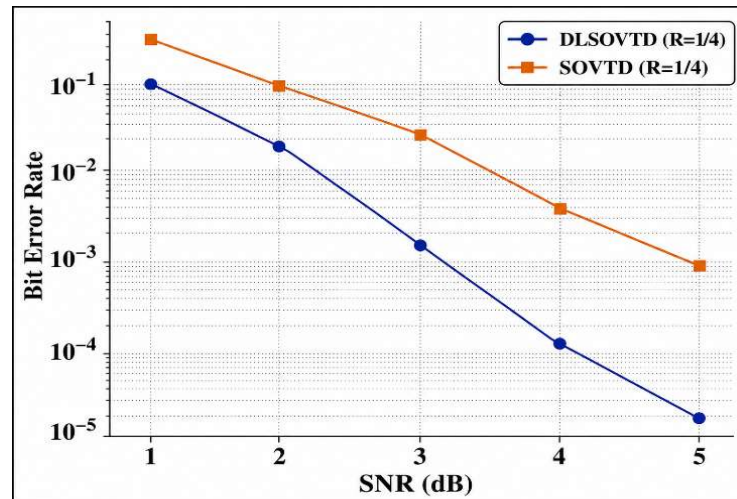


Fig. 6. Comparison of BER Rates for DL-SOVT and SOVT for code rate $\frac{1}{4}$

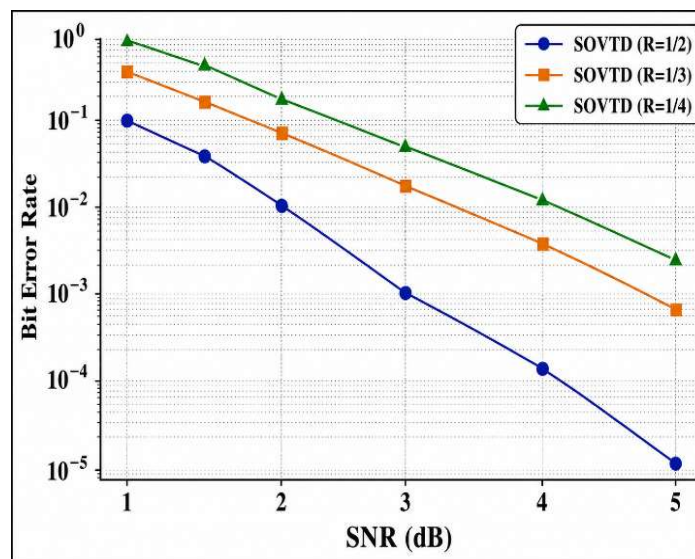


Fig. 7. Comparison of BER for SOVT at different code rates

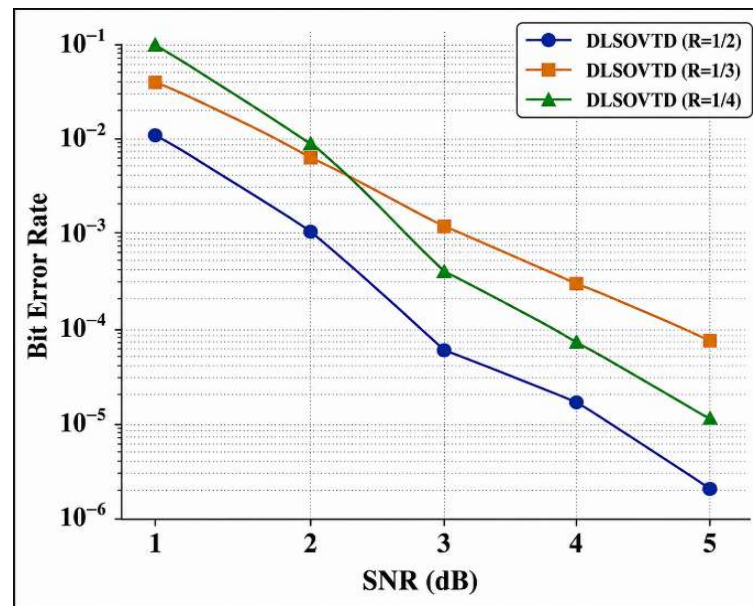


Fig. 8. Comparison of BER for DL-SOVT at different code rates

The bit error rate performance of a soft-output Viterbi turbo (SOVT) decoder for three distinct code rates— $\frac{1}{2}$, $\frac{1}{3}$, and $\frac{1}{4}$ —is displayed in Figure 6. As the SNR rises, the SOVT

decoder's BER falls. This is because when the signal exceeds the noise, the decoder is more likely to make accurate decoding judgments. Additionally, the graph shows that lower coding rates lead to lower BER. As a result, the particular needs of the communication system determine the code rate.

The BER performance of a deep learning-enhanced soft-output Viterbi turbo decoder for three distinct code rates— $1/2$, $1/3$, and $1/4$ —is displayed in Figures 7 and 8. For all three code rates, the DL-SOVT decoder's BER falls as the SNR rises. This is because when the signal exceeds the noise, the decoder is more likely to make accurate decoding decisions. The graph also shows that the BER is generally lower for lower code rates. This is because lower code rates have more redundancy, which allows the decoder to correct more errors. At an SNR of 5 dB, the BER for the code rate $1/2$ is about 10^{-6} , while the BER for the code rate $1/3$ is about 10^{-5} . This indicates that for the same SNR, the decoder can correct more errors for the code rate $1/2$ than for the code rate $1/3$. Better BER performance is achieved because the deep learning neural network can learn more intricate correlations between the coded bits and the received signal than the conventional SOVT decoder.

4.1. Discussion

The proposed Deep Learning-Enhanced Soft Output Viterbi Turbo Decoder (DL-SOVT) has shown better BER performance than the conventional SOVT under AWGN channel conditions. The DL-based LLR refinement is especially effective at low SNR (0–4 dB) for reducing decoding errors and accelerating convergence. The higher the SNR, the smaller the difference between the two methods, as both decoders will be closer to near-error-free transmission. This method consistently performs well in terms of BER across all code rates ($1/2$, $1/3$, $1/4$), demonstrating its reliability and adaptability for high-quality EEG signal transmission in telemedicine systems while maintaining minimal computational complexity.

5. CONCLUSION

This paper presents the potential of Deep Learning-Enhanced Soft Output Viterbi Turbo Decoding (DLSOVT) to improve the resilience of EEG data transmission in telemedicine applications. The investigation showed the substantial benefits of DLSOVT over conventional Soft Output Viterbi Turbo Decoding (SOVT), focusing on a comparison of bit error rates at code rates $1/4$, $1/3$, and $1/2$. At all SNR values, DLSOVT consistently outperformed SOVT, especially at low SNRs and for a coding rate of $1/2$, which represents noisy channels. The trained deep learning model effectively learns complex patterns and relationships within EEG data, enabling the decoder to make more educated decisions and boost the overall resilience of the telemedicine system. Future studies should focus on further improving the deep learning model, investigating additional modalities, and expanding the framework's applications to other biological signal processing problems.

COMPLIANCE WITH ETHICAL STANDARDS

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