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Investigation of FSO Communication System Using Various Neural Networks

Ritu Gupta[1,*], Sandeep Kaur[1]

Abstract

A prospective method for high-speed data transfer via light propagation in free space, such as between buildings, satellites, or metropolitan areas, is free space optics communication. Free space optics systems have great promise, but their performance can be severely hampered by atmospheric disturbances. Problems, like fog, rain, and turbulence, cause the optical signal to be absorbed and scattered, increasing bit error rate. To address these challenges, various neural network techniques, such as recurrent neural networks and convolutional neural networks, have been investigated. According to the study, convolutional neural networks perform better than artificial neural networks and recurrent neural networks among the neural network approaches investigated in controlling for the spatial changes brought on by atmospheric circumstances. Convolutional neural networks' ability to analyze spatial data is probably the reason for this advantage, which makes it perfect for addressing localized free space optics communication problems. Convolutional neural networks hence result in a more dependable link by improving bit error rate and signal-to-noise ratio, particularly in adverse weather conditions.

Keywords*:* Free Space Optics (FSO), Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), Signal-to-Noise Ratio (SNR), Bit Error Rate (BER)

INTRODUCTION

In FSO communication, data are wirelessly sent across the environment using light.

It offers several advantages over traditional radio frequency communication, including enhanced bandwidth, secure transmission, and resilience to electromagnetic interference. However, weather-related conditions, like rain, fog, and turbulence, can significantly hinder the performance of FSO lines. Light beams are used in free space for FSO communication to send data. The main barriers to FSO transmission are air attenuation and turbulence because of their capacity to severely reduce signals. Variable air turbulence conditions cause FSO to have a range of ripple effects in disaster relief, military applications, line-of-sight (LOS) link for communication between planes, ships, etc., and back-haul connection. Aerosols and water particles generate air turbulence, which lowers link performance and alters the refraction. index, which in turn affects how the LASER beam propagates through the atmosphere. High hindrance is provided by atmospheric turbulence since the LOS requirement is not contested.

Prior studies have examined a variety of diversification strategies to lessen the effect of turbulence on FSO link performance. Fog is the main meteorological factor that impacts the consistency and dependability of the FSO link, among other factors, including rain, haze, snow, hail, and other atmospheric phenomena [1].

***Author for Correspondence**
Ritu Gupta
E-mail: iciai2025@gku.ac.in

[1]Associate Professor, Department of ECE, Chandigarh University, Gharuan, Punjab, India

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Because of increasing customers' requirements, like large bandwidth, high speed, and capacity, to overcome the processing power limitation, optical neural networks (ONNs) have come out as a promising alternative. Thanks to advancements in optics and nano-photonics, complex ONNs may now be implemented on free-space and nano-photonic platforms.

Since the 1980s, artificial neural networks, or ANNs, have been a hot issue in artificial intelligence (AI). When it comes to deep learning, ANN has advanced significantly. Improved algorithms, larger training data sets, and more processing power are the three main improvements that have been found for ANN. Computing power continues to be the most difficult constraint in NN development, despite the fact that researchers have significantly improved NN architectures and found enough training data to provide desired results.

This paper explores the application of NN models for these impact predictions and mitigation with the goal of enhancing the reliability of FSO systems. The brief of FSO communication and various NN has been discussed in Section 2. In Section 3 delineates the approach used for structuring the communication network. The results have been analyzed and discussed in sections 4 and 5. And finally, the research has been concluded in section 6.

BACKGROUND SURVEY

Communication by Free Space Optics (FSO) Using NNs

NNs can be used in FSO communication to overcome obstacles such as system nonlinearities, hardware limitations, and environmental disturbances. The basic requirements for their use are Channel Modeling: Rain, fog, scattering, and air turbulence all have an impact on FSO channels. Such impacts can be modeled and predicted using NN. NN is useful for tasks like signal recovery, equalization, and noise reduction in FSO systems. To enhance system performance, NN can be used to apply adaptive modulation, coding, or power control techniques. Select a model that strikes a balance between prediction accuracy and computing complexity. When feasible, models should shed light on the FSO communication process.

