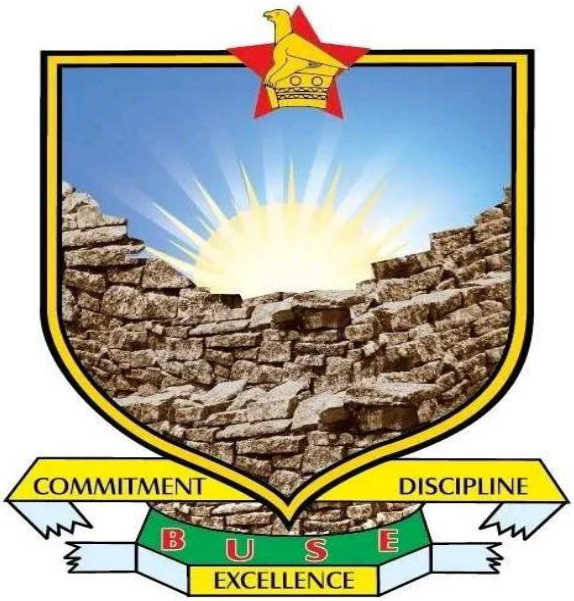
BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF SCIENCE

DEPARTMENT OF COMPUTER SCIENCE



PREDICTIVE NETWORK-TRAFFIC MANAGEMENT USING MACHINE LEARNING FOR CLOUD-BASED LEARNING SYSTEMS IN MUREWA DISTRICT, ZIMBABWE

BY

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A RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR BACHELOR OF SCIENCE HONOURS DEGREE IN NETWORK ENGINEERING

JUNE 2026

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APPROVAL FORM

The undersigned certify that they have supervised B221949B Martin Mandizvidza dissertation entitled **"**Predictive Network-Traffic Management Using Machine Learning for Cloud-Based Learning Systems in Murewa District, Zimbabwe**"** submitted in partial fulfilment of the requirements of the Bachelor of Science Honours Degree in Network Engineering.

Student Signature: Date:



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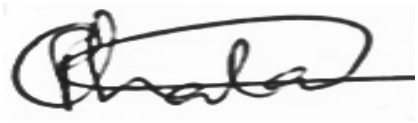
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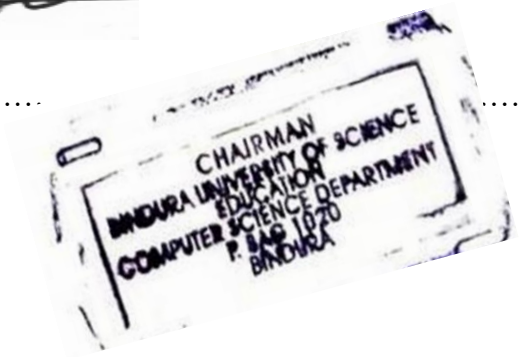
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DEDICATION

I dedicate this research to my family, whose unwavering support, prayers, and encouragement have shaped my academic journey. To my parents, for instilling in me the value of education and perseverance; and to my siblings and friends, who continually inspired and motivated me — this achievement is ours. I also dedicate this work to every student in Zimbabwe striving to excel in technology and innovation despite challenges. May this research be a step toward advancing digital learning in our nation.

ACKNOWLEDGEMENT

I extend my sincere gratitude to the Almighty God for granting me strength, wisdom, and resilience throughout this research journey.

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Special thanks to the school authorities, ICT personnel, and students in Murewa District, whose cooperation and input contributed significantly to the success of this research. Your participation made this work meaningful and applicable to the real world.

Finally, I acknowledge my colleagues and friends for their encouragement, discussions, and academic companionship. To everyone who contributed in any way, your support is deeply appreciated.

ABSTRACT

The increasing adoption of cloud-based learning systems in Zimbabwean educational institutions has created growing demands on network infrastructure, often resulting in bandwidth congestion and performance degradation. This research investigates the application of machine learning techniques to predict network traffic patterns and optimize bandwidth allocation for cloud-based learning environments in Murewa District. The study utilizes supervised learning algorithms to analyze historical network-usage data and traffic behavior, enabling proactive decision-making to minimize network bottlenecks. A predictive model is developed and evaluated based on accuracy, efficiency, and ability to support dynamic learning activities such as virtual classes, online examinations, and digital resources access. Findings demonstrate that machine learning-driven traffic prediction significantly enhances network performance, reduces latency, and improves user experience within e-learning platforms. The research contributes a scalable and practical model that can support digital-education initiatives in Zimbabwe and similar resource-constrained environments. Recommendations for further deployment and integration into school networks are provided

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LIST OF ACRONYMS

Acronym	Meaning
AI	Artificial Intelligence
ARIMA	AutoRegressive Integrated Moving Average
GBM	Gradient Boosting Machine
ICT	Information and Communication Technology
IDE	Integrated Development Environment
ISP	Internet Service Provider
Keras	Kernel-based Deep Learning API
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
ML	Machine Learning
Moodle	Modular Object-Oriented Dynamic Learning Environment
NIC	Network Interface Card
NS-3	Network Simulator 3
POTRAZ	Postal and Telecommunications Regulatory Authority of Zimbabwe
PRTG	Paessler Router Traffic Grapher
QoS	Quality of Service
R^2	Coefficient of Determination
RBZ	Reserve Bank of Zimbabwe
RMSE	Root Mean Square Error
SDN	Software-Defined Networking
SQL	Structured Query Language
SVR	Support Vector Regression
Wi-Fi	Wireless Fidelity

CHAPTER 1
INTRODUCTION

1.1 Introduction

Digital transformation in the education sector has led to increased adoption of cloud-based learning platforms such as Google Classroom, Microsoft Teams, Moodle, and national digital learning portals. These platforms enable remote instruction, digital content delivery, and collaborative e- learning. However, effective utilization of such technologies in developing regions depends heavily on reliable and optimized network performance.

In Zimbabwe's rural and semi-urban communities, including Murewa District, most schools face challenges such as limited bandwidth, network congestion, high latency, and frequent service disruptions. These issues significantly hinder efficient online teaching and learning, particularly during peak usage periods or during synchronized classroom digital activities. Current network management strategies in these schools are largely reactive, addressing issues only. after performance degradation occurs. This reactive approach reduces e-learning effectiveness and slows educational digitalization. Machine Learning (ML) offers a proactive solution, enabling the prediction of network traffic patterns and adaptive resource allocation to minimize congestion.

This study proposes a predictive network-traffic management system that uses machine-learning algorithms integrated with Software-Defined Networking (SDN) to forecast bandwidth demand and optimize network resource allocation across multiple schools in Murewa District.

1.2 Background of the Study

Zimbabwe's education policy encourages integration of ICT-enabled learning, with support from government, development partners, and telecommunications authorities such as POTRAZ. While adoption of digital learning has improved, rural and semi-urban schools continue to struggle with unreliable network performance and insufficient bandwidth.

In Murewa District, schools vary in infrastructure maturity, student population, and digital system deployment. Many institutions use shared networks supporting hundreds of learners concurrently, resulting in network congestion, latency spikes, and frequent disconnections.

Globally, ML-enabled traffic management has improved network efficiency across cloud data centers and enterprise networks (Kumar et al., 2023). Techniques such as LSTM neural networks, Gradient Boosting, and Random Forests have demonstrated effective traffic forecasting capabilities. Integrating ML with SDN can achieve autonomous bandwidth allocation and proactive congestion control.

This study seeks to adapt these advances to the context of public-school networks in Murewa District, strengthening digital learning infrastructure and supporting equitable access to modern education technology.

1.3 Statement of the Problem

Murewa District Schools' cloud-based learning environment faces frequent network congestion, high latency, and low throughput, especially during online classes, video lessons, and simultaneous file uploads. The district currently uses a reactive network management approach, where interventions occur only after users experience problems. This results in reduced learning efficiency, poor user experience, and wasted bandwidth. There is no system in place to predict traffic surges or dynamically allocate resources to prevent congestion. Without predictive traffic management, investment in ICT infrastructure and e-learning systems fails to deliver optimal results. Hence, the core problem this research seeks to address is the lack of a predictive network management mechanism within Murewa District that can anticipate traffic fluctuations and enable proactive optimization using machine-learning algorithms.

1.4 Research Aim

The primary aim of this study is to design and implement a predictive network-traffic management system using machine learning to enhance the performance of cloud-based learning performance within Murewa District's Schools. The system will forecast network traffic patterns and dynamically allocate bandwidth to ensure stable, efficient, and uninterrupted online learning.

1.5 Research Objectives

i. To analyze the existing network management practices in selected schools within Murewa District and identify challenges affecting cloud-based learning performance.

ii. To develop machine-learning models capable of predicting network traffic patterns and congestion based on historical and simulated data.

iii. To integrate the predictive models into a Software-Defined Networking (SDN) control framework for automated bandwidth management and traffic prioritization.

iv. To evaluate system performance in terms of latency, throughput, packet loss, and resource utilization compared to existing reactive management approaches.

v. To propose recommendations for district-wide deployment of predictive network management to support sustainable e-learning growth.

1.6 Research Questions

i. What network challenges affect cloud-based learning in Murewa District schools?

ii. Which machine-learning techniques effectively predict network traffic in school environments?

iii. How can SDN-based systems automate traffic management and enhance network performance?

iv. What improvements in performance metrics can be achieved through predictive management?

v. How can the developed system support long-term ICT goals for education in the district?

1.7 Significance of the Study

The proposed study is significant because it directly supports Zimbabwe's Smart Education Agenda and ICT Policy Framework (2021–2025), which advocate for the integration of intelligent technologies to enhance digital learning. For Murewa District, the project provides a practical and low-cost solution to improve the performance of its existing network infrastructure. Implementing predictive traffic management can:

i. Enhance the quality of cloud-based learning by reducing latency and packet loss.
ii. Improve the reliability of online lessons and resource sharing.
iii. Support ICT teachers and administrators with data-driven insights for bandwidth management.

From an academic perspective, the study contributes to the emerging field of AI-driven network optimization in education, a topic with limited local research. Nationally, the findings can guide other schools and educational institutions in adopting similar technologies, thereby supporting equitable access to digital learning across Zimbabwe.

1.8 Assumptions

i. The schools' ICT infrastructure supports cloud-based learning through a local area network connected to the internet.
ii. Network logs and usage data can be collected or simulated for model training.
iii. Machine-learning algorithms can accurately predict traffic surges and enable proactive management.
iv. School administrators are willing to adopt AI-assisted network management systems in future deployments.
v. Internet service stability during data collection will be sufficient for analysis.

1.9 Limitations / Challenges

i. Limited access to real network traffic data due to privacy concerns.

ii. Potential variability in internet connectivity affecting simulation accuracy.

iii. Constraints in computational resources for training deep-learning models.

iv. Lack of full SDN infrastructure at the school may limit real-world implementation.

v. Limited timeframe for extensive field testing.

1.10 Scope / Delimitation of the Study

This research focuses on selected secondary schools within **Murewa District**. The study will analyze and model network data to design and evaluate a predictive management system. Due to time and resource limitations, the research will be limited to prototype simulations using real and synthetic datasets rather than live implementation in all district schools. The research scope includes:

i. Development of ML models (e.g., LSTM, ARIMA, Random Forest) for traffic forecasting.

ii. Simulation of SDN-based control for automated bandwidth management.

iii. Performance evaluation through latency, packet loss, and throughput metrics.

iv. It excludes national-level ISP infrastructure and large-scale hardware deployment.

