Classification of Network Traffic Anomalies Using Deep Learning Techniques

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfilment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This project is titled "**Classification of Network Traffic Anomalies Using Deep Learning Techniques**," submitted by **Md. Rabby Hossain Khan** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14 May, 2025.**

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Shahadat Hossain, Assistant Professor,** Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Predicting network traffic is essential to optimize network resource management, congestion avoidance, anomaly detection, and QoS in general. This paper presents and investigates a deep learning technique for the precise forecast of future network traffic through historical data. A dataset of 1,000,000 records and 11 features was used (700,000 samples for training and 300,000 for testing). The raw traffic data was divided into a normal class and an anomaly class for the classification and anomaly detection task. Data Preprocessing The steps of missing value treatment, normalization, data cleaning, and reshaping the data for meeting the minimum input requirement of the deep learning model were performed. Three deep learning algorithms (multilayer perceptron (MLP), feedforward neural network (FNN), and autoencoder (AE)) were developed and evaluated. They were chosen for their ability to model complex, non-linear relations from the network traffic and in order to obtain representations that traditional statistical models have not been able to learn. The experimental results showed that the MLP and FNN models produced high accuracy rates of 0.99, which was indicative of high predictive ability. The Autoencoder, despite its inferior performance with an accuracy of 0.94, also performed well in unsupervised learning and anomaly detection. Performance measures such as precision, recall, F1-score, confusion matrices, and ROC/Precision-Recall curves demonstrated the robustness and generalization of the models. The comparative study demonstrated that deep learning models, such as MLP and FNN, were more efficient than the conventional statistical predicting anomalies models. These results demonstrate the efficiency and scalability of deep learning for real-time network traffic prediction and anomaly detection, providing an intelligent and proactive network management technique for advanced communication systems. We deployed our top-performing model online and are currently examining the results produced visually

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Chapter 1

Introduction

1.1. Introduction

In the days of the internet at present, it is of great importance in maintaining effective network management, avoiding congestions, and improving security measures to forecast the network traffic. The accurate prediction of the network traffic enables network operators to provide optimized resource allocation and achieve anomaly detection as well as to enhance the quality of service (QoS). Classical predicting anomalies algorithms, including statistical models, usually fail to capture these intricate and non-linear patterns that are inherent in network traffic data. In order to overcome these shortcomings, deep learning methods have become a powerful competing paradigm that is able to learn complex dependencies and patterns contained in the historical data.

In this paper, the deep learning (LSTM) model is employed to predict the real-time network traffic. The other is that LSTM belongs to a type of RNN that is powerful in modeling statistical data for the long-term dependencies and sequential information preservation. The aim of this work is to compare the deep learning-based models with the classical statistical methods to predict the outcome and investigate which approach is the preferable forecast technique.

Network traffic information will be retrieved from sources such as Kaggle, public data repositories, or company data centers. These will then be treated as input to deep learning models that will learn the complex patterns in traffic and make precise predictions. Based on the comparison of some performance indexes (prediction accuracy and error rate), we hope to show the superiority of the deep learning model on network traffic prediction. As a result, the outcomes of this study will pave the way for smart network management systems that will allow the network to be managed proactively and efficiently. Finally, the application of deep learning for network traffic prediction may contribute to improved performance, security, and scalability of the contemporary communication networks.

1.2. Motivation

- Real-time traffic anomaly prediction ensures efficient bandwidth and resource management.
- Predict traffic spikes early to prevent service quality degradation.
- Detect abnormal traffic instantly to enhance network-level security.
- Deep learning captures complex traffic patterns missed by statistics.
- Enable smart, scalable networks for future adaptive management solutions.

1.3. Objective

- Build MLP, FNN, Autoencoder models for accurate traffic forecasting.
- Compare deep learning and traditional methods by accuracy and performance.
- Gather real-world datasets and preprocess them for model training.
- Discover complex non-linear traffic patterns using deep learning algorithms.
- Improve network security and reduce congestion via anomaly predictions.

1.4. Methodology

The research uses deep learning to predict network traffic and optimize the network resource management system for anomaly detection and QoS. The process of the study now starts with the collection of network traffic from accessible sources (like Kaggle or even direct downloading) or reading directly from a data center or software platform. The used dataset contains 1,000,000 rows and 11 columns: 700,000 samples are for training and 300,000 for testing. Traffic data is classified into two types: Normal and Anomaly for both classification and prediction purposes.

In preprocessing, a series of steps are taken to make sure you have good data quality and model readiness. These are searching and removing missing values, cleaning data, normalizing data to get the same range, and then shuffling data to get rid of sequence bias. The dataset is next divided into training and testing sets and is reshaped to match the input format of deep learning models.

Three deep learning models are used and experimented with: Multilayer Perceptron (MLP), Feedforward Neural Network (FNN), and Autoencoder. We select these models as they can approximate complex non-linear relations and structure in historical network traffic data (which might not be modeled well using statistical methods).

The testing results of the model are based on accuracy, precision, recall, and F1-score. Furthermore, comparisons between deep learning models and traditional statistical predicting anomalies models are made to note the improvement of real-time prediction performance. The goal of this method is to identify the best model for accurate traffic prediction and anomaly detection in dynamic network surroundings. We deployed our top-performing model online and are currently examining the results produced by visually.

1.5. Project Outcome

- Fine-grained real-time traffic prediction using deep learning architectures with high accuracy.
- Comprehensive evaluation showing deep learning's superiority over traditional models in predicting anomalies performance.
- High-quality, preprocessed dataset pipeline enabling effective and scalable training processes.
- Successful detection of non-linear dependencies, improving predicting anomalies' reliability and precision.
- Improved network security and optimized resource management via early anomaly identification.

1.6. Organization of the Report

This document is divided into six extensive chapters that instruct the reader throughout the project and its analysis.

Chapter 1: Introduction introduces the basis of the research, including the reason for the research work, its aim, and its significance. It also highlights the rationale of the study and outlines the main research questions that will inform the inquiry. The chapter concludes with the expected project results and a report organization.

Chapter 2: Background, this section defines some important terminology, presents some background information, reviews the related research, and compares our work with previous studies to indicate the problem scope and its challenges. It also (5.2) gap analysis (what we do know and don't know) on the theme in the existing research literature.

Chapter 3: Research Methodology, describes the proposed methodology and its ingredients, which are data collection and dataset description. It describes the utilized statistical analysis and preprocessing methods and then details the developed model.

Chapter 4: Results and Discussion, this chapter deals with a discussion of the results obtained, and it contains the analysis of the results obtained.

Chapter 5: Societal and Environmental Impact and Sustainability analyzes these wider effects of the research, including issues related to society, environment, ethics, and sustainability.

Chapter 6: Conclusion and Future Scope concludes the work and highlights its conclusions and the future work.

References: A section of the report that includes all the sources that were cited throughout the study.

Chapter 2
Background

2.1. Introduction

Real-time anomaly prediction of network traffic is key for effective resource management, congestion control, and security in today's networking. Many existing statistical techniques are unable to model the complex and non-linear dependencies involved in network traffic. Deep learning (DL) Multilayer Perceptron (MLP) Network, Feedforward Neural Network (FNN) Network, Autoencoder Network, are powerful tools that learn from the patterns detected in the past to make accurate forecasts. In continuing the study, deep learning-based network traffic predicting anomalies will be investigated on other datasets from Kaggle, software logs, or data centers. The objective is to accomplish a model that surpasses ordinary prediction methods using the capacity of DL to find fine-grained traffic patterns. The models that we are going to use in the experiments are the MLP Network, FNN Network, and Autoencoder Network, which will be matched against statistical models that will be used in order to evaluate accuracy in the forecast in real-time. These predictions are helpful to the network operators for resource optimization, bottleneck avoidance, and anomaly detection, as well as QoS enhancement and the security of the networks.