Architecture of NNs

The various architectures of NNs used in FSO communication have been discussed here.

ANN

ANN are computer systems that draw inspiration from biological NNs. They comprise networked nodes, or neurons, that process information in layers. A possible method for processing vast quantities of data is the use of light rather than energy. An ANN's structure requires a lot of matrix computing. Eq. (1) illustrates the feed-forward NN. The activation function (nonlinear link) then transmits the outcome of the linear calculation to the next layer of neurons. Figure 1 shows the feed-forward NN's artificial neuron structure and linear computation portion in accordance with the aforementioned idea. To put it succinctly, optical matrix computing serves as the basis for the development of ONN.

$$\begin{aligned} Z &= \sum_{i=1}^{N} W_i * X_i + b_i \\ Y &= f(Z) \end{aligned} \tag{1}$$

Xi is top-layer neuron:
Wi is associated with weight, while bi is bias.

The ANN is a machine learning framework that is used to extract complex correlations between the input and target. Using the label and features, it picks up a certain activity without needing explicit rule programing. Bit detection, for example, uses an ANN to learn from manually labeled sample bits whether a given bit of input is 0 or 1. ANN technology may find applications in both the optical and electrical worlds. However, it is feasible to process QPSK labels and route photonic labels using an ANN in an optical framework [2]. An optical ANN that translates detection into pattern recognition might aid in the categorization of distorted signals [3]. Because ANN can infer intricate nonlinear correlations between the target and the output, it is a superior choice for complicated jobs like equalization. Like SVM, most ANN implementations are associated with Fibre OC. By using ANN NLE, the fibre effects might be successfully countered [4].

As a lifeless body, the ANN minimizes a loss function (by modifying its weights) using iterative algorithms, least mean square (LMS) approaches, or K-means clustering, or (iterative algorithms are frequently used for this purpose) [5, 6]. This research's primary focus is on the use of ANN in OWC systems, namely FSO or VLC. The primary issue with the FSO technology is the turbulence in the propagation medium. To overcome this challenge, Lapsiwala et al. employed long short-term memory (LSTM) with ANN models to study the consequence of air turbulence on FSO communication. The results exhibit that higher wavelengths are less attenuated than lower wavelengths in the presence of fog. An examination of the attenuation of different wavelengths in the presence of fog using ANN and LSTM models shows that higher wavelengths undergo less attenuation in comparison to lower wavelengths [7]. ANN is often more useful than SVM due to its nonlinear nature; one example use is the adjustment of optical amplification strength. Since it may cause nonlinearity and ASE noise, adjusting the amplification level is essential; this is beneficial in real applications [8]. White light-emitting diodes (LEDs) in VLCs allow for simultaneous data transmission and lighting [9, 10]. The two most significant problems with VLC are fluorescent light interference (FLI) [10] and multi-path-induced ISI [11], both of which result in a large optical power cost. An ANN could potentially reduce ISI if the transmission rate surpasses the bandwidth of the system's modulation. Like in a single-input single-output (SISO), an ANN can serve as an equalizer in a system that uses multi-input multi-output (MIMO)-VLC.

Filtering the blue portion of the LED at the expense of power contribution from the yellowish wavelengths is a popular method for boosting data throughput. However, when utilizing an ANN equalizer, it is possible to obtain higher data rates from white light than from the blue component due to the high SNR that is created by maintaining the yellowish wavelengths [10]. A feed-forward ANN with one or more hidden layers, the Extreme Learning Machine (ELM), as shown in Figure 1, is useful for classification, regression, clustering, and sparse approximation. Hidden nodes' parameters can be inherited from their predecessors without modification, allocated at random, and never modified. They also do not require tuning. As with linear model training, hidden layer output weights are usually acquired in a single step.