1.11 Definition of Terms

i. **Cloud-Based Learning:** The use of internet-hosted platforms to deliver, manage, and monitor educational content.

ii. **Network Traffic:** The amount of data moving across a network at a given time.

iii. **Machine Learning:** A branch of AI enabling systems to learn from data and make predictions.

iv. **Predictive Management:** The use of analytical models to forecast future states and optimize performance.

v. **Software-Defined Networking (SDN):** A network architecture that separates the control plane from the data plane to allow dynamic, programmable configuration.

vi. **Latency:** The delay in transmitting data across a network.

vii. **Throughput:** The rate at which data is successfully transmitted.

1.12 Summary

This chapter introduced the study by outlining the background, motivation, and context for improving network-traffic management in cloud-based learning environments within Murewa District. The problem of bandwidth limitations, network congestion, and degraded user experience in digital learning platforms was highlighted, emphasizing the need for intelligent, predictive solutions. The research objectives, questions, hypotheses, and scope were clearly defined, supporting the justification for employing machine learning as a proactive approach to network optimization. Limitations and significance of the research were also presented.

CHAPTER 2
LITERATURE REVIEW

2.1Introduction

Cloud-based learning platforms are increasingly deployed in educational institutions worldwide, including regions such as Murewa District, Zimbabwe. These platforms such as; Google Classroom, Moodle, Microsoft Teams depend critically on network performance; especially available bandwidth, latency, and reliability. Without effective network-traffic management, learning systems degrade, causing interruptions, slow access and diminished quality of experience. Traditional reactive network management approaches (manually increasing capacity, static QoS rules) often fall short in dynamic, high-demand educational settings. Machine learning (ML) has emerged as a promising alternative to predict network traffic and enable proactive resource allocation and optimization. This literature review examines theoretical foundations and empirical studies related to network traffic prediction, ML in networking and cloud-learning systems; identifies gaps and positions the current study in the context of Murewa District's schools. This chapter critically reviews theoretical and empirical literature on predictive network-traffic management, identifies relevant frameworks, and highlights gaps justifying the current study.

2.2 Conceptual Framework

The study conceptualizes a Predictive Network-Traffic Management Model integrating three domains:

2.2.1 Cloud-Based Learning Systems

Cloud-based e-learning systems (such as Google Classroom, Moodle, Microsoft Teams) have transformed access to educational content, enabling remote collaboration, real-time assessment and digital resource sharing (Tarus, Gichoya & Muumbo, 2015). In Sub-Saharan Africa, the shift to e-learning was accelerated by the COVID-19 pandemic, but many schools face infrastructural limitations, including insufficient bandwidth, intermittent connectivity and weak network management (Mahlangu, 2022). In Zimbabwe, rural and semi-urban schools report slow internet speeds, network instability, and lack of intelligent traffic management tools (Chigona & Davids,

2019).Such learning environments place high and variable demand on network infrastructure. For instance, synchronous video lessons create spikes in throughput demand, while file-uploads and downloads generate bursts and background traffic. Without predictive bandwidth allocation, these spikes result in congestion, delay, and interrupted lessons; highlighting the need for proactive traffic management aligned with ML approaches.

2.2.2 Machine Learning Algorithms

Predicting future network conditions based on historical usage (Kumar et al., 2023). Applying ML to educational network traffic involves predicting peak usage times (e.g., online exams), distinguishing between different traffic types (video, file upload, synchronous chat) and dynamically prioritizing learning-critical traffic. In school networks such as those in Murewa District, where infrastructure is limited and traffic patterns may be erratic, ML prediction offers potential to pre-empt congestion, allocate bandwidth to cloud-learning platforms, and ensure uninterrupted service.

2.2.3 Software-Defined Networking

Provides centralized, programmable control enabling dynamic bandwidth allocation (Zhou, 2022). Software-Defined Networking (SDN) facilitates centralized, programmable control of network traffic by decoupling the control and data planes. In doing so, it enables dynamic routing, traffic shaping and resource allocation in real time (Salau & Beyene, 2024). When ML prediction is integrated with SDN controllers, networks can adjust flow rules proactively based on forecasted demand. For example, Zhang et al. (2021) demonstrated ML + SDN for traffic optimization in campus networks.

In cloud-learning contexts, such an architecture means that predictions of high demand (say, 300 students accessing video lessons) can trigger pre-allocation of bandwidth or routing rules to prioritize those flows. This reduces latency, packet loss and throughput dips. Yet, most of the literature focuses on enterprise or data-center networks; less is documented about applying ML + SDN in educational settings with constrained resources. Within this framework, historical network-usage data serve as inputs; ML prediction outputs inform SDN controllers that automatically optimize resource allocation. The conceptual interaction can be summarized as:

Network Data → ML Prediction → SDN Decision → Optimized Traffic Flow → Enhanced Cloud-Learning Performance.

This framework guides the investigation into how ML can proactively manage network performance in Murewa District's educational networks.

2.3 Theoretical Framework

Three core theories underpin predictive network-traffic management:

2.3.1 Queueing Theory

Queueing theory models the behavior of packets waiting for service (routers, switches), providing insight into congestion, delay and throughput in networked systems (Kleinrock, 1976). In an educational network context, bursts of traffic (e.g., during online exams or video lessons) create queue buildups that degrade performance. Understanding these dynamics provides a theoretical base for why predictive traffic management matters.

2.3.2 Machine Learning Theory

Machine learning theory provides the conceptual basis for how systems learn from historical data to forecast future states (Mitchell, 1997). In networking, ML can recognize traffic patterns, learn temporal dependencies and make predictions that a rule-based system cannot. Within the proposed study, ML supports forecasting of network demand to inform resource allocation in cloud-based learning. In networking, algorithms such as Long Short-Term Memory (LSTM) and Gradient Boosting predict future traffic patterns to support proactive decisions.

2.3.3 Quality of Service (QoS) Theory

QoS theory considers how network performance metrics (latency, jitter, throughput, packet-loss) impact application performance and user experience (Cisco, 2021). In a school e-learning setting, high throughput and low latency are critical for synchronous digital lessons and cloud-resource access. This theory guides measurement of performance improvements resulting from predictive traffic management**.** It provides evaluation metrics for assessing network optimization outcomes of the predictive model. Together these theories provide both computational and service-level

foundations for designing an ML-enabled predictive traffic-management system.

2.4 Empirical Evidence

Several studies have demonstrated the increasing application of Machine Learning (ML) and Software Defined Networking (SDN) in network traffic management and cloud computing environments. Kumar et al. (2023) developed an LSTM-based traffic prediction model that achieved 92% accuracy in forecasting data-centre traffic surges. Their study showed that predictive analytics can significantly reduce latency and improve bandwidth utilization in cloud environments. Similarly, Lin et al. (2021) compared different machine learning techniques for traffic prediction and concluded that deep learning models such as LSTM and Gated Recurrent Unit (GRU) outperform traditional statistical models like ARIMA when handling non-linear and time-dependent traffic patterns. These findings demonstrate the effectiveness of deep learning approaches in modern network traffic forecasting.

Research on the integration of ML and SDN has also shown promising results in intelligent traffic management. Zhou (2022) integrated Random Forest algorithms within an SDN controller to support dynamic load balancing across cloud servers. The study revealed that combining SDN with predictive analytics enables automated bandwidth allocation and efficient traffic routing. In another study, Patel and Singh (2023) highlighted that SDN-ML integration improves context-aware Quality of Service (QoS) control in heterogeneous educational networks. Their findings indicated that intelligent traffic prioritization enhances the performance of cloud-based learning systems, especially during periods of high demand. Abdullahi et al. (2022) further demonstrated the potential of reinforcement learning in SDN environments, where real-time decision-making improved network throughput by 30%.

Studies conducted within educational environments also confirm the importance of predictive traffic management. Ahmed and Rahman (2021) applied Gradient Boosting algorithms to university networks in Bangladesh and reported a 25% reduction in congestion events. Their study established that predictive analytics can improve user experience and ensure uninterrupted access to e-learning platforms. Similarly, Munyoro and Moyo (2023) examined bandwidth allocation mechanisms in Harare school networks and recommended the adoption of predictive analytics to minimize congestion and improve service delivery in educational institutions.

In the African context, empirical studies continue to reveal significant challenges affecting digital learning infrastructure. Oguya et al. (2022) observed that many African secondary schools suffer from under-provisioned bandwidth, outdated infrastructure, and reactive network management approaches. These limitations negatively affect the reliability and accessibility of cloud-based learning systems. In Zimbabwe, Chikowore and Nyatsanza (2024) found that rural schools lack automated network monitoring and analytics tools, making it difficult to manage increasing internet traffic effectively. Their study emphasized that the absence of intelligent infrastructure limits the success of e-learning initiatives in rural areas. Supporting this argument, Ndlovu (2024) evaluated Zimbabwean ICT education policies and stressed the importance of intelligent infrastructure monitoring and predictive technologies in supporting sustainable digital education.

Although previous studies confirm the effectiveness of machine learning and SDN in predictive traffic management, most existing research has focused on data centres, universities, and urban networks. Limited attention has been given to district-level educational networks in rural areas such as Murewa District. This creates a research gap that the current study seeks to address by investigating how predictive network traffic management using machine learning can improve the performance of cloud-based learning systems in Zimbabwean secondary schools.

2.5 Research Gap Analysis

The literature convincingly shows that ML techniques can enhance traffic forecasting and network performance in various contexts. However, key gaps remain:

i. Little focus on school or educational networks, especially in developing regions where cloud-learning is becoming essential for example in Murewa District, Zimbabwe.

ii. Limited research combining ML with SDN specifically for cloud-learning traffic management in resource-constrained networks.

iii. Sparse data and case studies examining district-wide school networks, rather than campus or enterprise environments.

iv. Few studies using real-world, dynamic traffic data in such environments; many rely on simulations or enterprise networks.

Given these gaps, the present study seeks to apply ML-based predictive traffic management in the context of Murewa District schools, integrating cloud-based learning systems, forecasting of traffic patterns, and SDN-based dynamic allocation; thereby addressing a pivotal need for improved digital-learning connectivity in rural Zimbabwe.

2.6 Summary

This chapter reviewed the theoretical underpinning (Queueing Theory, ML Theory, QoS Theory), examined cloud-based learning environments and the network-traffic challenges they face, analyzed machine-learning techniques for traffic prediction and their empirical application, considered SDN-ML integrated systems and identified gaps in applying these to educational networks in developing contexts. QoS theory considers how network performance metrics (latency, jitter, throughput, packet-loss) impact application performance and user experience (Cisco, 2021). In a school e-learning setting, high throughput and low latency are critical for synchronous digital lessons and cloud-resource access. This theory guides measurement of performance improvements resulting from predictive traffic management. Consequently, the current research proceeds to design and evaluate an ML-driven predictive network-traffic-management framework suitable for cloud-based learning systems in Murewa District.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the methodological procedures adopted to investigate the effectiveness of machine learning techniques in predicting and managing network traffic in cloud-based learning environments in Murewa District, Zimbabwe. As educational institutions increasingly rely on cloud-based platforms such as Google Classroom, Moodle, and digital libraries, the need for stable and predictable network performance has become critical. However, many rural districts face persistent challenges such as network congestion, inadequate bandwidth, outdated infrastructure, and unpredictable user traffic patterns. To address these challenges, the current study employs a series of methodological strategies aimed at collecting comprehensive, reliable, and valid data.