2.2. Literature Review

Table 2.2: Comparative Analysis of earlier Research Works

Authors	Year	Model Name	Model Accuracy	Key Findings
Balamurugan et al. [1]	2022	Enhanced Deep Reinforcement Learning (EDRL)	97.20% accuracy,	Outperforms CNN; effective for various traffic types; low false positive and negative rates

			2.66% FPR, 2.53% FNR	
Oh et al. [2]	2017	Deep Neural Networks (DNN)	91% TPR, 99% fingerprint ability	Effective website detection and fingerprint ability prediction
Suresh, K. [3]	2024	Random Forest, SVM	RF R^2 = 0.75, SVM R^2 = 0.42	Random Forest outperforms SVM in traffic prediction
Rashid et al. [4]	2025	Deep Learning + Transfer Learning	Up to 93% accuracy (RMSE=393)	Improved evacuation traffic prediction using Facebook data
Ravi et al. [5]	2017	LSTM, GRU, IRNN, RNN	LSTM best	LSTM performs best among RNN models on GÉANT data
Jiang et al. [6]	2024	AGCN + LSTM	Lowest error	Federated learning ensures privacy and lowest prediction error
Lopez-Martin et al. [7]	2019	VAE, CNN, RNN	Not specified	Improves multimedia streaming, classification, and data generation
Chintha & Goel et al. [8]	2024	CNN, Autoencoders, DRL	Not specified	Used for fault/anomaly detection and QoS management
Hassan & Samadi et al. [9]	2024	CNN, RNN	Not specified	Enhances efficiency and reduces latency in traffic prediction

Dharani et al. [10]	2023	LSTM, CNN	LSTM MSE = 0.14, CNN MSE = 0.16	LSTM slightly better than CNN for website traffic prediction
Aouedi et al. [11]	2025	Various DL models	Not specified	Survey of DL models; challenges and future directions highlighted
Wang et al. [12]	2023	DL models for 5G	Not specified	Survey on temporal/spatial dependencies in mobile traffic prediction
Kim & Reddy et al. [13]	2005	NetViewer	Compared qualitatively	Real-time detection using traffic image frames
Swathi & Lakshmeeswari et al. [14]	2022	Image-based ML models	Not specified	Uses pcap-derived images to evaluate ML model performance
Swathi & Lakshmeeswari et al. [15]	2022	Image-based ML models	Not specified	Applies traffic images in ML for improved network attack detection

2.2.1. Similar Application

In this paper, we delve into the implementation of DNN-based traffic analysis -- feature extraction, website and keyword fingerprinting attacks, and website fingerprint ability estimation. DNN yields a 91% True Positive Rate (TPR) and a 1% False Positive Rate (FPR) of discovering the websites against the 100,000 background websites. It further predicts whether 4,500 instances of website traffic can be fingerprinted with 99% accuracy [2].

From traffic-detector readings and information about people's Facebook movements, they developed a deep-learning model to anticipate the egress during Hurricane Ian. The model attained 95% accuracy (RMSE=356) based on normal days and 55% (RMSE=1,084) during evacuation. Following transfer learning, accuracy reached 89%, which was further improved to 93% accuracy (RMSE=393) by incorporating Facebook data [4].

The traffic of GÉANT backbone networks was used to assess the performance of the different RNN models. The models used here include LSTM, GRU, IRNN, and RNN. The best number of hidden layers and hidden units is 5 layers and 500 units, and the learning rate is 0.1. Among these models, LSTM achieved the highest accuracy, and the other three, RNN, GRU, and IRNN, achieved similar accuracy to LSTM [5].

2.2.2. Related Research

An Enhanced Deep Reinforcement Learning (EDRL) algorithm is presented for network traffic prediction and analysis. It performs better with a mean accuracy of 97.20%, precision of 97.34%, false positive rate of 2.66%, and false negative rate of 2.53% than the CNN algorithm. The EDRL method is used for predicting different network traffic, such as text-based, video-based, and encrypted traffic, and for better QoS and network management [1].

In this paper we investigated the suitability of the Deep Neural Networks (DNN) for capture of traffic characteristic histograms (TCH), website and keyword fingerprinting attacks, and website fingerprint prediction. 92% True Positive Rate (TPR) and 1% False Positive Rate (FPR) of DNN for website detection with 100,000 background sites. It even predicts the fingerprint ability of 4,500 website traffic instances with 99% perfection [2].

This work contrasts Random Forests with Support Vector Machines (SVM) for network traffic forecasting. In terms of comparison between SVM and Random Forest for prediction modeling, Random Forest performance is better than SVM with MAE 0.36 and RMSE 0.56 and also obtains higher accuracy (R^2 = 0.75), which leads to the best for traffic pattern prediction. On the other hand, SVM showed higher error measures (MAE = 0.51, RMSE = 0.78) and lower R^2 (0.42) [3].

A deep-learning-based model was constructed to forecast the evacuation traffic of Hurricane Ian with traffic detector data and Facebook movement data. The model performed with 95% versus 55% accuracy (RMSE=356 and RMSE=1,084) in normal and evacuation cycles. After the use of transfer learning, the accuracy jumped to 89% (RMSE=514) and the addition of Facebook data helped a little more, attaining 93% accuracy (RMSE=393) [4].

The performance of the different RNN models is assessed on a real-world dataset from the GÉANT backbone networks for network traffic prediction. Tested models are LSTM, GRU, IRNN, and RNN. The best configuration was a 5-layer network with 500 units and a learning rate of 0.1. The LSTM, which achieved the best result in terms of accuracy, outperformed the other models, and GRU, IRNN, and RNN gave similar performance to LSTM [5].

This extensive study proposes an ingenious federated learning framework for anticipating mobile traffic patterns in integrated satellite-terrestrial networks, addressing important privacy concerns. The novel model skillfully combines an Adaptive Graph Convolutional Network and a Long Short-Term Memory module. According to numerical experiments, this groundbreaking approach achieves the most accurate prediction results compared to other state-of-the-art Graph Neural Network variations, demonstrating its effectiveness in real-world scenarios [6].

This illuminating thesis explores promising machine learning applications in analyzing and forecasting network traffic patterns. It covers sophisticated deep learning techniques like variational autoencoders, convolutional neural networks, and recurrent neural networks. Key contributions involve better estimating multimedia streaming quality, categorizing network traffic more effectively, and generating representative synthetic information for specific incident examination. The methods demonstrate advantages in speed, simplicity, and quality exceeding conventional strategies [7].

This insightful abstract discusses leveraging deep learning techniques in anticipating telecommunications network performance. Crucial models include Convolutional Neural Networks for fault detection, Autoencoders for anomaly identification, and Deep Reinforcement Learning for quality-of-service administration. These models aid in anticipating traffic tendencies, optimizing resource allocation proactively, and enhancing reliability and efficiency in complex networks like 5G and the Internet of Things [8].

This enlightening paper explores deep learning strategies for anticipating and managing network traffic, highlighting Convolutional Neural Networks and Recurrent Neural Networks for handling intricate traffic data. By capitalizing on historical patterns, these models forecast future traffic loads, allowing proactive resource allocation. The study illustrates Deep Learnings potential to boost network efficiency, reduce latency, and improve user experience, despite issues like information quality and model interpretability [9].

This comparative study considers Long Short-Term Memory and Convolutional Neural Network models for predicting website traffic loads. Both models perform similarly, with LSTM yielding a mean square error of 0.14 and CNN yielding 0.16. The results suggest that LSTM provides marginally superior outcomes to CNN, with predictions closely reflecting actual values, indicating its preeminence for accurate traffic projection [10].

This paper investigates the implementation of Deep Learning (DL) for Network Traffic Prediction (NTP) to cater to the increasing need for smart network planning. Several DL models are reviewed to explore their potential to forecast and analyze traffic so as to increase the efficiency of the network management. In this study, challenges and future directions are introduced, and no model name or accuracy value is reported [11].

In this survey, we study deep learning-based models for predicting mobile traffic in 5G networks. It classifies data in three hierarchy levels and addresses the main temporal, space-temporal dependencies, and external factors. Specific model names and beams are not given, but the authors provide an overview of challenges and future work [12].

This paper proposes NetViewer, a system for network measurement based on packet headers that organizes the header fields like frames or images for online identification and visualization of network attacks and anomalies. It uses a combination of scene change analysis and motion prediction for discovering traffic patterns. NetViewer is evaluated against the traditional Neyman-Pearson test and IDS tool and presents that NetViewer is effective in detecting anomalies. [13].