In the presence of cross-LED interference and LED nonlinearity, ELM in OC is only utilized as a VLC MI MO detector, despite its exceptional speed and performance [12]. The bulk of ANN research in OC investigated common NN layer kinds; nevertheless, ANNs are dynamic systems, and their hyperparameters can be varied in addition to being manually or indiscriminately modified. For example, an algorithm known as ELM may be used to adjust the number of neurons in an adaptable manner, which may be helpful in situations when no data is provided [13].

Recurrent Neural Networks (RNN)

RNNs are a type of ANN where the network maintains a "memory" of past inputs through directed cycles formed by node connections. One kind of RNN is the LSTM, which consists of four gates: an input gate, an output gate, a forget gate, and a cell. The cell can hold a value for an endless amount of time because the gates control the flow of data into and out of the cell. By regulating the flow of data into and out of the cell, these gates allow the cell to retain values for variable periods of time. To achieve a high QoS network that is dependable and adaptable, OSNR monitoring is essential. With great accuracy and quick reaction times, the OSNR relationship of time-varying data may be found using LSTM-RNN [14]. A generalized RNN with an input layer, four hidden layers, and an output layer is shown in Figure 2. The constraints of RNNs with respect to future input data (as they are unable to process it) and the rigidity of input data in MLP and time delay NN (TDNN), which have fixed input structures, are addressed by bidirectional LSTM. When LSTM-RNN is bidirectional, it increases the input data by tie-in two hidden layers operating in opposite directions (forward and backward states) to the same output. Additionally, a multi-domain routing model was proposed that leverages AI and data analytics to solve the inter-domain routing problem as an alternative to heuristic methods.

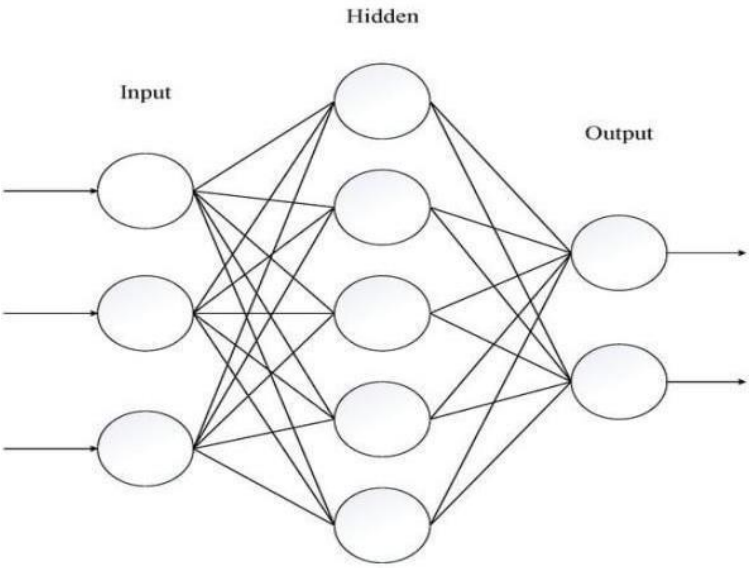

Figure 1. Structure of an ANN.

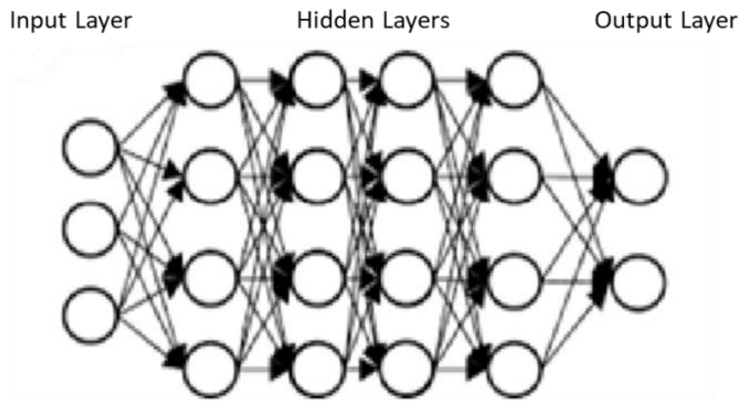

Figure 2. Structure of an RNN.

