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Deep Learning Based Autoencoder Communication System

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Abstract: *Modern wireless communication systems rely on independently designed transmitter and receiver components a modular approach that, while well-established, introduces significant complexity and limits adaptability to dynamic channel conditions. This project proposes and implements an intelligent end-to-end communication system using a deep learning-based Autoencoder architecture as an alternative to conventional modulation and coding designs. The proposed system models the transmitter as an encoder neural network and the receiver as a decoder neural network, with an Additive White Gaussian Noise (AWGN) layer representing the communication channel. By training the entire communication chain jointly through back propagation, the system automatically learns optimal signal encoding and decoding strategies without manual feature engineering or predefined modulation schemes. The implementation is built using Python, TensorFlow, NumPy, Matplotlib, and a Streamlit-based interactive web interface. Three optimization algorithms — Adam, RMSProp, and Gradient Descent — are evaluated across 10,000 training iterations with varying batch sizes (256, 512, 1024) and a training SNR of 7 dB. Adam achieved the fastest convergence with a final cross-entropy loss of 0.054, outperforming RMSProp (0.113) and Gradient Descent (0.421). Block Error Rate (BLER) analysis across SNR values from 0 to 14 dB confirms substantial improvement in communication reliability at higher SNR levels., versus 0.016 and 0.009 respectively.*

Key Words: *GELU, activation function, FPGA, Verilog HDL, CORDIC, fixed-point arithmetic, hardware–software co-design, edge AI, Artix-7, Basys 3.*

I. INTRODUCTION

The accelerated Comparative evaluation against conventional QPSK and 8PSK modulation schemes demonstrates that the autoencoder achieves a lower BLER of 0.006 at 10 dB developments in wireless data communication technologies have necessitated a significant need for high-performance, intelligent, and reliable communication systems. Modern communication networks such as 4G, 5G, Internet of Things (IOT), satellite communication, and future 6G networks require advanced techniques to transmit information accurately over noisy communication channels. The design of conventional communication systems employs separate blocks such as source encoding, channel encoding, modulation, transmission, demodulation, and decoding. Each component is optimized independently, which often leads to increased system complexity and suboptimal overall performance. Latest progress in Deep Learning (DL) has revolutionized diverse such as natural language processing, computer vision, healthcare, and telecommunications. DL methods excel at uncovering intricate patterns directly from raw data, eliminating the need for manual feature extraction. This strength has motivated researchers to investigate how DL can be leveraged in the design of modern communication systems. Among several DL architectures, the Autoencoder stands out as a prominent candidate for point-to-point digital communication. An autoencoder is an Artificial Neural Network (ANN) model that can be trained to efficiently compress input data by encoding it and then reconstructing it at the output. In communication engineering, the transmitter and receiver can be represented as neural networks, while the communication channel acts as a noise layer between them. The entire communication system can then be trained jointly in an end-to-end manner to minimize transmission errors.

System Architecture

The system architecture utilizes an Auto encoder comprising of three primary components:

Transmitter (Encoder): The transmitter receives a message represented as a one-hot encoded vector and generates a lower dimensional data ready for transmission over the communication channel.

Communication Channel: The communication channel is represented based on an AWGN model, which adds random noise to the transmitted signal and emulates real-world channel conditions.

Receiver (Decoder): The receiver processes the noisy signal and attempts to reconstruct the original message using neural network-based decoding. The entire system is trained jointly using back propagation to minimize communication errors.

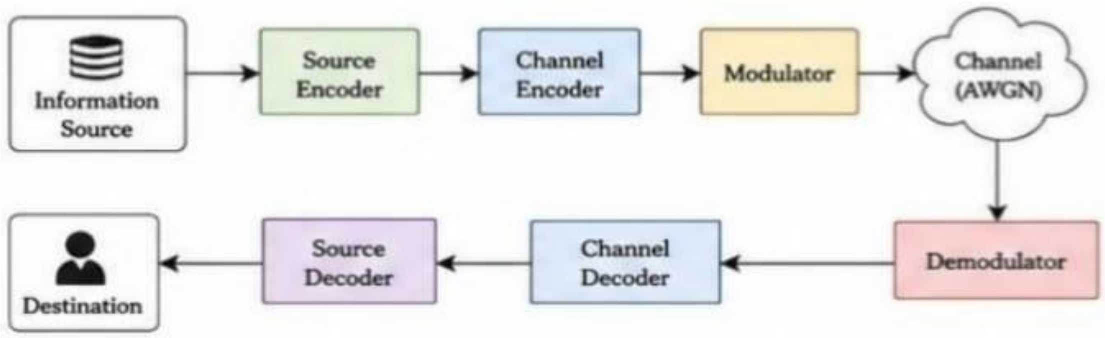


Fig: Architecture of communication system

II. MATERIAL AND METHODS

Proposed System

Overview: The proposed system employs a Deep Learning-based Auto encoder architecture that learns optimal encoding and decoding strategies automatically. Instead of designing the transmitter and receiver separately, they are trained jointly using neural networks. The communication channel is modeled using an Additive White Gaussian Noise (AWGN) layer.