The chapter begins by establishing the research philosophy that underpins the study and explaining how this philosophical stance influences methodological choices. According to Saunders, Lewis, & Thornhill (2019), a sound methodology ensures that the research findings are credible, replicable, and scientifically grounded. It then discusses the research design, population and sampling procedures, research instruments, data collection methods, and data analysis techniques. Reliability and validity considerations are detailed, followed by ethical principles that governed the research process. The chapter concludes with a summary of the methodological steps taken, highlighting their alignment with the research questions and hypotheses.

3.2 Research Philosophy

The study is guided by a pragmatic research philosophy, which is widely used in applied ICT, education technology, and data analytics research where both measurable outcomes and contextual understanding are essential. Pragmatism rejects the idea that research must exclusively follow either a positivist or interpretivist approach; instead, it embraces methodological pluralism. This makes it particularly suitable for research exploring technological interventions within real-life educational settings.

In this study, the positivist dimension is critical because network performance can be objectively measured using quantifiable indicators such as latency, throughput, jitter, and packet loss. Positivism supports the use of controlled comparisons between baseline network performance and performance after implementing machine learning models. It also justifies the statistical testing of hypotheses, which is fundamental to evaluating whether ML interventions significantly improve network efficiency.

The interpretivist dimension, on the other hand, is necessary for understanding user experiences, perceptions, and contextual challenges that numbers alone cannot explain. Teachers, learners, and ICT administrators provide insights into how unstable networks affect the teaching-learning process, how often disruptions occur, and how cloud-learning tools are perceived in practice. These perspectives enrich quantitative data and ensure that the technical solution addresses real educational needs.

By combining these philosophical lenses, pragmatism ensures that the study develops a holistic understanding of the problem, produces practically applicable findings, and supports both statistical and contextual interpretations.

3.3 Research Design

A mixed-methods research design was selected due to the complex nature of the research problem, which involves both technical (network performance) and social (user experience) dimensions. Mixed-methods research offers a more comprehensive analytical perspective, allowing the researcher to triangulate findings and strengthen the validity of conclusions.

3.3.1 Quantitative Component

The quantitative aspect adopts an experimental research approach, allowing the researcher to manipulate the independent variable (machine learning algorithms) and observe their impact on dependent variables (network performance metrics). The study compares network performance before and after the deployment of ML predictive models such as LSTM, Random Forest, and Support Vector Regression. A quasi-experimental setup is used in which real-world conditions and constraints of school environments are preserved, making the findings more practically applicable.

Quantitative data is collected through automated monitoring tools configured to log performance indicators at regular intervals. Statistical analysis then determines whether improvements are significant, thus directly addressing the research hypotheses.

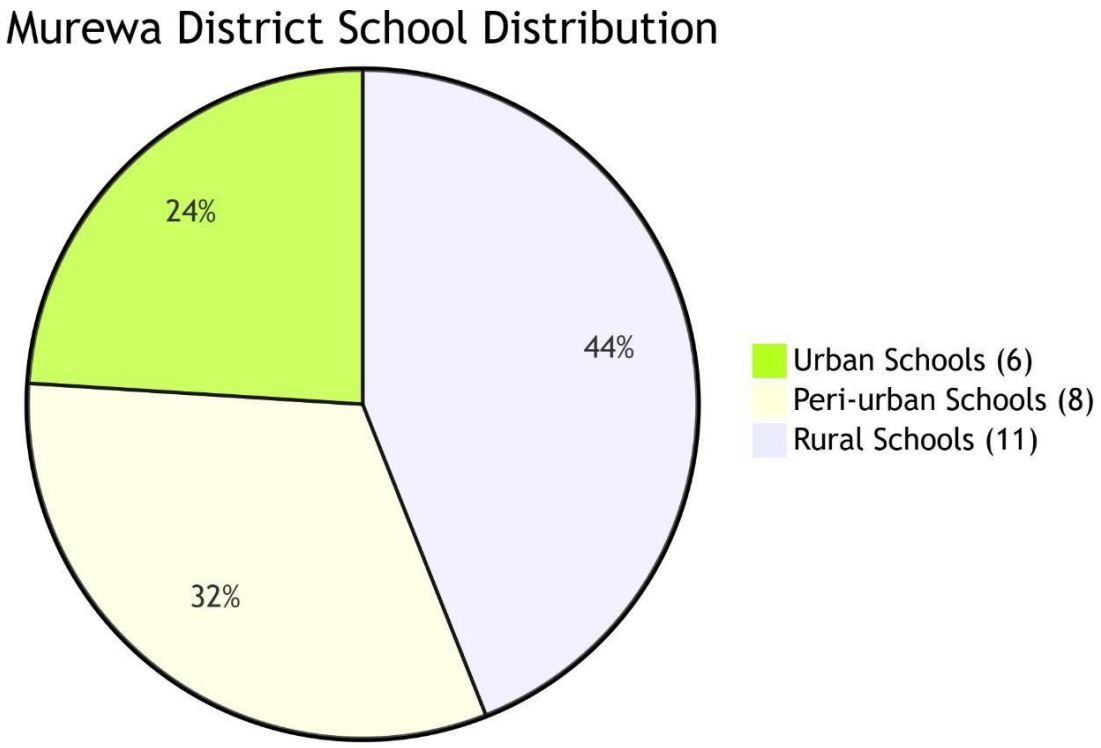
3.3.2 Qualitative Component

The qualitative component uses semi-structured interviews, observational assessments, and document reviews. Interviews allow participants to discuss challenges such as slow loading times, disconnections during lessons, or difficulties accessing cloud-based platforms during peak periods. Observations allow the researcher to witness network usage patterns, login difficulties, or hardware limitations.

Using qualitative insights, the study contextualizes the numerical performance data and identifies human or systemic factors influencing network behavior. The integration of both methods ensures a deeper understanding of whether machine learning solutions are feasible, acceptable, and sustainable within real educational settings.

3.4 Population and Sample

The population for this investigation includes all schools in Murewa District that use cloud-based learning systems. The district consists of approximately 25 registered schools, situated both in rural for example Nyamuzuwe High and peri-urban where there are schools like Murewa High, Hurungwe Secondary. These institutions vary significantly in terms of ICT infrastructure, bandwidth availability, device-to-learner ratios, and internet reliability.



The targeted population for this study consists of:

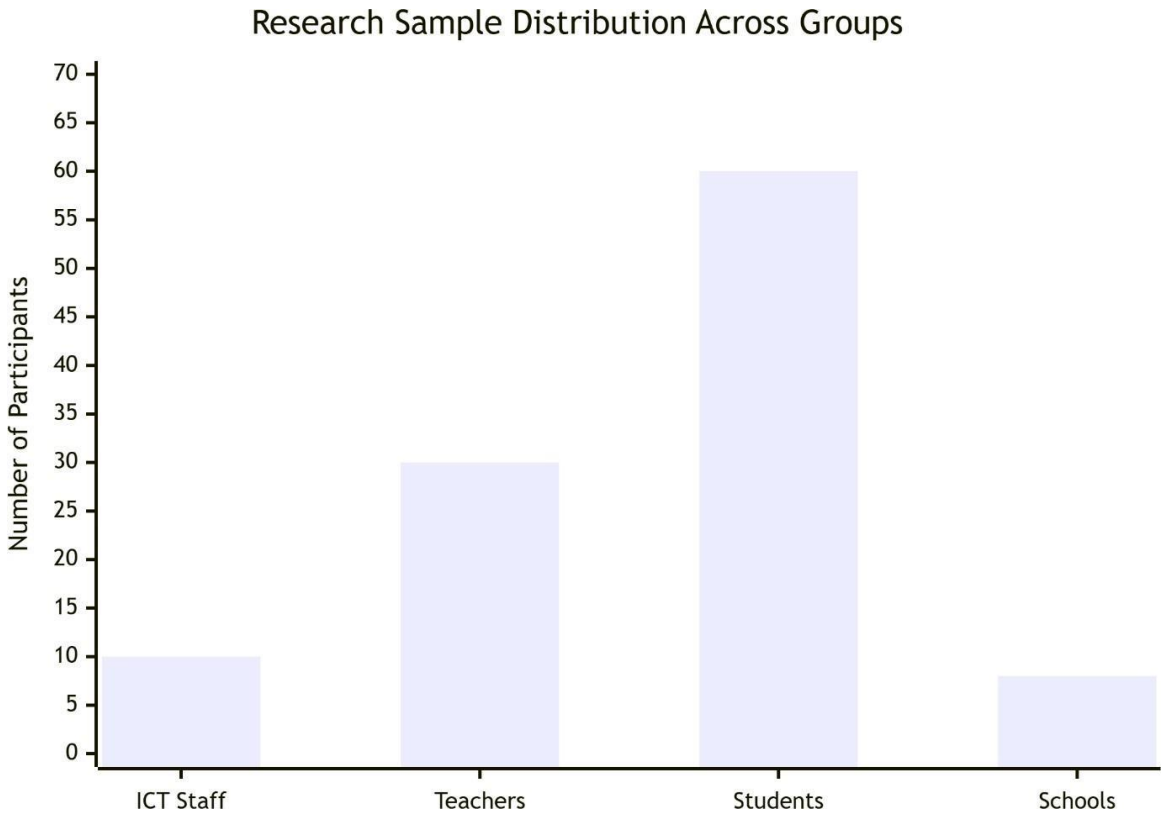
i. ICT administrators and technicians managing school networks

ii. Teachers and learners using cloud-based learning systems

iii. Network traffic logs from schools within Murewa District

iv. Data from cloud platforms such as Google Classroom, Moodle, and e-learning portals

Since the study aims to produce generalizable results, a representative sample was drawn from the population. The sample includes:


Research Sample Distribution Across Groups
Number of Participants
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
ICT Staff
Teachers
Students
Schools

i. 10 ICT personnel who oversee network infrastructure

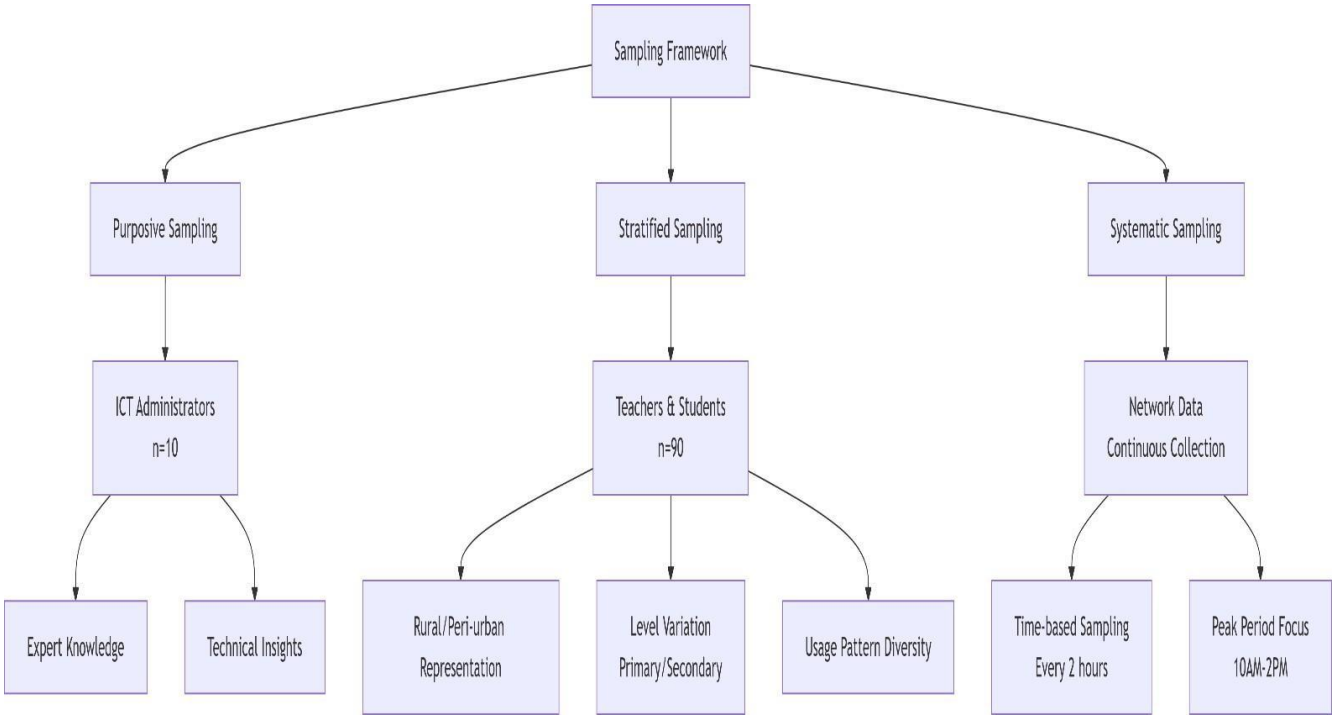
ii. 30 teachers who frequently use cloud-based learning tools

iii. 60 learners selected from different schools

iv. Real network traffic data collected from at least 8 schools with active internet-based learning platforms

This sample is sufficiently diverse to provide accurate technical performance data and a broad range of user experiences.

3.5 Sampling Procedures



Three sampling techniques were used:

i. Purposive Sampling

ICT administrators were purposively selected because they possess expert knowledge about the technical operation of school networks. This ensures that responses related to infrastructure limitations, router configurations, and network management protocols are technically sound.

ii. Stratified Sampling

Teachers and learners were selected through stratified sampling to ensure representation across:

i. rural and peri-urban schools

ii. primary and secondary levels

iii. high-usage and low-usage institutions

Stratification prevents the exclusion of important subgroups and ensures that results reflect the broader experiences of the district.

iii. Systematic Sampling

Real network traffic logs were extracted using systematic sampling, where data was recorded at consistent intervals (e.g., every 2 hours or during specific peak periods such as morning lessons). This ensured uniformity and reduced sampling bias in network performance measurements. These combined techniques enhance representativeness and improve the validity of the research findings.

3.6 Research Instruments

3.6.1 Network Monitoring and Data Extraction Tools

The technical aspect of the study relies heavily on network-monitoring tools such as Wireshark, PRTG Network Monitor, and SolarWinds. SDN controllers were also used to capture real-time network data under ML-managed conditions. These tools automatically measure:

i. bandwidth consumption
ii. latency and delay
iii. packet loss
iv. jitter
v. connection stability
vi. peak traffic periods

They provide objective and replicable measurements suitable for statistical analysis.

3.6.2 Machine Learning Models

Python-based libraries such as Scikit-Learn, TensorFlow, and Keras were used to build and evaluate ML models. Historical traffic data was fed into models such as:

vii. Long Short-Term Memory (LSTM) for time-series prediction
viii. Random Forest Regressor for non-linear traffic patterns
ix. Gradient Boosting Models for high-accuracy forecasting
x. Support Vector Regression (SVR) for optimized regression

These models were compared using performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 Score.

3.6.3 Semi-Structured Interviews

Interview guides allowed participants to express their experiences with cloud-learning challenges. Questions explored issues such as frequent disconnections, impact of network failures on learning, and perceptions of digital learning platforms.

3.6.4 Document Analysis

ICT policy reports, network utilization logs, and school-admin records were analyzed to obtain additional insights into existing infrastructure, usage patterns, and institutional readiness.

3.7 Reliability and Validity

3.7.1 Reliability

Reliability was achieved through several methods:

i. Instrument reliability: network monitoring tools were tested for consistency across multiple time periods.

ii. Model reliability: ML algorithms were validated using cross-validation techniques and repeated testing.

iii. Inter-rater reliability: qualitative coding was reviewed by two independent reviewers to ensure consistency in thematic interpretations.

3.7.2 Validity

Validity measures ensured that the study accurately assessed the effect of ML on network performance:

i. Construct validity: variables such as throughput and latency correctly represented network performance.

ii. Internal validity: experimental controls reduced external influences on network

performance, ensuring accurate comparisons.

iii. External validity: selecting diverse schools enhances generalizability to other districts with similar ICT challenges.

iv. Content validity**:** interview instruments were reviewed by ICT and educational experts.

3.8 Data Collection Process

Data collection followed four detailed phases:

Phase 1: Baseline Measurement

Network performance was measured over a 30-day period without ML intervention. This established a "status quo" against which improvements could be tested.

Phase 2: Model Training and Validation

Historical traffic data was pre-processed and fed into ML algorithms. Seventy percent of the dataset was used for training, while the remaining 30% was used for validation to test predictive accuracy.

Phase 3: ML-Based Network Implementation

After validating the best-performing ML model, it was deployed into a controlled SDN-managed environment. Real-time data was recorded to observe changes in network behavior, congestion reduction, and allocation efficiency.

Phase 4: Qualitative Data Collection

Teachers, learners, and ICT staff participated in interviews and observations. This helped explain the human and environmental factors influencing cloud-learning system performance.

3.9 Data Analysis Techniques

3.9.1 Quantitative Analysis

Quantitative data was analyzed using:

i. Descriptive statistics to summaries baseline and ML-enhanced network performance.

ii. ML performance measures such as RMSE, MAE, classification accuracy, and prediction error distribution.

3.9.2 Qualitative Analysis

Interview transcripts were analyzed using thematic analysis. Patterns related to user experiences, challenges, and perceived impact of predictive network management were categorized into themes. This helped interpret quantitative findings and explain contextual challenges.

3.10 Ethical Considerations

Ethical principles were strictly followed to protect participants and institutions:

i. Informed consent was obtained from all participants.

ii. Confidentiality was maintained through data anonymization.

iii. Data protection measures such as encryption were implemented.

iv. Non-disruption policy ensured that network monitoring activities did not interfere with learning.

v. Voluntary participation ensured participants could withdraw at any point.

Ethical approval was sought from district education authorities and school administrators

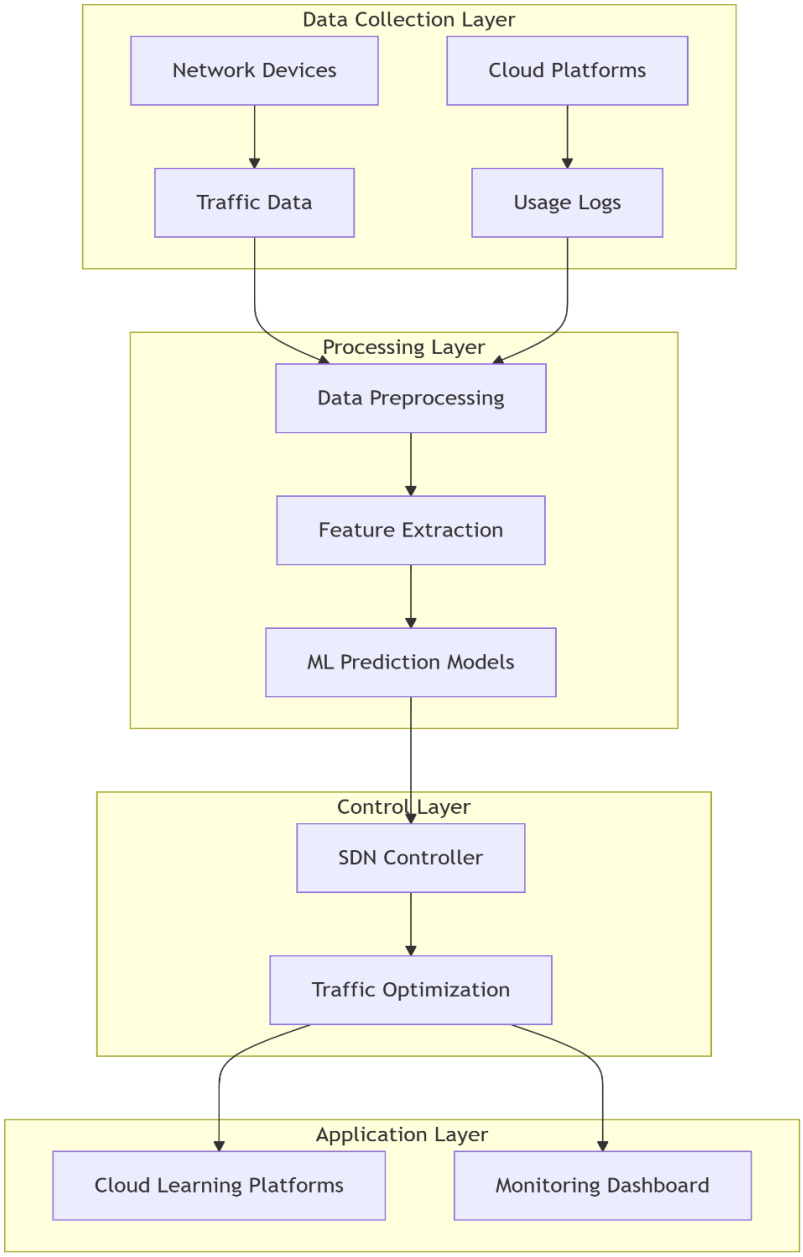
3.11 System Documentation

System documentation provides a detailed description of the proposed predictive network-traffic management system developed for cloud-based learning environments in Murewa District. The documentation outlines the system architecture, functional components, data flow, and interaction between machine learning models and network control mechanisms. Proper documentation is essential to ensure system transparency, reproducibility, maintenance, and future scalability.

The proposed system is composed of four primary layers. The data acquisition layer captures historical and real-time network traffic metrics from school networks, including bandwidth usage, latency, packet loss, jitter, and active user counts. The data processing layer performs data cleaning, normalization, feature extraction, and transformation to prepare datasets suitable for machine learning analysis. The machine learning layer applies predictive models such as Long Short-Term Memory (LSTM), Random Forest, and Support Vector Regression to forecast future traffic demand. The network control layer, implemented through Software-Defined Networking (SDN), dynamically allocates bandwidth and prioritizes traffic based on predicted demand.

Comprehensive system documentation ensures that the solution can be understood and replicated by ICT personnel in educational institutions, supporting long-term sustainability beyond the scope of this study.