Convolutional Neural Networks (CNNs)

CNNs are made expressly to process data with a grid-like structure such as images.

CNN, a type of DNN (a regularized form of MLP), has a different regularization technique and is mostly used for picture signal analysis.

CNN builds increasingly complex patterns from smaller, simpler patterns by considering hierarchical patterns in the input. The structure of the animal visual cortex is like the core principle of the CNN's neuronal connection network. The whole visual field is covered by restricted, distinct stimulation zones (receptive fields) that are partially overlapped by other cortical neurons. The primary usage of CNN is in image processing. Few publications have examined this approach because of its high processing cost; other NN are favored. The primary use of CNN, in contrast to earlier ML algorithms, is optical performance observation. By self-learning, CNN can identify the image, determine intrinsic attributes of the original image, and perform very well in OC employment such as optical performance monitoring

[15, 16].

Figure 3 displays the CNN schematic diagram.

When it comes to image processing, CNN can handle constellation diagrams as raw data – that is, as individual pixels in an image – without the need for data statistics or human intervention.

For MFI and OSNR monitoring, eye diagrams or AHH may be input into CNN [17]; this approach performed better than decision trees, KNN, SVM, and ANN. In a coherent optical receiver, the MFI is critical to recover the carrier phase because constellation patterns of modulation signals are sensitive to different noises. It is a good idea to adopt a hybrid machine learning approach in which the amplitude data is processed by CNN after an ML MFI-based clock recovery has been built [18].

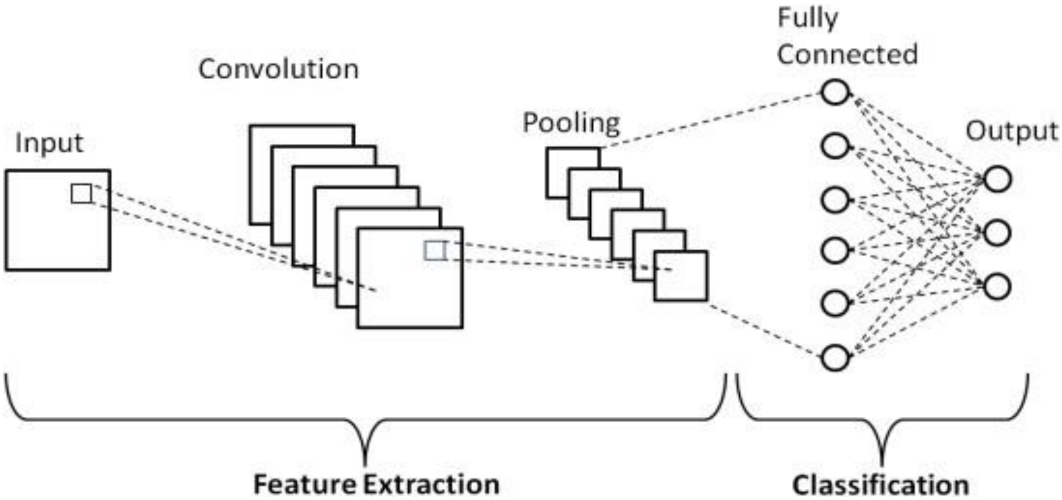

Figure 3. Schematic diagram of a CNN.