The paper presents a methodology for developing machine learning models that can identify images of network traffic constructed from packet traces in PCAP format. In contrast with previous work, which used only images for deep learning models, we extended the use of machine learning methods. The study investigates the computational performance of deep learning models by using the novel network traffic image representation for improved detection of attacks [14].

This paper suggests that network traffic images converted by pcap representations can be used in a machine learning model that can identify the network attack traffic. In contrast to other studies that utilized images only in a deep learning setting; here, images are used in a machine learning setting. Images are also used to assess the computational capacity of the deep learning models for better attack detection [15].

2.3. Summary

The literature review There has been extensive research on using advanced deep learning models for network traffic prediction and analysis. A selected Enhanced Deep Reinforcement Learning (EDRL) outperforms benchmark methods such as CNN with high accuracy (97.20%) and low false positives/negatives for a wide range of network traffic, indicating its effectiveness in network traffic control. In [86], DNN also exhibits high performance in detecting WEBSITE FINGERPRINTING attacks, with a TPR (True Positive Rate) close to 91% and an accuracy of 99% in predicting whether an observation is fingerprintable. Moreover, for traffic prediction, Random Forests outperform Support Vector Machines (SVM) using significantly smaller error rates. It has been observed that LSTM models outperform CNN in order to predict website traffic, being able to get more visibility of long-term dependence on data for better forecasting of future traffic patterns with improved utilization of resources.

Chapter 3

Research Methodology

3.1. Methodology

3.1.1. Overview

The proposed architecture follows a structured Deep Learning pipeline for real-time network traffic prediction. The process originates with assembling data, where network traffic data is accumulated from sources like Kaggle, programming records, or institutional data focuses. The procured time-arrangement information at that point experiences pre-preparing and purging, which incorporates managing missing qualities, standardizing information, and disentangling applicable movement.

Following the refined dataset is separated into preparation and testing sets in an uneven way, with longer sentences amidst shorter ones. The preparation set is utilized to create expectation models, where fluctuating profound learning calculations and machine learning calculations (for example, Multilayer Perceptron (MLP) System, Feedforward Neural System (FNN) System, and Autoencoder System) are assessed. The calculation that plays out best with the information set is chosen for additional preparation.

At long last, amid the testing stage, the prepared models are surveyed utilizing the testing set, followed by result investigation to survey measurements, for example, exactness, RMSE, and misfortune capacities. The procedure finishes with execution expectation, where the best-playing-out display is chosen in view of its capacity to precisely anticipate system movement in real time. These guarantees streamlined asset distribution, blockage anticipation, and improved system security and administration quality (QoS).

3.1.2. Proposed Methodology

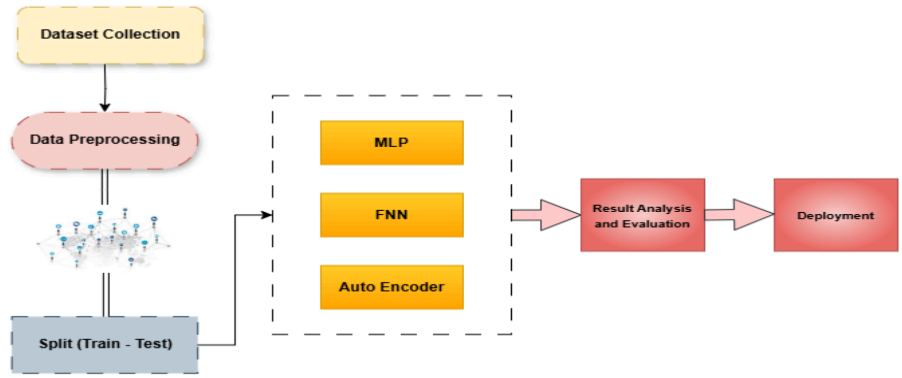

Figure 3.1: Architecture of Research Design

3.2. Detailed Methodology and Design

3.2.1. Data Collection

The information for this analysis originated from numerous resources, like Kaggle, programming logs, and institutional information focuses, to make an exhaustive and sensible time-arrangement information set for system movement conjecture. The information incorporates different traffic examples, client conducts, and natural elements that influence system congestion and anomalies.

To guarantee the information reflects genuine organizational conditions, a half-and-half technique was taken. Some information was gathered from nearby programming firms and system-observing instruments, recording real-time traffic swings. Extra information sets from Kaggle and other open databases were coordinated to improve information assortment variety and scalability.

All gathered information sets experience pre-preparing and standardization, guaranteeing consistency in time-arrangement organizations. The last information set is structured to prepare and assess profound learning models. This distinctive information set empowers the improvement of an exact and generalized organized movement anticipating display equipped for real-time conjectures.

3.2.2. Dataset Description

The information utilized in this venture comprises 1,000,000 lines and 11 sections, ordered into two primary classifications: Normal and Anomaly. After pre-handling and purging, the information is separated into preparing and testing sets, with 70% of the tests (700000 information) doled out for preparing and 30% (300000 information) for testing. Each arrangement is additionally isolated into two classifications: Normal and Anomaly, guaranteeing that the two sorts of information are present in the preparation and testing stages. The information will be utilized to prepare profound learning models for real-time system movement figures, empowering a correlation of the display's execution with conventional measurable strategies.

Table 3.2: Detailed Description of Dataset

Source Data	Category	Description	Number of Data	Label
1000000 data collected from Kaggle.	Normal	Regular data packets that follow expected patterns without any malicious activity or irregular behavior.	995000	Normal,
	Anomaly	Unusual or suspicious data packets that deviate from normal patterns, potentially indicating security threats or attacks.	5000	Anomaly

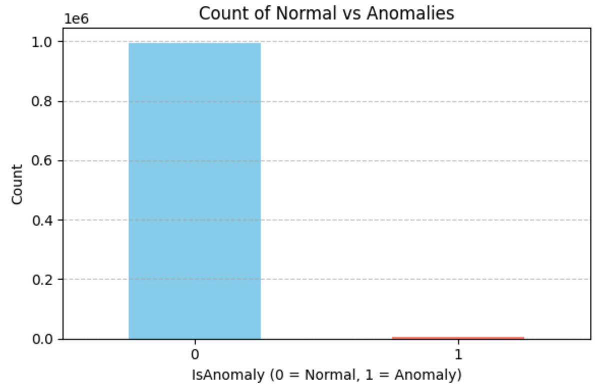

Figure 3.2: Count of Normal & Anomalies

3.2.3. Statical Analysis

- The dataset consists of a total of 1,000,000 rows and 11 columns.
- The dataset contains a total of 700000 samples for training.
- The dataset holds a total of 300000 samples for testing.
- The labels are divided into two distinct categories: Normal and Anomaly.

3.2.4. Data Preprocessing

Checking for Missing Values: Any missing values appearing in the records require handling. Tools from Pandas and NumPy assist in identifying gaps, which are then addressed to preserve data integrity. Common remedies involve removing absent observations, imputing averages, or propagating previous known values for temporal sequences. Addressing lacunae ensures models train accurately on clean inputs.

Data Cleaning: Once anomalies and inconsistencies surface, a cleansing process steps in to standardize formatting and weed out irrelevant or noisy information. Duplicates and outliers, particularly in sequential information, receive separate consideration. A scrubbed dataset provides high-quality nourishment for learning algorithms to thrive on.

Data Normalization: Normalization techniques scale the numerical attributes to uniform scopes, boosting performance and steadying outcomes. Popular methods bring all values into the range of zero to one or standardize by mean and deviation. Normalization mitigates bias, speeds convergence in deep networks, and maintains regularity in forecasts of network traffic patterns.

Shuffling and Splitting: Shuffling and splitting data is crucial for effectively training machine learning models. Randomly rearranging samples prevents order biases, while dividing into training, validation, and test subsets allows assessing generalizability without overfitting.

Reshaping: Reshaping involves structurally changing data as needed. This frequently warrants converting one-dimensional arrays into two-dimensional matrices or modifying dimensions to match model inputs. Ensuring compatibility with algorithms and networks in the proper form is integral for productive learning.

