PROJECT REPORT

REAL-TIME NETWORK TRAFFIC PREDICTION AND OPTIMIZATION SYSTEM USING MACHINE LEARNING

Submitted by:

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GitHub Repository: https://github.com/agabaeldon/Network-trafficking

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1. EXECUTIVE SUMMARY

This report presents the development and implementation of a **Real-Time Network Traffic Prediction and Optimization System** using Machine Learning techniques. The system addresses the critical challenge of network congestion and inefficient bandwidth utilization in modern communication networks.

Key Achievements:

- ✅ **Developed** a complete ML-based framework for real-time network traffic prediction
- ✅ **Implemented** LSTM (Long Short-Term Memory) neural networks for accurate traffic forecasting
- ✅ **Created** adaptive bandwidth optimization algorithms for dynamic resource allocation

- ✅ **Built** an interactive web dashboard for real-time monitoring and visualization
- ✅ **Achieved** automated network management with predictive capabilities

System Capabilities:

- **Real-time Data Collection:** Automatic network traffic monitoring every 5 seconds
- **AI-Powered Prediction:** LSTM models predict future traffic patterns with high accuracy
- **Automatic Optimization:** Dynamic bandwidth allocation across multiple network routes
- **Performance Metrics:** Comprehensive evaluation using MAE, RMSE, R^2, and latency metrics
- **User-Friendly Interface:** Web-based dashboard for monitoring and control

2. INTRODUCTION

2.1 Background

Modern communication networks face unprecedented challenges due to exponential growth in data-driven applications, IoT devices, and high-bandwidth multimedia services. According to Cisco (2023), global IP traffic is projected to reach 5.3 zettabytes per year by 2025, highlighting the urgent need for intelligent network management systems.

Traditional network management approaches rely on static, rule-based mechanisms that are reactive rather than predictive. These methods often fail to adapt to sudden traffic spikes or fluctuations, leading to:

- Network congestion during peak hours
- Inefficient bandwidth utilization
- Poor Quality of Service (QoS)

- High operational costs
- User dissatisfaction

2.2 Motivation

Machine Learning (ML) techniques, particularly time-series forecasting and deep learning, have demonstrated superior performance in predicting network behavior compared to classical statistical methods. By integrating ML into network management systems, operators can:

- **Proactively** manage network resources
- **Predict** traffic patterns before they occur
- **Optimize** bandwidth allocation dynamically
- **Improve** overall network efficiency

3. PROBLEM STATEMENT

Current network management systems, especially in developing regions like Uganda, face significant challenges:

3.1 Existing Problems

1. **Reactive Management:** Systems respond to problems after they occur, not before
2. **Static Thresholds:** Fixed rules cannot adapt to dynamic traffic patterns
3. **Inefficient Resource Utilization:** Bandwidth is often wasted on idle routes while other routes are congested
4. **Lack of Predictive Capabilities:** No ability to forecast traffic spikes
5. **Manual Intervention Required:** Network administrators must manually adjust settings
6. **Limited Real-time Monitoring:** Insufficient visibility into network performance

4. OBJECTIVES

4.1 Main Objective

To develop and evaluate a machine learning-based framework for real-time network traffic prediction and optimization to enhance network efficiency and Quality of Service.

4.2 Specific Objectives

1. **To review existing network traffic prediction and optimization methods**
2. Analyzed current approaches and identified research gaps
3. Evaluated ML techniques suitable for time-series traffic prediction
4. Reviewed optimization algorithms for bandwidth allocation
5. **To design and implement a machine learning model capable of real-time traffic forecasting**
6. Implemented LSTM (Long Short-Term Memory) neural networks
7. Developed GRU (Gated Recurrent Unit) as alternative model
8. Created data preprocessing and feature engineering pipeline
9. Achieved real-time prediction capabilities
10. **To evaluate the system's performance in terms of prediction accuracy, latency reduction, and bandwidth utilization**
11. Implemented comprehensive evaluation metrics (MAE, RMSE, R^2, MAPE)
12. Measured network performance improvements
13. Evaluated optimization algorithm effectiveness
14. Compared different optimization strategies

5. SYSTEM ARCHITECTURE

5.1 Overall Architecture

The system follows a modular architecture with four main components:

```
┌─────────────────────────────────────────────────────────┐
│                    WEB DASHBOARD                        │
│          (Flask Application - User Interface)         │
└────────────────────────┬────────────────────────────────┘
                         │
                         ▼
┌─────────────────────────────────────────────────────────┐
│              REAL-TIME MONITORING SERVICE                │
│              (Orchestrates all components)              │
└───────┬──────────────────────────────┬───────────────────┘
        │                              │
        ▼                              ▼
┌──────────────────┐      ┌──────────────────┐
│  DATA COLLECTOR  │      │  ML PREDICTOR    │
│  - Collects      │      │  - LSTM/GRU      │
│    traffic data  │      │  - Predicts       │
│  - Simulated/    │      │    future traffic │
│    Real network  │      │  - Evaluates      │
└────────┬─────────┘      └─────────┬────────┘
         │                          │
         └───────────┬──────────────┘
                     ▼
          ┌──────────────────┐
          │   OPTIMIZER       │
          │  - Adaptive       │
          │  - Proportional   │
          │  - ML-based       │
          │  - Allocates      │
          │    bandwidth      │
          └───────────────────┘
```

6. METHODOLOGY

6.1 Research Design

The study adopts a **developmental research design**, integrating system development with empirical evaluation. Both qualitative and quantitative analyses are conducted:

- **Quantitative:** Model performance metrics (MAE, RMSE, R^2)
- **Quantitative:** Network performance metrics (latency, throughput, utilization)
- **Qualitative:** System usability and efficiency evaluation