Network

Keeping in mind CNN applications, OC networks allow in target quantity identification/estimation, OPM [19], and QoT estimation [20]. CNN manages the amount of training data mandatory for convergence as well as the human engineers' preprocessing of the input data required for feature extraction, in contrast to other ML algorithms. Additionally, fibre connection failures, for which the fibre speckle gram sensors are extremely sensitive, might be detected using CNN [21]. For FSO investigations, WOC: CNN is well thought out by most of the ML algorithms. CNN may also be utilized in conjunction with an orbital angular momentum FSO system for the detection and demodulation of atmospheric turbulence [22]. It has been demonstrated that this method is more accurate than earlier ones. Recently, CNNs have been employed to address this challenge by extracting features from the intensity distributions of received Laguerre–Gaussian beams [23]. In VLC systems, CNNs are primarily used for demodulation [24].

STRUCTURE OF PROPOSED METHODOLOGY

Gathering and Preparing Data

FSO connection performance measurements under different atmospheric conditions are included in the dataset. SNR, BER, and meteorological data are examples of features. Three sets of data are separated: test, validation, and training. The basic end-to-end structure of NN-based FSO communication system is shown in Figure 4.

Model Structures

Title must be in 20 pt Regular font. Author name must be in 11 pt Regular font. Author affiliation and email must be in 10 pt.ANN: An input layer, two hidden layers, and an output layer comprise a feed-forward NN.

- *RNN:* An RNN employs LSTM units to identify temporal connections within the data.
- *CNN:* Using convolutional layers, a network is utilized to identify spatial patterns in atmospheric data.

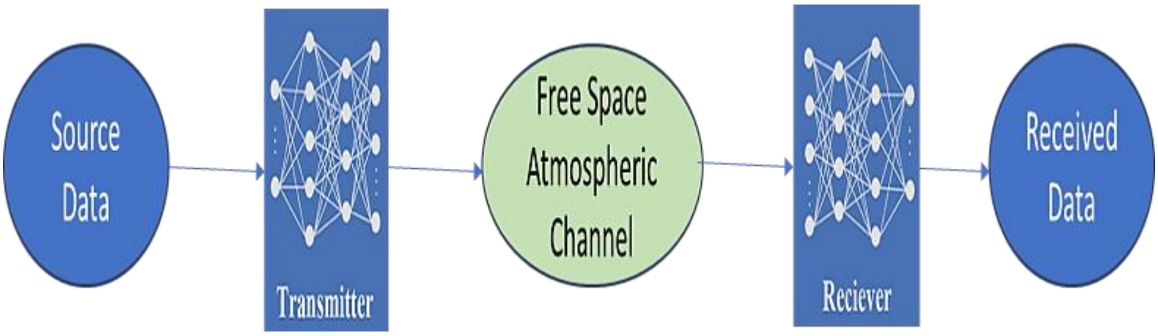

Figure 4. Block diagram of NN-based FSO communication system.

The training set is utilized to train the models, while the test set is used to evaluate their performance. Performance is measured using metrics such as accuracy for classification tasks and Mean Squared Error (MSE) for regression tasks.

RESULTS AND DISCUSSION

Performance Metrics

The performance of different models with respect to these parameters has been shown in Table 1 and graphically analyzed in Figure 5.

Model Comparison

ANN

- *Architecture:* 3 layers (input, 2 hidden, output).
- *Test MSE:* 0.015.

RNN

- *Architecture:* 1 LSTM layer, 2 dense layers.
- *Test MSE:* 0.012.

CNN

- *Architecture:* 2 convolutional layers, 1 dense layer.
- *Test MSE:* 0.009.

Analysis

- *ANN:* The ANN provides a good baseline for performance but struggles with dynamic atmospheric conditions. Its simplicity results in lower computational costs and faster training times, making it suitable for less complex scenarios.
- *RNN:* In situations with time-varying circumstances, the RNN performs better than the ANN due to its capacity to grasp temporal relationships. Longer training durations and more computing complexity are the price of this, though.
- *CNN:* The CNN demonstrates the best performance, effectively handling spatial variability in atmospheric data. Its architecture captures intricate patterns in the input data, resulting in the lowest BER and highest SNR improvements. The training time and computational costs are reasonable compared to RNN, making it the most robust model for FSO communication systems.