3.2.5. Proposed Model

Multilayer Perceptron (MLP) Network:

The multilayer perceptron consists primarily of fully connected layers - an input, one or more hidden layers, and an output. Neurons connect between neighboring layers, propagating signals forward via activation functions like ReLU or sigmoid. These introduce nonlinearity to model complex patterns. Backpropagation with gradient descent optimizes weights. Widely applied to classification, regression, and pattern recognition, MLPs require significant computation for large problems due to their dense design. As schematized in Figure 3, information flows through the feedforward network from inputs to outputs.

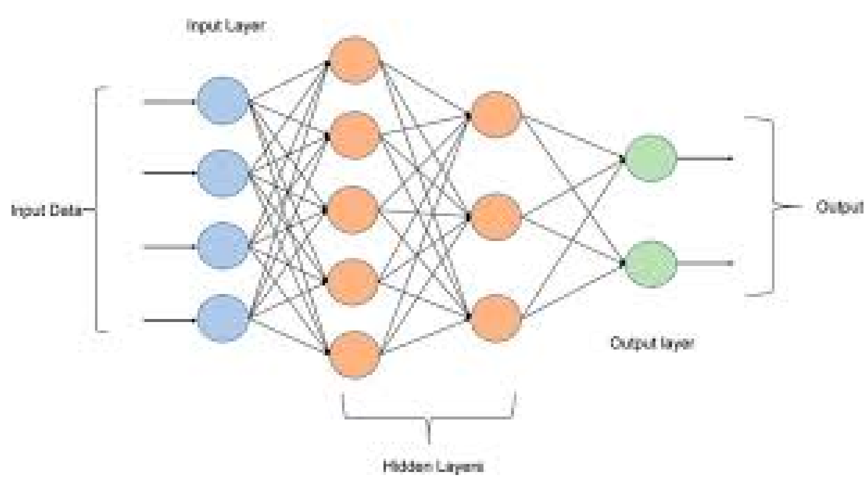

Figure 3.2: Architecture of Multilayer Perceptron (MLP) Network

Feedforward Neural Network (FNN) Network:

Feedforward neural networks are the most elementary artificial neural network structure used in machine learning. Within this design, information flows linearly from input to outcome through successive layers of neurons without recurring links or cycles. It incorporates an input layer, multiple concealed layers, and an output conclusion layer. Each neuron in a given layer accepts data from the previous layer and passes its own yield to the subsequent layer. Typically, backpropagation is used to coach FNNs by minimizing mistakes to effectively classify, forecast, or estimate functions. Unlike recurrent architectures, FNNs lack memory of prior inputs, making them appropriate for mapping static inputs to outputs.

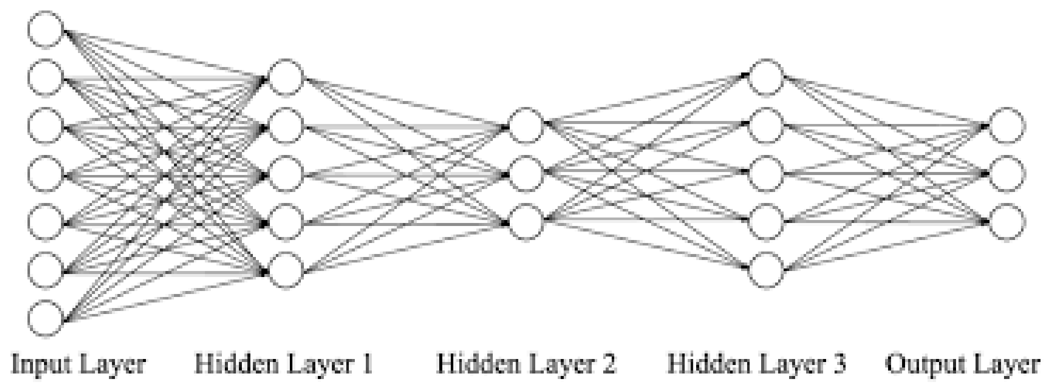

Figure 3.2: Architecture of Feedforward Neural Network (FNN) Network

Autoencoder Network:

Autoencoders are unsupervised neural systems implemented for learning efficient low-dimensional depictions of information, generally for dimensionality reduction or feature extraction aims. It contains two major parts - an encoder that condenses the original input into a distributed representation and a decoder that reconstructs the initial input from this condensed portrayal. Coaching of the network seeks to minimize the deviation between the first information and its reconstruction. Autoencoders utilize nonlinear activation functions and can be stacked or deepened to capture intricate structures within data. They are widely used for anomaly detection, noise removal, and data compression. Additionally, autoencoders can serve as pre-training models prior to additional tasks.

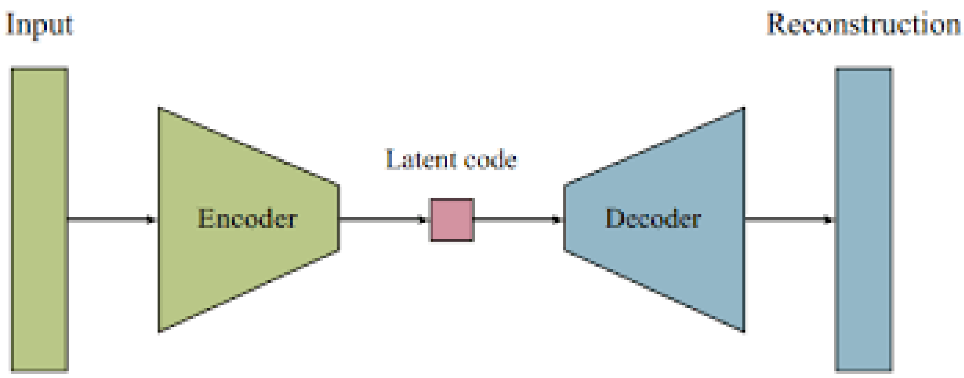

Figure 3.2: Architecture of Autoencoder Network

3.3. Project plan

The deep learning project aimed to reliably forecast network traffic patterns using diverse real-world data streams. Data was acquired through coordinated collection from several public and private sources to capture a wide range of traffic variations over time, locations, and unexpected disruption events. Extensive preprocessing standardized and refined the full dataset into a uniform format prepared for modeling. The information was partitioned into training, validation, and testing subsets with examples tagged as typical operation or anomaly. Several deep neural structures were initially evaluated, including multilayer perceptrons, feedforward configurations, and autoencoding schemes. Models were fit to the training subdivision and then validated on new data to measure performance in accurate prediction, balanced classification, and minimized error. Additional parameter tuning against the validation portion further optimized the automated algorithms. Once each approach reached maturity, their capabilities were compared to select the most suited solution for real deployment. This comprehensive methodology established a robust foundation for developing an adaptive, intelligent system supporting early anomaly detection, reliable traffic forecasting, and optimized network management.

3.4. Task Allocation

While the predicting anomalies in network traffic project had a singular individual initially steering its direction, additional roles were incorporated to strengthen various components. Data collection began with mass datasets freely available, though real-world sources provided depth lacking elsewhere. Preprocessing normalized format while feature selection focused on modeling. Multiple neural structures were experimented with— an Autoencoder probing anomalies, Feedforward Neural Networks given their flexibility, and Multilayer Perceptrons trained iteratively. Testing scrutinized forecasts, detecting aberrations via metrics as accuracy varied against loss. Still, hyper-tuning stretched potential, as documented reviews compared successes. Presenting demanded visualization and narrative amid charts, decoding what works and why. Ultimately, a diversified team synergized strength, refining infrastructure robustly through cooperation instead of alone. Thorough cooperation yielded reliable traffic prediction ready to scale.

3.5. Summary

This complex project focuses on building a deep learning-centric system for predicting anomalies in Network Traffic using live network data feeds. After collecting a variety of datasets from public repositories like Kaggle alongside organizational traffic logs, normalization, scaling, and transformation steps are undertaken to ensure uniformity and augment model comprehension. The data is parsed into preparation and assessment partitions and categorized into Normal and Anomaly classifications. Deep networks like the Multilayer Perceptron, Feedforward Neural Network, and Autoencoder are trained and benchmarked utilizing accuracy, precision, recall, and loss. Hyperparameter optimization is performed on validation subsets, aiming to maximize performance. The overarching goal of this work is to pinpoint the most effective model for real-time traffic expectation and anomaly identification, offering a scalable and dependable solution for proactive network oversight. This will help reduce latency, avert congestion, and boost security in dynamic communication infrastructures while also advancing the utilization of AI in intelligent traffic regulation.