Figure 3.11: Architecture of the machine learning-based predictive network traffic management system



3.12 Hardware Requirements

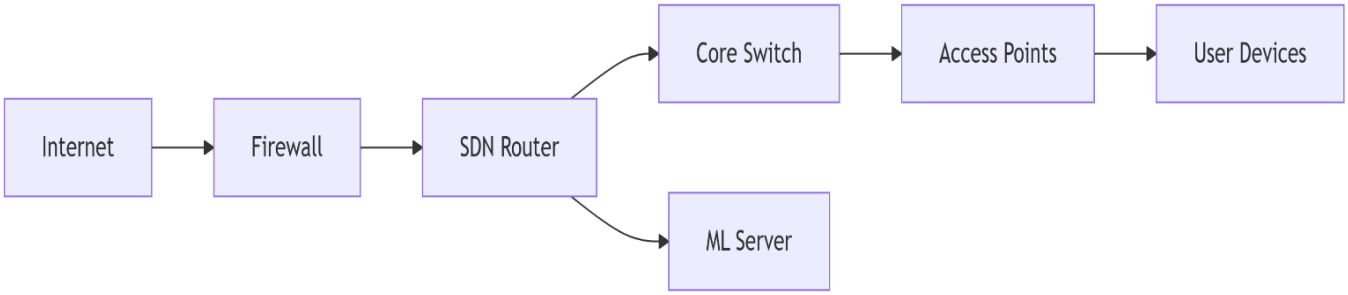
The hardware requirements were selected based on availability, affordability, and compatibility with school environments in Murewa District. The system does not require specialized or high-cost equipment, making it suitable for resource-constrained institutions.

The required hardware includes:

- Network routers and switches supporting traffic monitoring
- A server or high-performance workstation for ML model training
- End-user devices such as desktops, laptops, or tablets
- Internet connectivity via fibre, wireless, or mobile broadband
- Network Interface Cards (NICs) for data capture

These components enable effective traffic monitoring, data processing, and system simulation without disrupting live school networks. Below is:

Figure 3.12: Hardware setup



3.13 Software Requirements

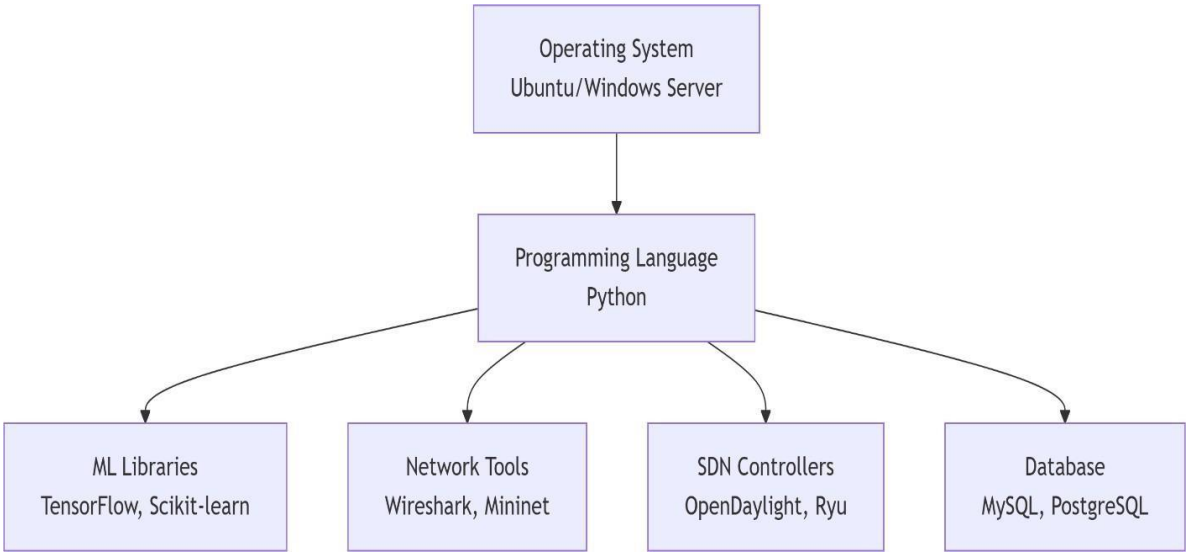
The system relies primarily on open-source and widely supported software technologies to minimize cost and maximize flexibility. The required software includes:

- Operating Systems: Linux (Ubuntu) or Windows Server

- Programming Language: Python
- Machine Learning Libraries: TensorFlow, Scikit-learn, Keras
- Network Simulation Tools: Mininet, NS-3
- Monitoring Tools: Wireshark, PRTG Network Monitor
- Database Systems: MySQL or PostgreSQL
- SDN Controllers: Open Daylight or Ryu

These tools support data collection, predictive modelling, network control, and performance evaluation. Below is the software stack

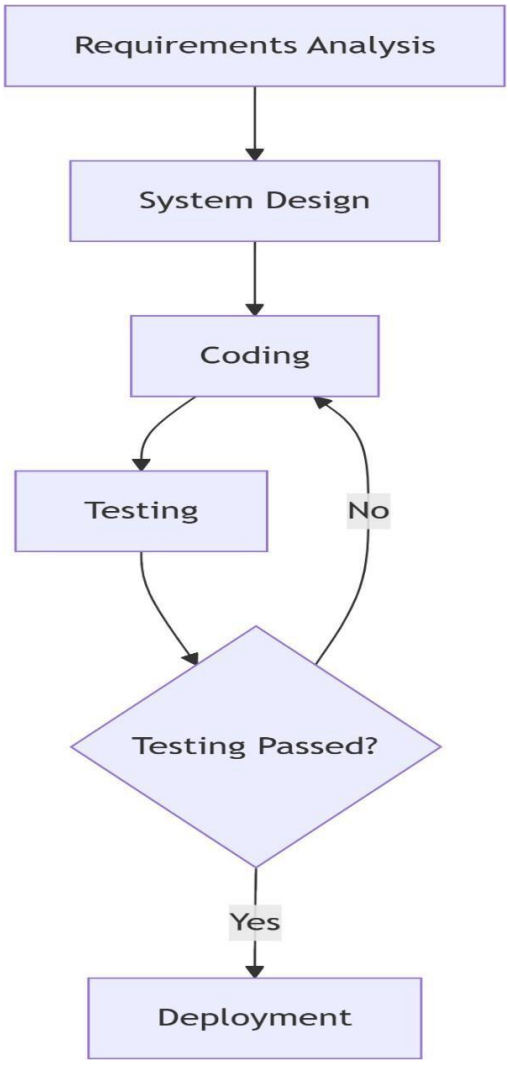
Figure 3.13: Software Stack



3.14 System Development

System development followed a structured and iterative approach to ensure reliability, scalability, and alignment with the research objectives. The development process focused on creating a functional prototype capable of predicting network traffic and optimizing bandwidth allocation for cloud-based learning systems.

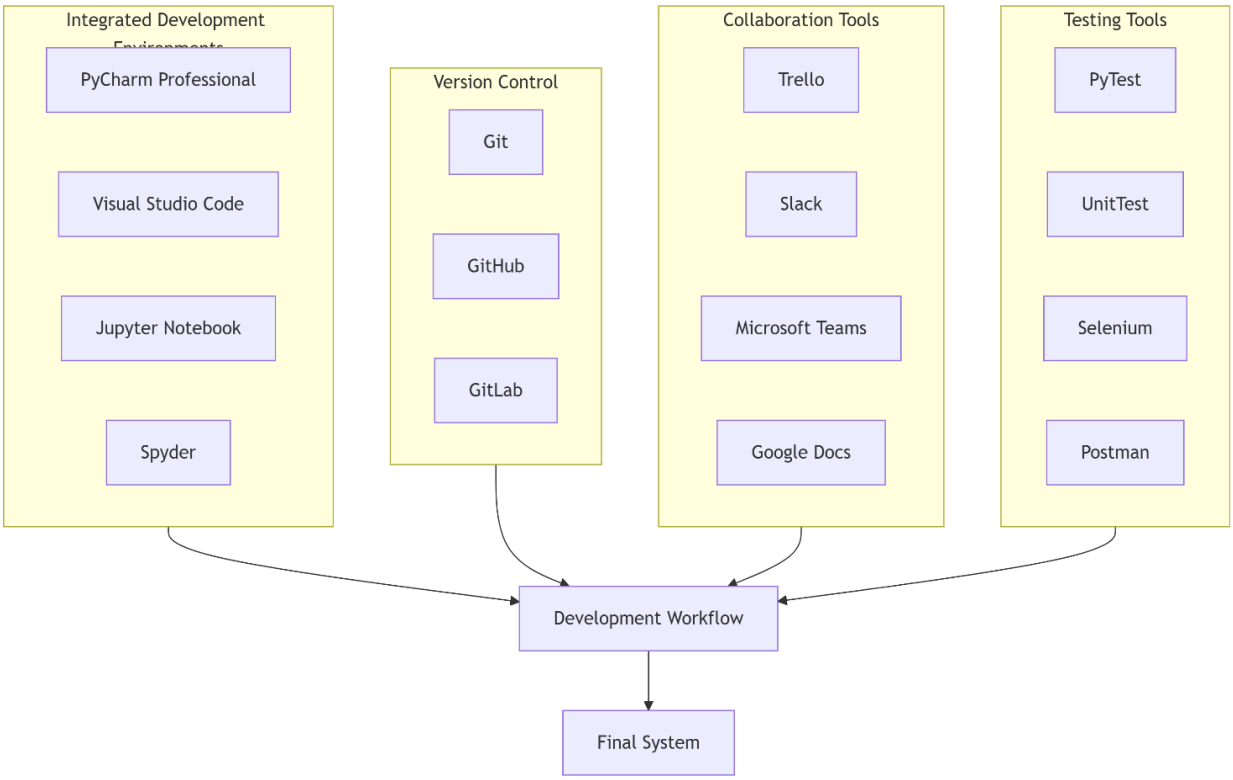
Figure 3.14: Development Process Flowchart



3.14.1 System Development Tools

Several development tools were used throughout the system lifecycle. Python served as the core development language due to its extensive support for machine learning and networking applications. Integrated Development Environments (IDEs) such as PyCharm and Jupyter Notebook were used for coding, testing, and model visualization. Version control was managed using Git to ensure code integrity and facilitate incremental development. Network simulators enabled safe testing of system behavior under different traffic loads.