Architecture of Proposed System

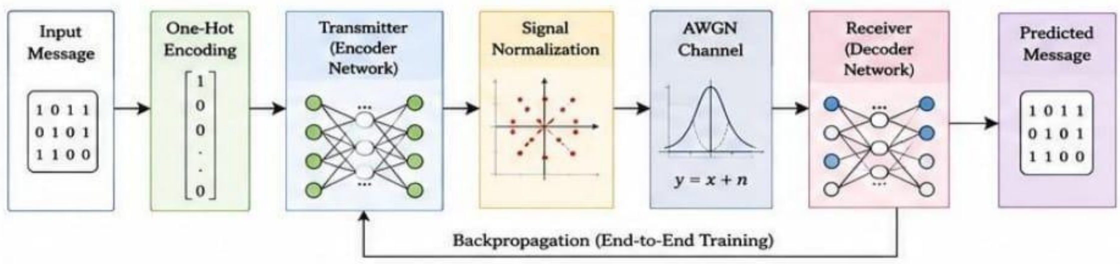


Fig: Architecture of proposed system

Working of Proposed System

In input Layer Random messages are generated and converted into one-hot encoded vectors. Transmitter layer network is a neural network learns how to encode messages into transmission symbols. In channel Layer AWGN noise is added to simulate real-world communication conditions. At the receiver network decoder learns to recover the original message from noisy signal.

Training Process: The system minimizes cross-entropy losses employing optimization algorithms such as:

- Adam
- RMSProp
- Gradient Descent

Comparison of the Existing System against the Proposed System

Feature	Existing System	Proposed System
Design Method	Manual Design	Deep Learning Based
Optimization	Separate Components	End-to-End Optimization
Adaptability	Low	High
Modulation	Fixed	Learned Automatically
Complexity	High	Reduced
Noise Handling	Limited	Improved

Software Requirement Specification (SRS)

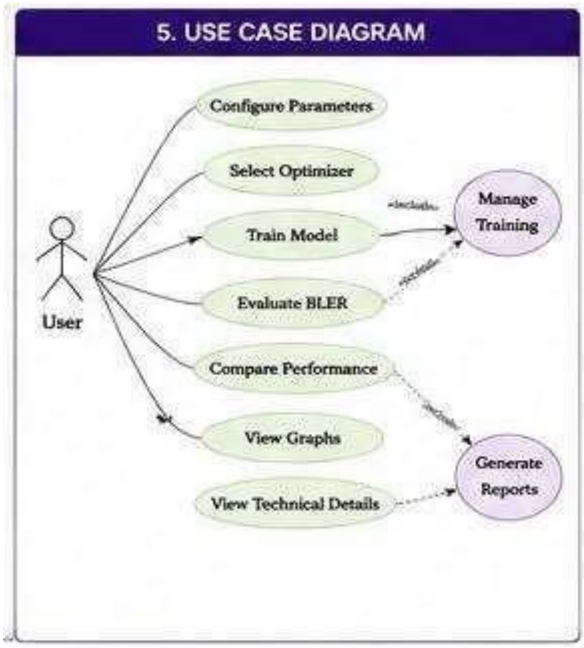
Software	Version
Python	3.x
TensorFlow	2.x Compatibility Mode
Streamlit	Latest
NumPy	Latest
Matplotlib	Latest

Hardware Requirements

Component	Specification
Processor	Intel i5/i7
RAM	8 GB or Higher
Storage	20 GB Free Space
Operating System	Windows/Linux

Use Cases:
- Configure Parameters
- Train Model
- Select Optimizer
- Evaluate Performance
- Compare Results
- Visualize Graphs

Use Case Diagram



III. IMPLEMETATION

Implementation is the process of converting the system design into a working software application. It involves coding, integrating modules, testing functionality, and validating system performance. The Deep Learning-Based Autoencoder Communication System is implemented using Python, TensorFlow, Streamlit, NumPy, and Matplotlib. The system trains an auto encoder model to learn optimal communication strategies over an Additive White Gaussian Noise (AWGN) channel. The implementation supports an interactive web interface that enables users to configure communication parameters, train models using different optimizers, and analyze communication performance through visualizations and comparative graphs.