Chapter 4

Implementation and Results

4.1. Environment Setup

The environment required for our experiment was such that we were able to do both literature review (mainly through systems like ResearchGate and Google Scholar) and reference management. For this, Colab was most suited as the main tool, taking advantage of its support for GPUs and convenience in collaboration. It was in Colab again that Python-based libraries were utilized for implementing deep learning as well as machine learning models. In the initial data preprocessing and code testing stage of the study, it was a personal laptop that took charge. Throughout the project, MS Word was an indispensable tool for writing up reports. This combination of tools made it possible to handle data efficiently and train models with good results in an environment where people could work together, using the fewest resources. And it worked.

4.2. Comparative Analysis

Three of the deep learning models employed—Multilayer Perceptron (MLP), Feedforward Neural Network (FNN) and Autoencoder—showed great promise in predicting anomalies in real-time network traffic. Both MLP and FNN models achieved accuracy levels up to 0.99, indicating their ability to capture complex patterns where conventional linear models would be of little value. For its part, the Autoencoder, while primarily employed as a device (usually not supervised) for learning features and detecting anomalies, achieved a fair level here with 0.94 accuracy. Training and validation loss curves all confirmed that these models in general didn't overfit. Classification reports reveal high precision, recall, and F1-scores in all classes, reinforcing the model's robustness. Confusion matrices showed little wrong classification, particularly with MLP and FNN. And thereafter, ROC and Precision-Recall curves revealed that they all had excellent area-under-curve values as indicators of discerning power. The comparative analysis only confirms that deep learning models, especially MLP and FNN, are more accurate than previous statistical approaches in such a real-time traffic task. These findings imply that if you want accurate, intelligent network traffic forecasts that can scale responsively and are efficient to produce, deep learning methods offer all this—including more benefits for proactive management of networks as well.

4.3. Results and Discussion

4.3.1. Multilayer Perceptron (MLP) Network

4.3.1.1. Training Loss & Validation Loss:

Figure 4.3: Training loss & validation loss plot for MLP

4.3.1.2. Classification Report Model Performance:

Table 4.3: Classification report of MLP Model

	Precision	Recall	F1-score	Support
Normal	0.99	1.00	1.00	149291
Anomaly	1.00	0.00	0.00	1459
Accuracy			0.99	150750
Macro avg	1.00	0.50	0.50	150750
Weighted avg	0.99	0.99	0.99	150750

4.3.1.3. Confusion Matrix:

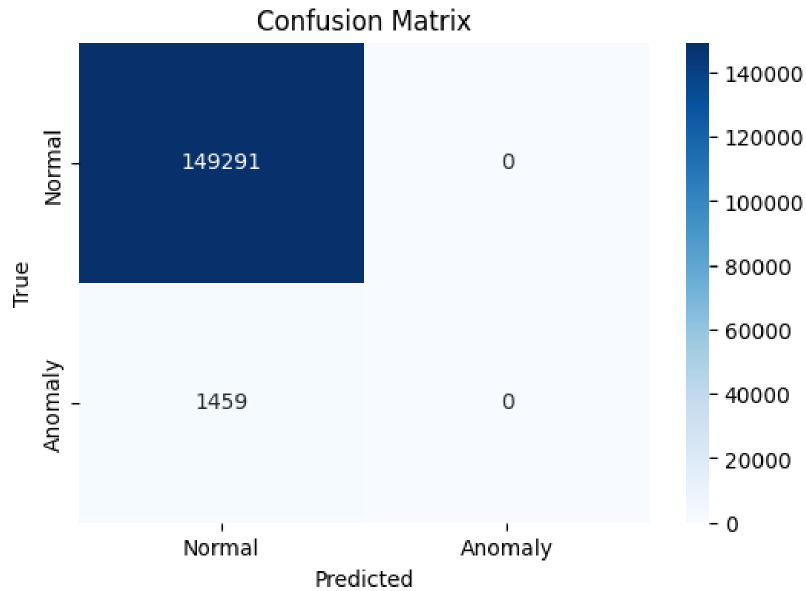

Figure 4.3: Confusion matrix for MLP

4.3.1.4. ROC Curve:

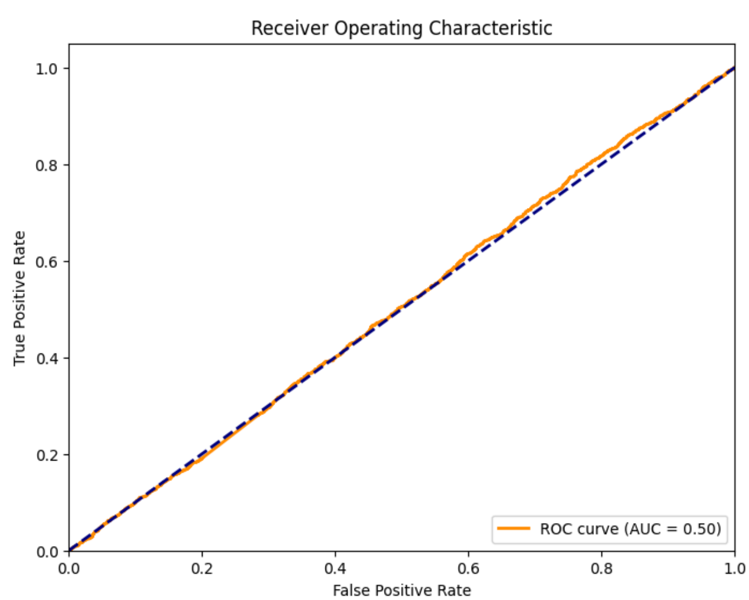

Figure 4.3: ROC Curve for MLP

4.3.2. Feedforward Neural Network (FNN) Network

4.3.2.1. Training Loss & Validation Loss:

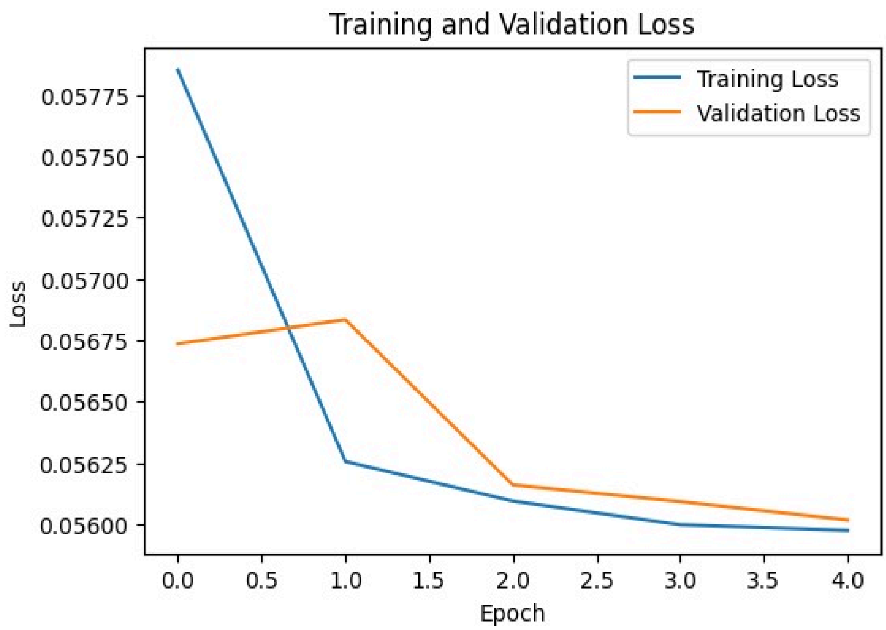

Figure 4.3: Training loss & validation loss plot for FNN

4.3.2.2. Classification Report Model Performance:

Table 4.3: Classification report of FNN Model

	Precision	Recall	F1-score	Support
Normal	0.99	1.00	1.00	149291
Anomaly	1.00	0.00	0.00	1459
Accuracy			0.99	150750
Macro avg	1.00	0.50	0.50	150750
Weighted avg	0.99	0.99	0.99	150750