Table 1. Performance metrics for each model.

Metric	ANN	RNN	CNN
Test MSE	0.015	0.012	0.009
Training time	10 minutes	20 minutes	15 minutes
BER improvement	10%	15%	20%
SNR improvement	5 dB	7 dB	10 dB
Computational cost	Low	High	Medium
Temporal dependencies	No	Yes	No
Spatial dependencies	No	No	Yes

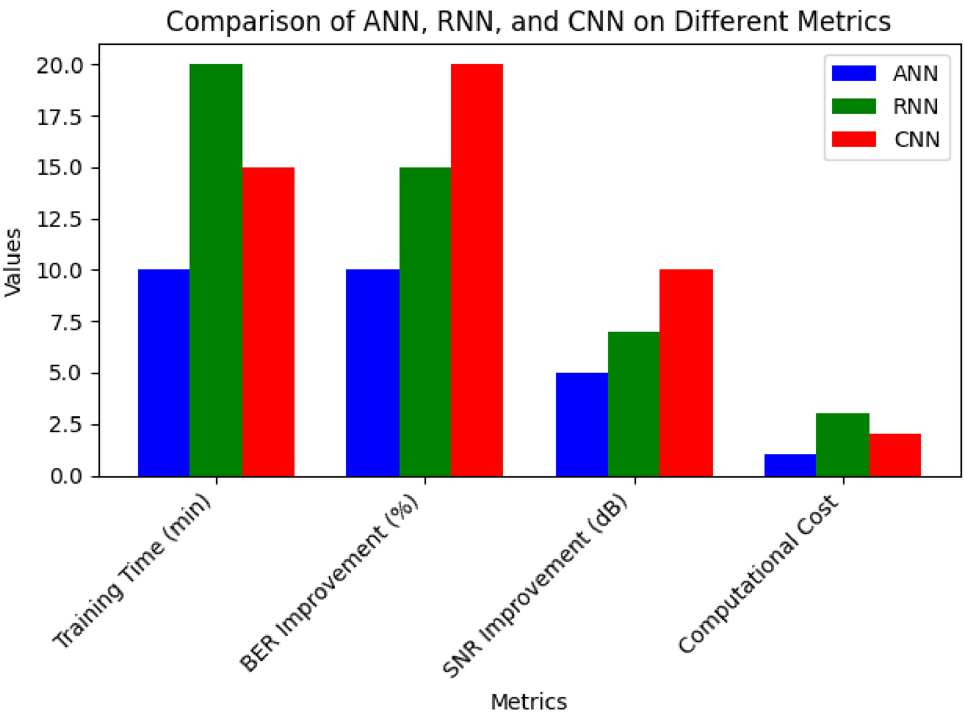

Figure 5. Comparison of ANN, CNN, and RNN on different metrics.

DISCUSSION

The results indicate that CNNs are particularly effective in handling the spatial complexity of atmospheric effects on FSO links. While RNNs also perform well due to their temporal modeling capabilities, the additional computational complexity may not always be justified. ANNs provide a good baseline but are less effective in highly dynamic environments.

CONCLUSIONS

This study demonstrates the potential of NN models, particularly CNN, in enhancing the reliability of FSO communication systems. NNs are a powerful signal processing tool in FSO communication systems. They are mainly used to improve the quality of received signals by reducing the effects of atmospheric turbulence, which severely degrades signal quality in FSO links. In essence, NNs function as sophisticated adaptive filters to correct atmospheric distortions. Future research will examine hybrid models that incorporate the best features of several architectures and evaluate the models in practical settings.

This research article presents the findings of a thorough investigation of the use of NNs in FSO communication systems, along with a transparent approach, findings, and recommendations.

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