Streamlit provides: Interactive web interface Real-time parameter tuning Dynamic graph visualization

Libraries Used

Library	Purpose
TensorFlow	Deep Learning
NumPy	Numerical Computation
Streamlit	User Interface
Matplotlib	Visualization
Warnings	Error Handling

Parameters

Parameter	Description
K	Information Bits
N	Channel Uses
Learning Rate	Training Speed
Batch Size	Training Samples
SNR	Noise Level
Iterations	Training Cycles

Communication Channel Model

The wireless communication channel is modeled as an Additive White Gaussian Noise (AWGN) channel represented by

$$y=x+ny$$

Where:
x is the transmitted signal,
n is Gaussian noise,
y is the received signal.

The AWGN model accurately represents thermal noise present in practical wireless communication systems and provides a benchmark for evaluating communication performance.

IV. RESULTS

The proposed Autoencoder successfully learned optimal communication strategies during training. The Cross-Entropy Loss decreased steadily with increasing iterations, indicating effective convergence of the neural network.

Among the three optimization algorithms, the Adam optimizer exhibited the fastest convergence rate and achieved the lowest training loss. RMSProp also converged effectively but required additional iterations, whereas Gradient Descent demonstrated comparatively slower convergence and higher residual loss.

Experimental Setup: The experiments were carried out with the following configuration.

System Configuration

Parameter	Value
Information Bits (k)	8
Channel Uses (n)	8
Number of Messages	256
Training Iterations	10000
Learning Rate	0.001
Training SNR	7 dB
Batch Sizes	256, 512, 1024
Communication Channel	AWGN

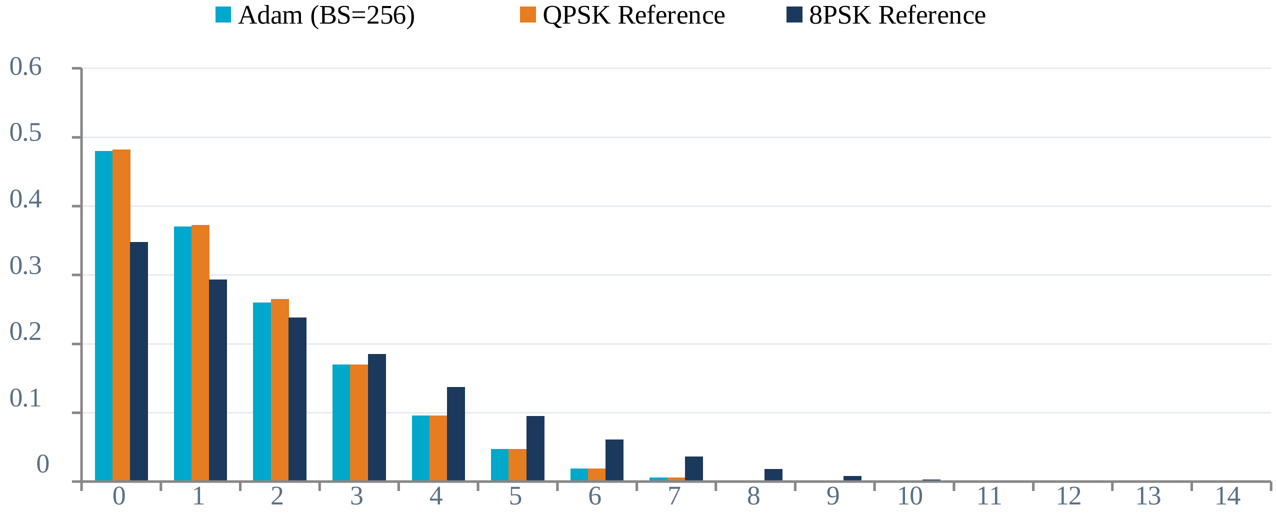


Fig: The final loss values obtained after 10,000 training iterations.

Optimizer	Final Cross-Entropy Loss
Adam	0.054
RMS Prop	0.113
Gradient Descent	0.421

Table: Optimizer Performance

The results indicate that adaptive optimization techniques significantly improve the learning efficiency of deep learning-based communication systems.

V.DISCUSSION

Block Error Rate (BLER) Analysis

Communication reliability was evaluated using the Block Error Rate (BLER), which represents the proportion of incorrectly decoded message blocks after transmission through the AWGN channel.

As the Signal-to-Noise Ratio (SNR) increased, the BLER decreased substantially for all evaluated communication schemes. The proposed Autoencoder consistently achieved lower error rates than conventional modulation techniques, demonstrating improved robustness under noisy channel conditions.

At an SNR of 10 dB, the proposed Autoencoder achieved a BLER of 0.006, outperforming both QPSK (0.016) and 8PSK (0.009).

These results demonstrate that the Autoencoder learns efficient signal representations capable of improving communication reliability while minimizing transmission errors.

VI.CONCLUSION

The results confirm that deep learning can effectively replace traditional communication block design by automatically learning robust signal representations. The proposed framework offers reduced system complexity, enhanced adaptability, and improved transmission reliability, making it a promising solution for next-generation intelligent wireless communication systems.

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