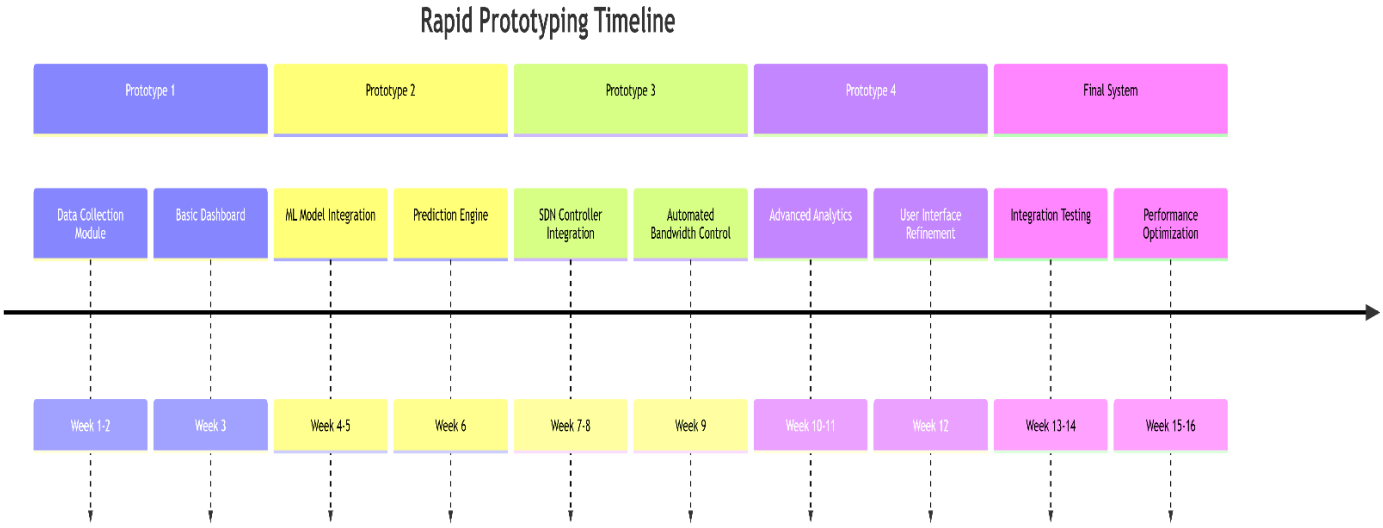
Figure 3.14.1: shows system development tools used.



3.14.2 Rapid Prototyping

Rapid prototyping was adopted to enable early testing and refinement of system components. Initial prototypes focused on traffic data collection and preprocessing. Subsequent iterations integrated machine learning prediction models and SDN-based control mechanisms. This approach allowed continuous evaluation of system performance, early detection of design flaws, and incremental improvement based on observed results.

Figure 3.14.2: shows system's rapid prototyping



3.15 Feasibility Study

A feasibility study was conducted to assess the practicality of implementing the proposed system in secondary schools within Murewa District. The study evaluated technical, economic, operational, and organizational feasibility to determine whether the system could realistically be adopted in resource-constrained educational environments.

3.15.1 Technical Feasibility

The system is technically feasible because it relies on widely available, open-source technologies such as Python, TensorFlow, Scikit-learn, Mininet, and SDN controllers. Existing school network infrastructure, including routers and switches, can support traffic monitoring without major hardware upgrades. The use of SDN enables centralized control without replacing the entire network infrastructure, making the system adaptable to current school environments.

3.15.2 Economic Feasibility

Economic feasibility is achieved through the use of open-source software, which eliminates licensing costs. The system enhances existing infrastructure rather than requiring expensive replacements. This makes the solution affordable for public schools operating under limited ICT budgets, a common challenge in Murewa District.

3.15.3 Operational Feasibility

Operational feasibility is supported by the system's automation capabilities. Once deployed, predictive traffic management reduces the need for continuous manual intervention by ICT staff. Basic training is sufficient for administrators to monitor system outputs, making adoption practical within the existing skills base.

3.16 System Analysis

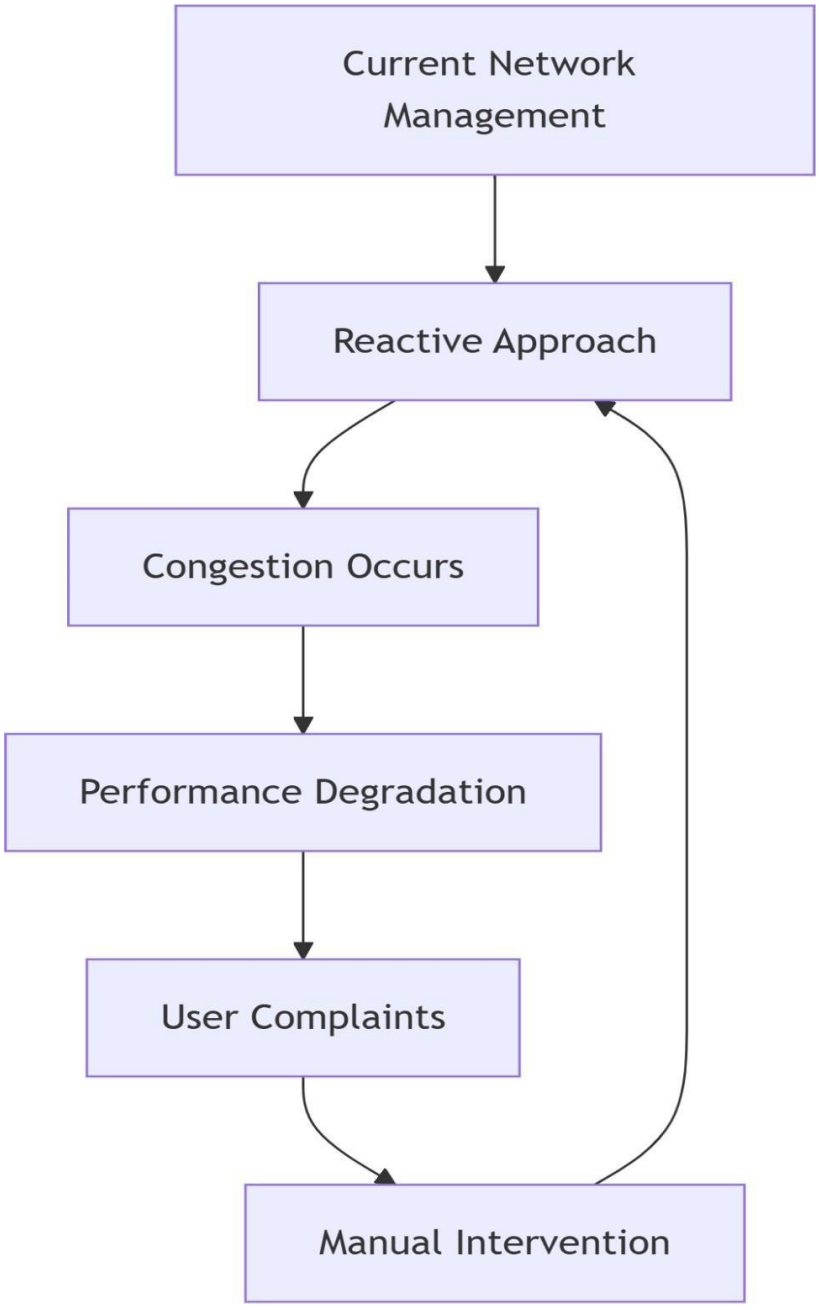
System analysis was conducted to identify weaknesses in the current network traffic management practices used by schools in Murewa District. The existing system operates on a reactive model, where network administrators respond to congestion only after service degradation occurs. This approach results in delayed responses, uneven bandwidth distribution, and frequent interruptions during cloud-based learning activities.

Key issues identified include:

- High network congestion during peak learning hours
- Poor prioritization of educational traffic

- Lack of predictive mechanisms
- Inefficient utilization of limited bandwidth resources

Figure 3.16: Shows Current System Issues.



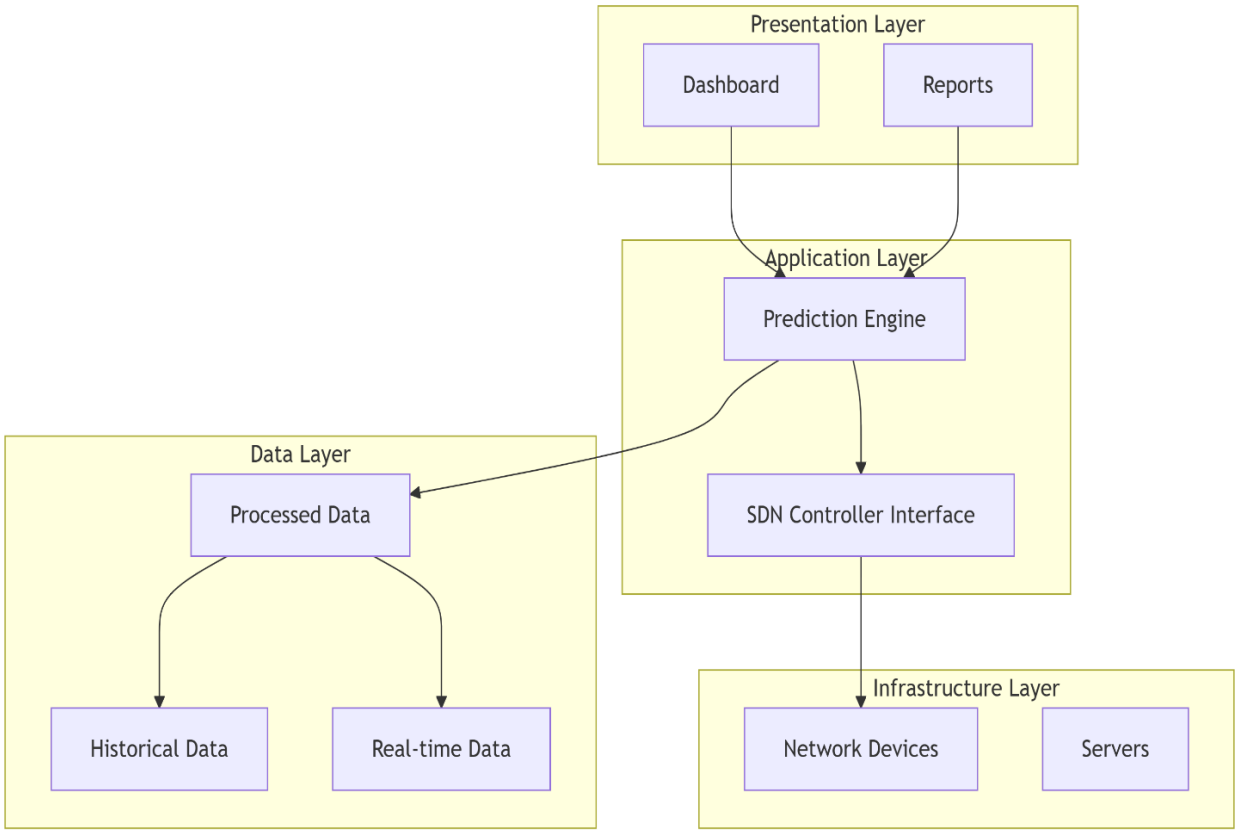
3.17 System Design

System design translated requirements into a structured solution. The system follows a layered architecture consisting of:

- Data collection layer
- Data preprocessing layer
- Machine learning prediction layer
- SDN-based traffic control layer

The design ensures modularity, scalability, and ease of maintenance.