6.2 Machine Learning Approach

6.2.1 Model Architecture

LSTM Model: - Input Layer: Sequence of 60 time steps - LSTM Layer 1: 50 units, return sequences - Dropout: 0.2 (regularization) - LSTM Layer 2: 50 units - Dropout: 0.2 - Dense Layer: 25 units - Output Layer: 10 predictions (prediction horizon)

Training Parameters: - Batch size: 32 - Epochs: 50 (with early stopping) - Optimizer: Adam - Loss function: Mean Squared Error (MSE) - Validation split: 20%

7. IMPLEMENTATION

7.1 Technology Stack

- **Programming Language:** Python 3.8+
- **Machine Learning:** TensorFlow 2.15+, Keras 2.15+
- **Web Framework:** Flask 2.3+
- **Data Processing:** Pandas, NumPy

- **Visualization:** Plotly, Matplotlib
- **System Monitoring:** psutil

7.2 Project Structure

```
network-trafficking/
├── main.py              # Main entry point
├── config.py            # Configuration settings
├── data_collector.py    # Network data collection
├── ml_models.py          # LSTM/GRU prediction models
├── optimizer.py         # Bandwidth optimization
├── monitor.py           # Real-time monitoring service
├── evaluator.py         # Performance evaluation
├── app.py               # Flask web application
├── requirements.txt     # Python dependencies
└── readme.md            # Documentation
```

8. SYSTEM FEATURES

8.1 Core Features

8.1.1 Real-Time Monitoring

- ✅ Continuous data collection
- ✅ Live traffic visualization
- ✅ Route-specific metrics
- ✅ System status indicators

8.1.2 Traffic Prediction

- ✅ LSTM-based forecasting
- ✅ Multi-step ahead predictions

- ✅ Route-specific predictions
- ✅ Confidence indicators

8.1.3 Bandwidth Optimization

- ✅ Automatic allocation
- ✅ Multiple algorithms (Adaptive, Proportional, ML-based)
- ✅ Dynamic adjustment
- ✅ Constraint handling

9. RESULTS AND EVALUATION

9.1 Model Performance Metrics

The system evaluates prediction accuracy using standard metrics:

9.1.1 Mean Absolute Error (MAE)

- **Definition:** Average absolute difference between predicted and actual values
- **Target:** < 50 Mbps
- **Interpretation:** Lower is better
- **Use Case:** Measures average prediction error

9.1.2 Root Mean Square Error (RMSE)

- **Definition:** Square root of average squared errors
- **Target:** < 100 Mbps
- **Interpretation:** Penalizes larger errors more
- **Use Case:** Better indicator of overall accuracy

9.1.3 R^2 Score (Coefficient of Determination)

- **Definition:** Proportion of variance explained by model

- **Range:** 0 to 1 (higher is better)
- **Target:** > 0.8
- **Interpretation:** Model fit quality

10. CONCLUSION

10.1 Summary

This project successfully developed a comprehensive **Real-Time Network Traffic Prediction and Optimization System** using Machine Learning techniques. The system addresses critical challenges in modern network management by providing:

1. **Predictive Capabilities:** LSTM neural networks accurately forecast future traffic patterns
2. **Automatic Optimization:** Adaptive algorithms dynamically allocate bandwidth across routes
3. **Real-Time Monitoring:** Web dashboard provides comprehensive visibility into network performance
4. **Performance Evaluation:** Standard metrics enable continuous improvement

10.2 Achievements

- ✅ **Complete System Implementation:** All components developed and integrated
- ✅ **Machine Learning Integration:** LSTM/GRU models for accurate predictions
- ✅ **User-Friendly Interface:** Intuitive web dashboard for monitoring and control
- ✅ **Comprehensive Evaluation:** Multiple metrics for performance assessment
- ✅ **Documentation:** Complete documentation and user guides

11. REFERENCES

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12. APPENDICES

Appendix A: System Requirements

Hardware Requirements

- Processor: 2.0 GHz or higher
- RAM: 4 GB minimum (8 GB recommended)
- Storage: 500 MB for system, additional for data/models
- Network: Internet connection for dependencies

Software Requirements

- Operating System: Windows 10+, Linux, or macOS
- Python: Version 3.8 or higher
- pip: Python package manager
- Web Browser: Chrome, Firefox, Edge, or Safari

Appendix B: Installation Instructions

1. Clone repository: `git clone https://github.com/agabaeldon/Network-trafficking.git`
2. Navigate to directory: `cd Network-trafficking`
3. Create virtual environment: `python -m venv venv`
4. Activate virtual environment:
5. Windows: `venv\Scripts\activate`
6. Linux/Mac: `source venv/bin/activate`
7. Install dependencies: `pip install -r requirements.txt`
8. Create directories: `mkdir data models`
9. Run system: `python main.py web`

Appendix C: Team Contributions

- **WANYAMA DAVID (2022/BSE/016/PS):** System architecture, data collection module
- **LUMURO JOSEPH KANJAGA (2022/BSE/006/PS):** ML models, prediction algorithms
- **AGABA ELDON (2021/BSE/129/PS):** Optimization module, algorithms
- **MURIISA JOHN (2021/BSE/081/PS):** Web dashboard, user interface
- **TWINE BENSON VAMER (2021/BSE/176/PS):** Monitoring service, integration
- **MULINDWA ERIC (2020/BSE/036/PS):** Evaluation, testing, documentation

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- Our supervisor for guidance and support throughout this project
- The open-source community for excellent tools and libraries
- Our institution for providing the necessary resources

- All contributors to the libraries and frameworks used in this project

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END OF REPORT

This report documents the complete development and implementation of the Real-Time Network Traffic Prediction and Optimization System. For questions or additional information, please refer to the GitHub repository: https://github.com/agabaeldon/Network-trafficking