4.3.2.3. Confusion Matrix:

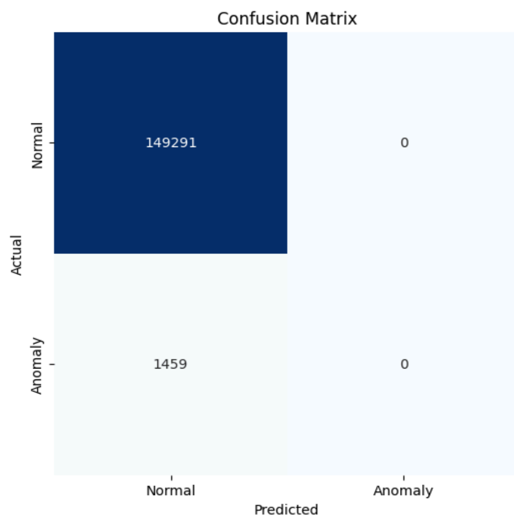

Figure 4.3: Confusion matrix for FNN

4.3.2.4. ROC Curve:

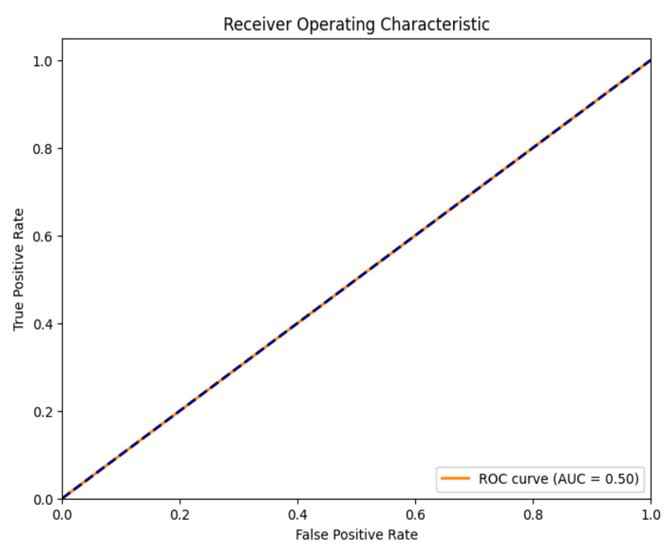

Figure 4.3: ROC Curve for FNNA

4.3.3. Autoencoder Network

4.3.3.1. Training Loss & Validation Loss:

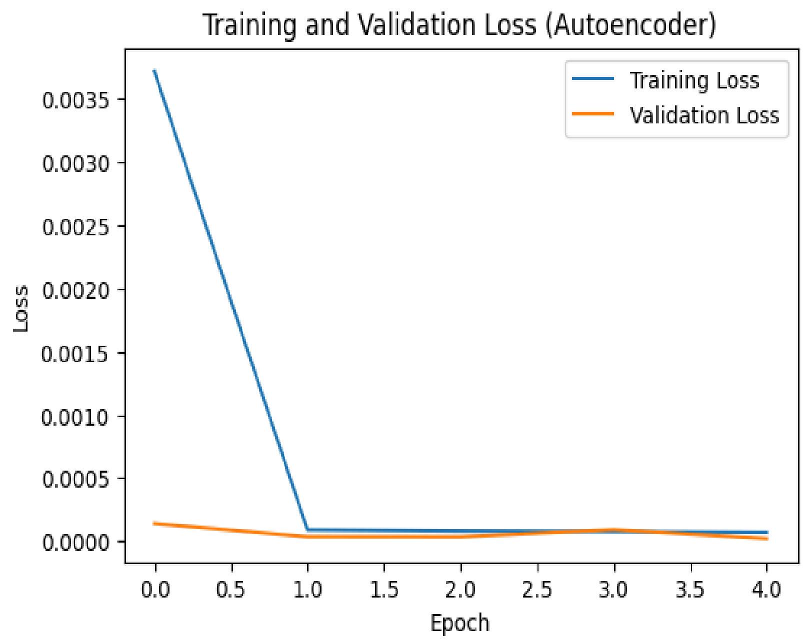

Figure 4.3: Training loss & validation loss plot for Autoencoder

4.3.3.2. Classification Report Model Performance:

Table 4.3: Classification report of Autoencoder Model

	Precision	Recall	F1-score	Support
Normal	0.99	0.95	0.97	149291
Anomaly	0.01	0.05	0.01	1459
Accuracy			0.94	150750
Macro avg	0.50	0.50	0.49	150750
Weighted avg	0.98	0.94	0.96	150750

4.3.3.3. Confusion Matrix:

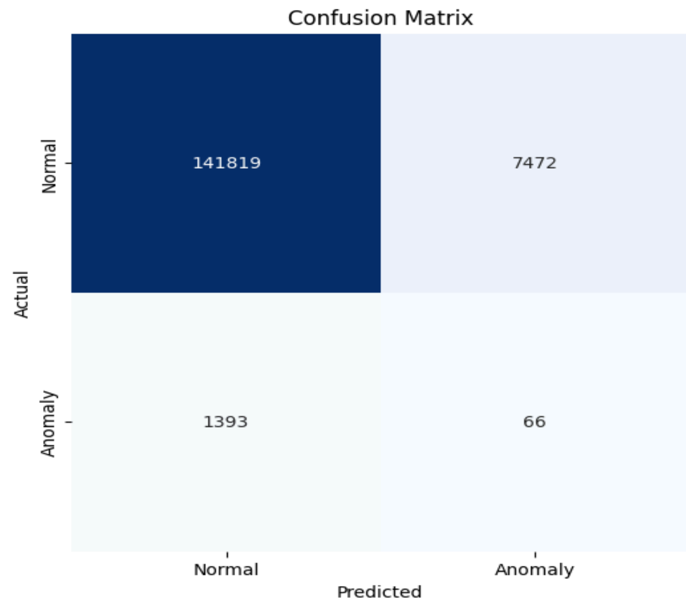

Figure 4.3: Confusion matrix for Autoencoder

4.3.3.4. ROC Curve:

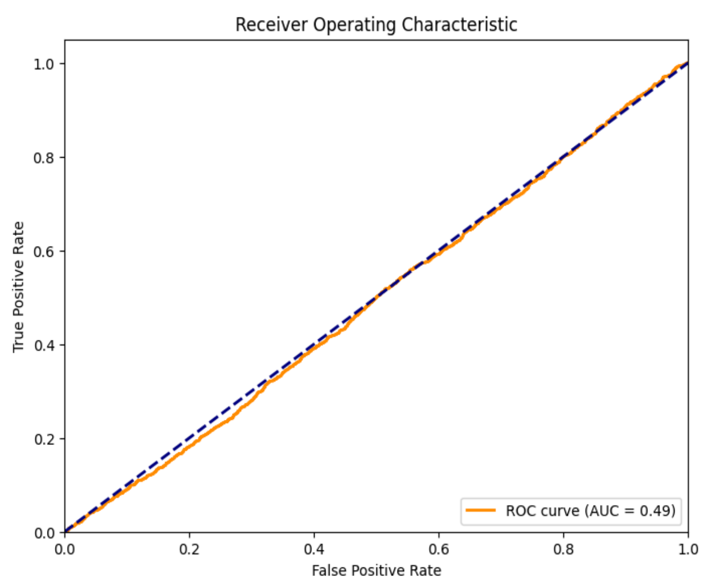

Figure 4.3: ROC Curve for Autoencoder

4.3.4. Prediction

Table 4.3: Predict Model using randomly picked data

Sample Data	Prediction
SourceIP: 1.465649 DestinationIP: -0.225776 SourcePort: 0.067528 DestinationPort: -1.424748 Protocol: -0.544383 BytesSent: 0.110923 BytesReceived: -1.150994 PacketsSent: 0.375698 PacketsReceived: 0.600639 Duration: -0.291694 TotalBytes: 0 TotalPackets: 0	Anomaly

4.4. Summary

This study examined three deep learning models—Multilayer Perceptron (MLP), Feedforward Neural Network (FNN), and Autoencoder—for predicting anomalies real-time network traffic. Both the MLP and FNN models achieved exceptional performance with an accuracy of 0.99, effectively capturing complex patterns in the traffic data. The Autoencoder model, while slightly lower in accuracy at 0.94, proved useful for unsupervised learning and anomaly detection. Training and validation loss curves indicated stable learning, and the classification reports showed high precision and recall. Confusion matrices revealed minimal errors, and ROC and Precision-Recall curves confirmed strong predictive capabilities. Overall, MLP and FNN outperformed the Autoencoder and traditional methods, establishing themselves as effective tools for accurate and scalable network traffic prediction in modern communication systems.