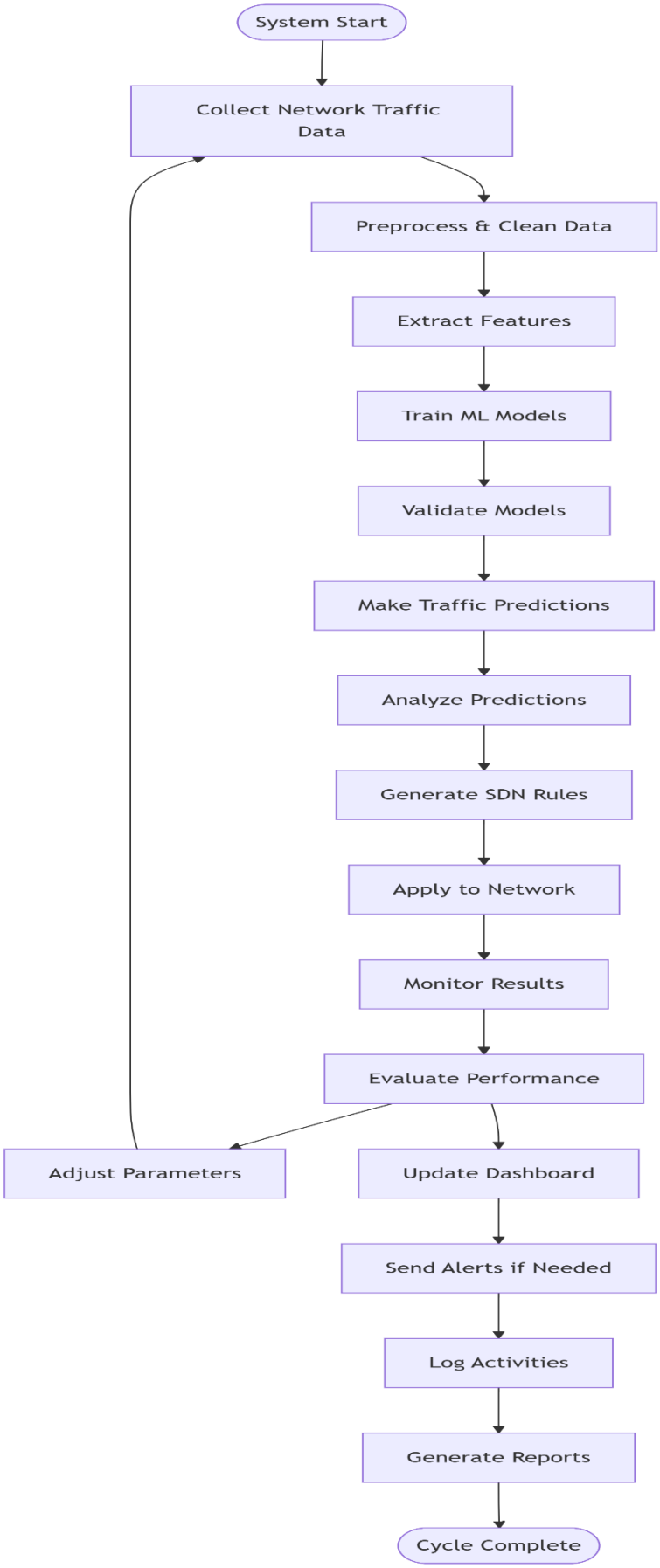
Figure 3.17: Shows Current System Issues.



3.17.1 Proposed System Flow Diagram

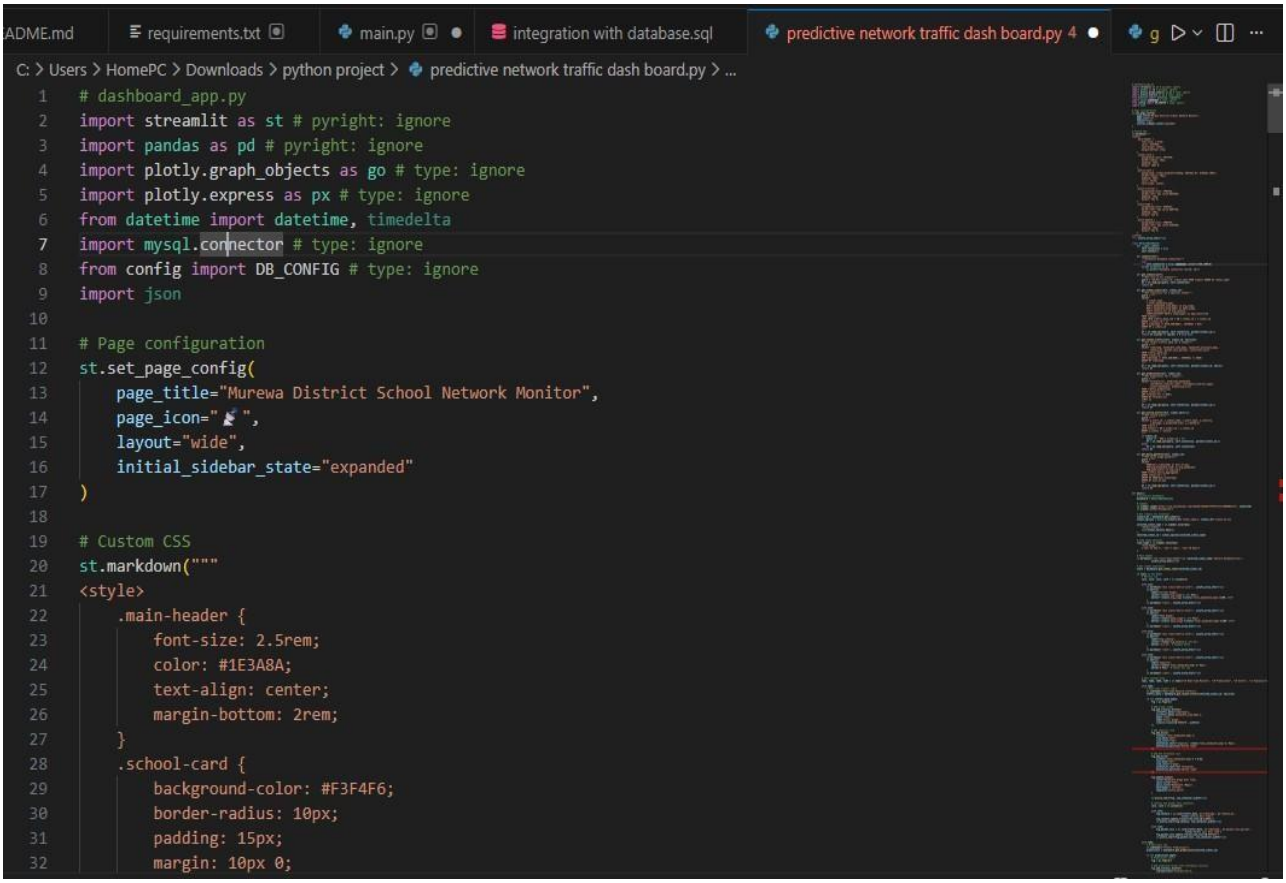
The proposed system flow begins with network traffic data collection, followed by preprocessing and feature extraction. Machine learning models then predict future traffic demand. Based on these predictions, the SDN controller dynamically allocates bandwidth and prioritizes cloud-based learning traffic, resulting in improved network performance. This flow diagram provides a visual representation of how data moves through the system from input to optimization.

Figure 3.5.1: Shows Proposed System Flow Diagram

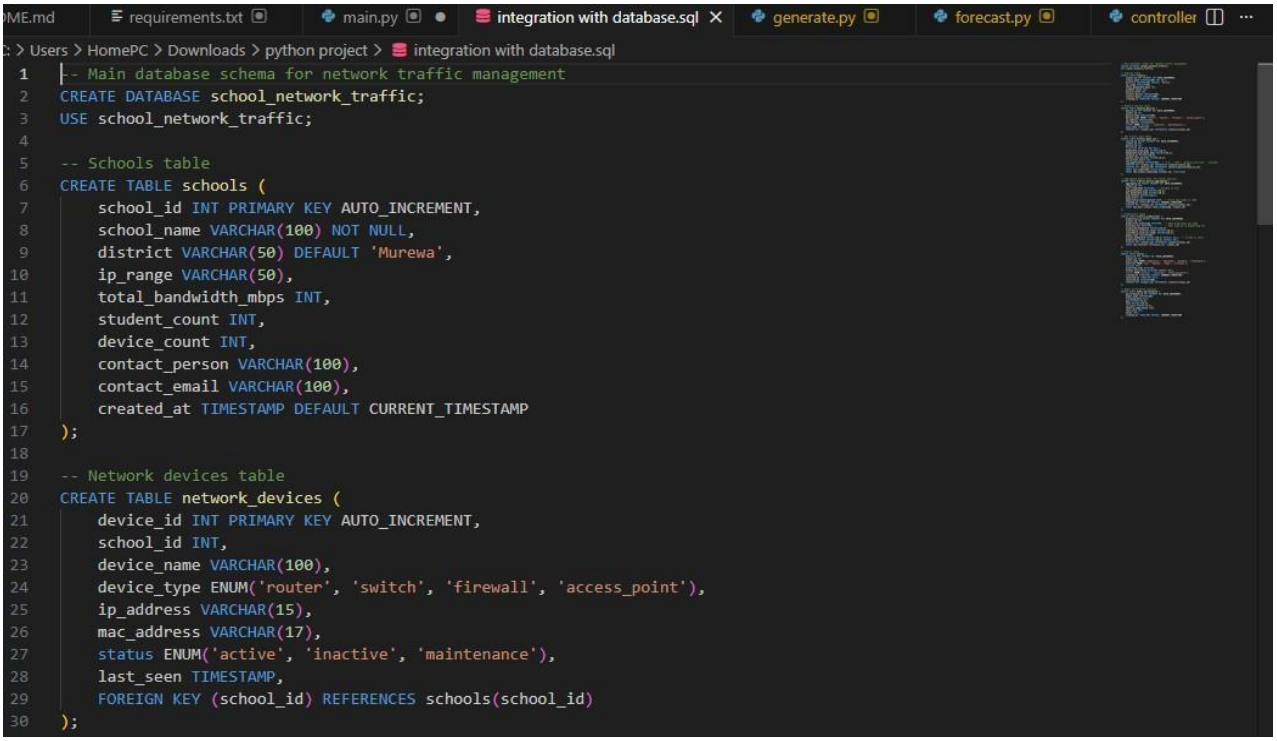

System Start
Collect Network Traffic Data
Preprocess & Clean Data
Extract Features
Train ML Models
Validate Models
Make Traffic Predictions
Analyze Predictions
Generate SDN Rules
Apply to Network
Monitor Results
Evaluate Performance
Adjust Parameters
Update Dashboard
Send Alerts if Needed
Log Activities
Generate Reports
Cycle Complete