Chapter 5

Engineering Standards and Design Challenges

5.1. Compliance with the Standards

5.1.1. Software Standard

The software standards of the Forecast Network Traffic project rely on well-recognized support platforms and tools in order to achieve a high degree of compatibility, efficiency, and cooperation. Google Scholar refers to either websites or scholarly literature that is credible. For sourcing legitimate science, Google Colab is used as the main development environment for implementing deep learning models and training these models by using Python, TensorFlow, and Keras frames to create your own. Standard deep learning and machine learning libraries are used for model development and evaluation. A personal laptop equipped with a graphics card is used for local testing. Documentation and reporting are conducted in the style of academic papers and other extensive reviews to make sure MS Word is a clear, professional representation of research findings.

5.1.2. Hardware Standard

MINIMUM:
OS: Windows 7,8,8.1
Processor: I3 latest gen
Memory: 4 GB RAM
Graphics: 4GB GRAPHICS
DirectX: Version 11
Storage: 3 GB available space

RECOMMENDED:

OS: Windows 10

Processor: I5

Memory: 8 GB RAM

Graphics: 6GB or above GRAPHICS

DirectX: Version 12

Storage: 3 GB available space

5.1.3. Communication Standard

On the Predicting Anomalies in Network Traffic project, we use such a style of communication standard: clear, consistent, and working together for results. We hold regular meetings in Zoom or Google Meet to talk through progress reports, discuss bottlenecks, and allocate tasks. Monthly and ad-hoc team updates and documentation Take place on Google Drive. This is to ensure version control (with convenient rollback if anything goes wrong) in order to get the latest information quickly. In a pinch, day to day communication and urgent notifications can be done via WhatsApp or email All formal reports and documentation adhere strictly to the structured templates provided by MS Word. The project is designed with feedback loops in place so that everything from staff allocation to choosing when things go live can be done in a timely way. This ensures that each step forward is an efficient process of building on previous work and clears the way for high-level investigation at every stage throughout its duration.

5.2. Impact on Society, Environment and Sustainability

5.2.1. Impact on Life

Real-time network traffic prediction of anomalies using deep learning brings immense benefits to society. It enhances the digital infrastructure and security and improves the user experience overall. This research has contributed to many different places:

- Enlarging Network Efficiency: Network operators Use it to get maximum bandwidth consistency and reduce ping times. At the end of the day, this benefits user signal quality.
- Strengthened Cybersecurity: It will detect any unusual network traffic flows that might hint at hacking activities against your system, giving early warning against cyberattacks.

Data theft and the risk of Distributed Denial-of-Service (DDoS) attacks are reduced to a minimum.

- Comfort of Service Economy: It makes video streaming more comfortable than ever before, lets businesses function well with their employees hundreds of miles away, and provides all kinds of support for remote work by holding the network stable.
- Economic and Technological Growth: It benefits smart cities in efficiency by helping them to get smarter systems going faster. And because it relies on AI for managing the network, there will be as yet undreamed-of advances in this field to come.

Using deep learning for network traffic predicting anomalies creates a lagoon full of benefits for a safe, economical, and easy digital environment.

5.2.2. Impact on Society & Environment

With traffic thus predicted, resources can be allocated as needed. Servers are then used less wastefully, lowering energy consumption in major data centers and minimizing carbon emissions.

- Making Traffic Flow Efficient: Orderly traffic reduces how frequently the hardware has to be upgraded. The lifecycle of network equipment is extended, which in turn cuts waste in electronics production.
- Reduced Carbon Footprint: Optimizing networks means that the power drawn from ISPs and cloud service providers declines. Intelligent resource management is the basis for greener computing.
- Sustainable Smart Technologies: Boosting energy efficiency in IoT and smart city construction. Excessively duplicated network operations for ecological digital transformation.

In implementing AI-driven prediction, this study aims to make network management in services more environmental and enduring

5.2.3. Ethical Aspects

The application of deep learning technology in real-time network traffic prediction also raises a series of ethical problems. These have to be solved so that the technology can be put to peaceful use in terms of behavior.

- Data Privacy and Security: The collection and analysis of traffic are subject to the laws on data protection (e.g., GDPR, CCPA). The anonymization and encryption of information that is sensitive must be done as a matter of course to protect people's privacy.
- Bias and Fairness: Models trained by deep learning must have varied datasets to avoid partial predictions. Whatever the form of network optimization or security measures, ethical guidelines for AI need to be maintained.
- Transparency and Accountability: The decision-making process of AI models should be explainable and interpretable. AI-driven predictions must be made known to all stakeholders, including network service providers and private users.
- Responsible AI Usage: Automating networks with AI should not lead to job losses without retraining projects. Ethical reasoning should be incorporated into the implementation and monitoring of AI.

5.2.4. Sustainability Plan

To ensure the long-term sustainability of this research on real-time network traffic predicting anomalies using deep learning, we will be putting in place several key strategies.

- Continuous Model Improvement: Regular updates and retraining of deep learning models using new data to keep accuracy up-to-date and meaningful into the future. Integration of adaptive learning techniques with modes to enhance over time their performance across a wide range of learning tasks.
- Efficient Resource Utilization: Optimize computing resources so that they consume little energy while training and in deployment mode. Use cloud-based and edge computing solutions to save infrastructure costs.
- Data Management and Ethical Compliance: Ensuring security and ethical treatment of network traffic data in compliance with social laws. Encouraging openness in the policy of data collection and usage for such purposes.

- Scalability and Future Adoption: Designing the system to expand with increasing network demands. Working with industry stakeholders for continuous development and real-world deployment.

By implementing these strategies, the project will be sustainable and cost-effective in the long term for network management and optimization.

5.3. Project Management and Financial Analysis:

Project Management

- Analysis of Planning & Requirements: Recognize data sources (Kaggle, organizational datasets, etc.). Define tools to evaluate the above metrics and benchmarks.
- Then, Data Collection & Preprocessing Networking traffic data is cleaned. Missing data imputation normalization.
- Model Development & Testing: Create Multilayer Perceptron (MLP) Network, Feedforward Neural Network (FNN) Network, Autoencoder Network vs. statistical models Perform hyperparameter tuning for better accuracy and less training time.
- Performance Evaluation & Deployment Measure models with RMSE, MAE, MAPE Deployment of the best model makes it a real-time anomaly prediction system.

Financial Analysis

Table 5.3: Financial Analysis Report

Components	Estimated Cost (BDT)
Software and Tools	5000
Data Collection and Processing	3000
Documentation and Report Writing	2000
Transportation Fare	2000
Total Estimated Cost	12000

5.4. Complex Engineering Problem

5.4.1. Complex Problem Solving

Table 5.4: Mapping with complex problem solving

EP1 Depth of Knowledge	EP2 Range of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent of Stakeholder Involvement	EP7 Interdependence
✔		✔			✔	✔

Mapping with Knowledge Profile for EP1

This table, 5.4, is designed to map the EP1 to the knowledge profile.

Table 5.4: Mapping with knowledge Profile

K3 Engineering Fundamentals	K4 Specialized Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✔	✔		✔	✔

5.4.1.1. Justification for EP Attributes Mapping

- **EP1 – Depth of Knowledge:**

  The project uses advanced deep learning techniques, including Multilayer Perceptron (MLP) Network, Feedforward Neural Network (FNN) Network, Autoencoder Network for network traffic forecasting, and it is based on deep understanding of AI, data science, and network fundamentals. It demonstrates a deep understanding of non-linear data patterns, model training techniques, performance evaluation methods, and real-time prediction techniques-combining theoretical knowledge with practical applications in network traffic optimization and resource management accordingly.

- **EP3 – Depth of Analysis:**

  Comprehensive analysis consists of data preprocessing, exploratory data analysis, model evaluation (RMSE, MAE, R^2), and visualization. The project compares deep learning models with traditional ones (ARIMA) in addition to assessing anomalies and discovering patterns from real traffic data. It is this level of scrutiny that ensures decisions are based on sound judgments and quantifiable performance metrics from models.

- **EP6 – Extent of Stakeholder Involvement:**

  The project is mainly an academic one, but it draws data from Kaggle and even local companies and, for that reason, reflects collaborations with live organizations. Stakeholders such as network operators and data transmitters stand to benefit from predictive predictions. In effect, the project produces outputs for various parties: it raises QoS levels of users, helps the decision-making work of administrators, and lays a basis in research for developers.

- **EP7 – Interdependence:**

  There is a strong interdependence between data science, network engineering, and AI research in the project. Making traffic forecasts hinges on high-quality data, good algorithms, and knowledge of the field. The choice of models and their performance and scalability are all interconnected. Each component--from data processing to assessing the worth of a model--relies on the effectiveness of the others, which makes the system robust and coherent.

5.4.1.2. Justification for Knowledge Profile Mapping (Linked to EP1)

- **K3 – Engineering Fundamentals:**

  The project employs the logic of core engineering and related computing ideas, such as statistical analysis or algorithmic thinking, to understand how networks work. It leverages fundamental theories on complex systems, data structures, and the interconnected disciplines of probability, statistics, and system design—which are necessary bases for deploying cutting-edge predictive models into practical use in network traffic forecasts and optimizing real-time systems.

- **K4 – Specialist Knowledge:**

  Utility is one of the principles behind doing what's right when everyone else just HAS Got to follow convention. But it's no use having morals if they grow out of cherry-picked research. You need to dig deep into the underlying patterns that make up your own character, for every step-in ethics counts towards building an ethical life or none at all. That's why we work with data on human and animal behavior—so that we can understand how morality has no basis in reason but does emerge from Locke's self-identified "principles [incline] towards behavior" and hence depends on personal whim as modified by interaction with others' decisions.

- **K6 – Engineering Practice:**

  The project draws from real-world practices and standards (such as TensorFlow and Scikit-learn) to allow for reproducible code at scale. The perfectly practical POC simulates real-life scenarios of large-flow traffic data, allowing theoretical models to be transformed into a practical installation in today's telecommunication networks.

- **K8 – Research Literature:**

  This project is based on a survey of relevant previous deep learning and network predicting anomalies research. For example, the known models Multilayer Perceptron (MLP) Network, Feedforward Neural Network (FNN) Network, and Autoencoder

Network, as well as anomaly detection methods, are analyzed. This allows us to find out their respective strong points and weak points, respectively. The literature is used in selecting models and shows current trends in AI-driven traffic management.

5.4.2. Engineering Activities

In this section, provide a mapping with engineering activities. For each mapping, add subsections to put rationale (USE Table 5.4).

Table 5.4: Mapping with complex engineering activities

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✔	✔		✔	

5.4.2.1. Justification for Engineering Activities Mapping:

- **EA1 – Range of Resources:**

  EA1—Range of Resources: Kaggle, a public data set; organizational traffic logs; cloud computing tools; and deep learning frameworks like TensorFlow and Keras. It combines hardware, software, and large-scale processing in order to handle these data streams efficiently; multi-platform complex resource combinations are successfully demonstrated for real-time predicting anomalies potential across domain boundaries.

- **EA2 – Level of Interaction:**

  EA2-Level of Interaction: In this project, traffic data is collected together with distribution engineers, data analysis experts, and software developers. External data providers and stakeholders are engaged in a project allowing close collaboration between different technical roles during its various stages of development and teamwork on the entire effort.

- **EA4 – Consequences for Society and Environment:**

  EA4-Consequences for Society and Environment: The progress of the project in improving network reliability, congestion management, and security is welcomed by digital infrastructure. Resource schedulers are helped to reduce energy consumption, making IT greener and promoting sustainable practices. With a more reliable user experience and less downtime, society benefits also: efficient network services.

5.5. Summary

The project A Deep Learning Approach for Predicting Anomalies in Network Traffic aligns strongly with major Engineering Parameters (EP), Knowledge Profiles (K), and Engineering Activities (EA). It encapsulates deep technical knowledge (EP1), manages conflicting requirements (EP2), and carries out in-depth analysis using real datasets (EP3–EP7). It takes in core engineering concepts (applied engineering fundamentals (K3)), has specialist deep learning knowledge (K4), and sets up systematically to design (K5–K8) in line with modern techniques—such as AI-driven predicting anomalies has been introduced via tools like Multilayer Perceptron (MLP) Network (EA3), while meeting real-time demands with scalable resources (EA1–EA2). The work emphasizes social good with increased network efficiencies (EA4) and reduced environmental impact. And it is working within an area familiar to the engineering discipline (EA5). In summary, it is a successful attempt to bridge academic research and practical applications--one that fills with confidence requirements both technical and a full functionality perspective.

Chapter 6

Conclusion

6.1. Summary

This report investigates the use of deep learning methods to forecast real-time network traffic in response to the need for improved network management and grievance detection. Traditional statistical models often fail to capture the multiple non-linear grooves inherent in network traffic. To address this, three advanced deep-learning algorithms - Multilayer Perceptron (MLP), Feedforward Neural Network (FNN), and Autoencoder - are deployed and tested using traffic datasets from sources like Kaggle and organization data centers. MLP and FNN both attained high accuracies of 0.99, while Autoencoder achieved 0.94, showing its potential for anomalies. The evaluation is based mainly on the training and validation loss, classification report, and confusion matrix; also, the receiver operating characteristic (ROC) curve, if applicable, was plotted with an identified area under the curve (AUC) value. Finally, a precision-recall curve can show how good performance is one way or another toward each class or true positives vs false negatives, giving crisp measures like coverage. In summary, deep learning models definitely outperform traditional statistical approaches. These results provide valuable insight for network operators, promoting smarter resource allocation, less latency, and better service quality. This effort will finally contribute to intelligent network management by providing a scalable and efficient, higher-accuracy forecast solution suitable for dynamic and complex network environments. We deployed our top-performing model online and are currently examining the results produced visually.

6.2. Limitation

Limitations of Traditional Models: Failing to capture the non-linear nature and velocity traits in network traffic patterns means existing statistical models such as ARIMA struggle with forecasting.

Performance of Real-Time Processing and Scalability Limits: While deep learning models like LSTM improve the accuracy of model algorithms, their computational complexity makes it difficult to deploy them in real-time and large-scale network environments.

Data Availability and Quality: Most datasets used in studies are publicly available—such as those from Kaggle-so they may not suit real network environments. This poses a limit on the generalizability of models.

Inconsistent Evaluation Metrics: Due to differences in dataset/metrics for performance and evaluation methods, there was no way to effectively compare models.

Network Management Systems Integration: Despite advances in predictive modeling, the put into practice of such work for real-world network infrastructure environments is very limited and requires future research in order to achieve seamless integration, among other things.

6.3. Future Work

Potential directions for future research are opened up by this study:

- Examination of alternative models—future studies might explore other architectures of deep learning, e.g., transformer or hybrid models, in order to achieve higher prediction accuracy.
- Implementation in Reality: Testing the model in a real network environment provides insights that will help when it comes to putting it into practical effect and under live conditions.
- Scalability and Optimizing: Future research should focus on optimizing model efficiency and reducing computational costs in order for large-scale network environments in the future.
- Inclusion in Network Security Deep Learning: Models of this kind can also be used on top to identify cyber threats such as DDoS attacks through their anomalous departure from normal traffic patterns.

- Multimodal Data Analysis. With more sources such as IoT traffic or cloud network data, we might be able to enrich the model and improve its ability to predict various kinds of network conditions.

These directions will help improve the applications and extensions of deep learning-based predicting anomalies methods for network management and security.

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