3.18 Coding

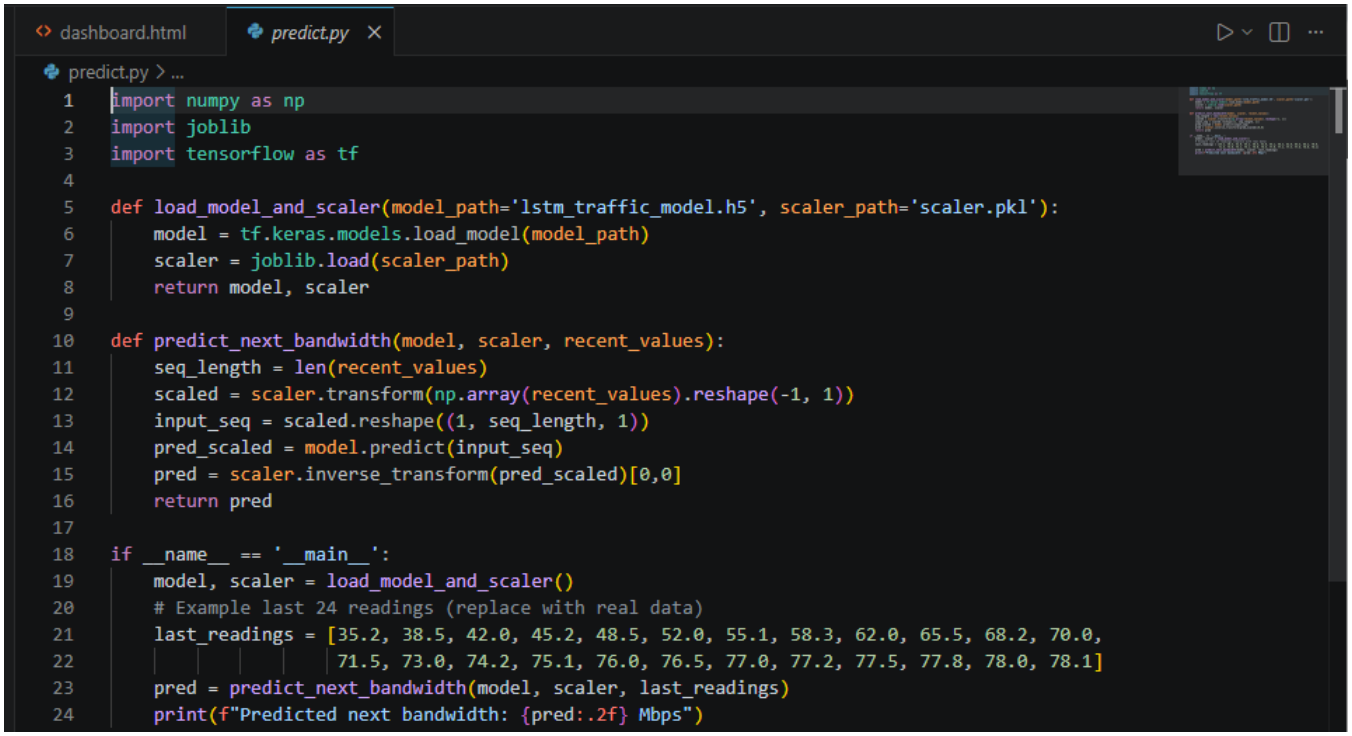
Coding was performed using Python, with modular scripts developed for data preprocessing, model training, prediction, and SDN policy enforcement. Machine learning algorithms such as LSTM, Random Forest, and Gradient Boosting were implemented and evaluated. The code was structured to ensure readability, reusability, and ease of debugging. Logging mechanisms were incorporated to monitor system behavior during simulation.



System's Dashboard Backend



Database Integration



ML Traffic Prediction Backend

3.19 Implementation

System implementation was carried out in a controlled simulation environment using Mininet and SDN controllers. This approach prevented disruptions to real school networks while allowing realistic testing of traffic patterns and congestion scenarios.

Implementation followed a phased approach:

i. Deployment of monitoring tools

ii. Training and validation of ML models

iii. Integration with SDN controller

iv. Performance testing under simulated workloads

3.20 Testing

System testing was conducted to verify the correctness, reliability, and effectiveness of the proposed predictive network traffic management system. Testing focused on ensuring that the system met functional requirements, produced accurate predictions, and improved network performance without disrupting cloud-based learning activities. Two major testing approaches were employed: black box testing and white box testing.

3.20.1 Black Box Testing

Black box testing was used to evaluate the functional behavior of the system without examining its internal code structure. The primary objective of this testing method was to determine whether the system produced correct outputs for given inputs under real-world conditions.

The black box tests focused on the following functional areas:

i. Accurate collection of real-time network traffic data

ii. Successful prediction of future network traffic using machine learning models

iii. Dynamic allocation and prioritization of bandwidth for cloud-based learning platforms

iv. Reduction of network congestion during peak usage periods

v. Continuous availability of cloud-learning services

During testing, network traffic data was fed into the system, and the predicted traffic patterns were observed. The system was expected to identify peak usage periods and proactively adjust network resources. Results showed that the system successfully predicted high-traffic intervals and prioritized educational traffic, resulting in fewer service interruptions.

Table 4.1 presents a summary of the black box testing results.

Table 4.1: Black Box Testing Results

Test Case	**Expected Outcome**	**Actual Outcome**	**Status**
Traffic data capture	Accurate data logging	Data logged correctly	Pass
Traffic prediction	Correct traffic forecast	Accurate predictions	Pass
Bandwidth allocation	Prioritized learning traffic	Learning traffic prioritized	Pass
System response	Reduced congestion	Congestion reduced	Pass

The results indicate that the system met all functional requirements, confirming its operational effectiveness within cloud-based learning environments.

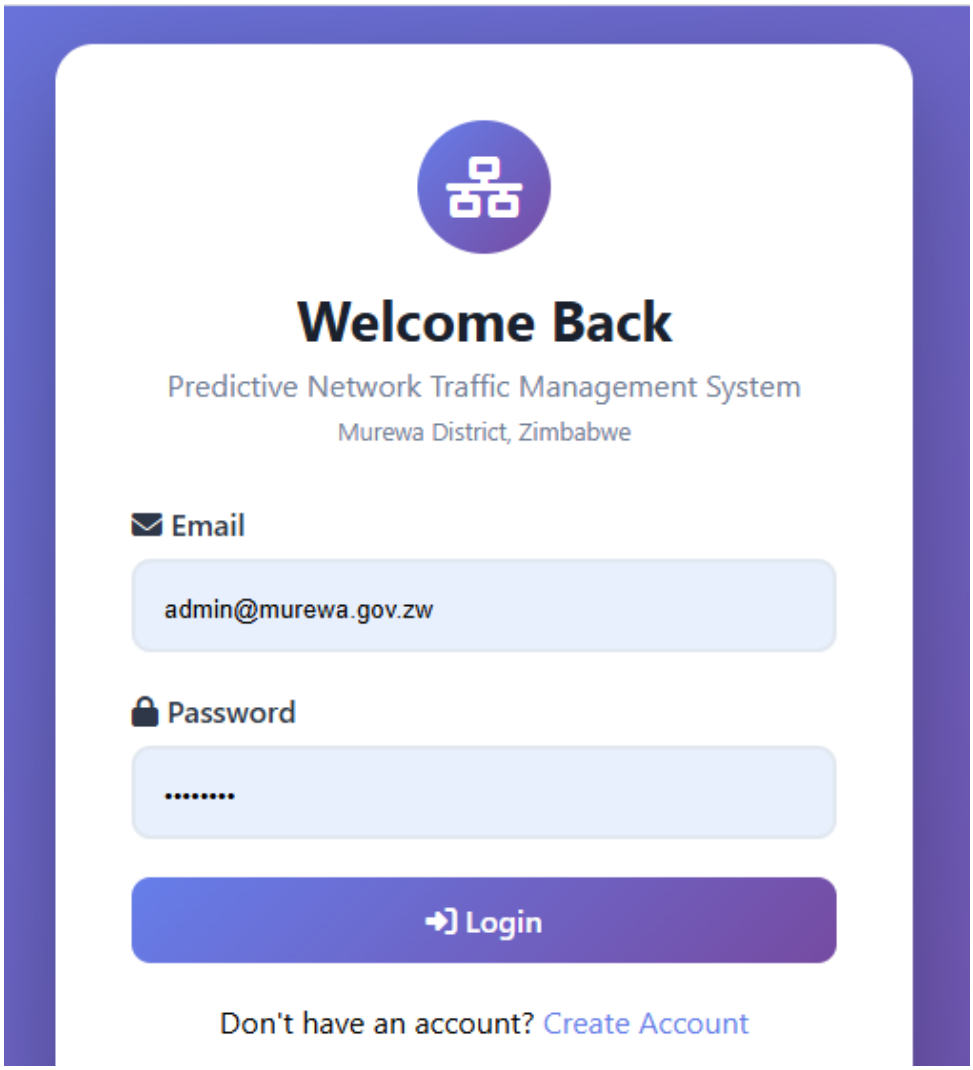


Fig 4.2.1 Predictive Network Traffic Management Login-Page.

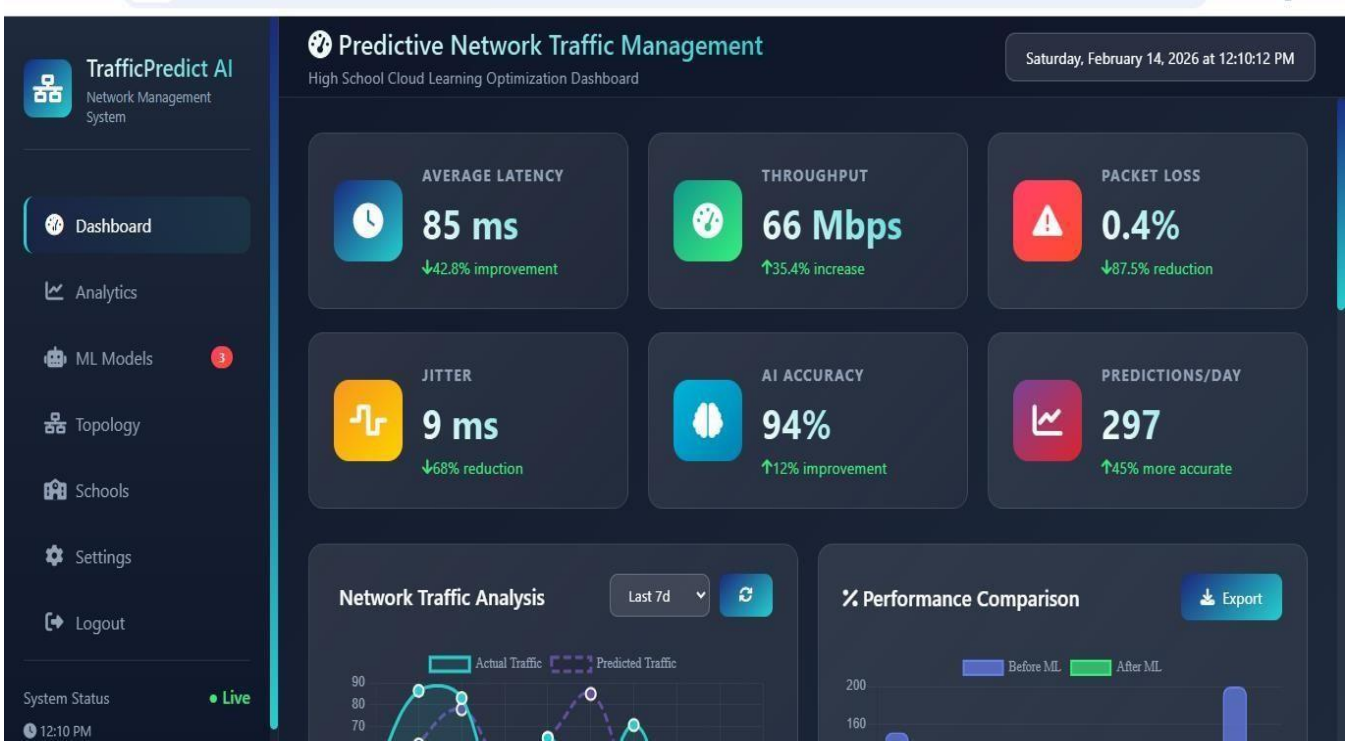


Fig 4.2.2 Predictive Network Traffic Management Dashboard

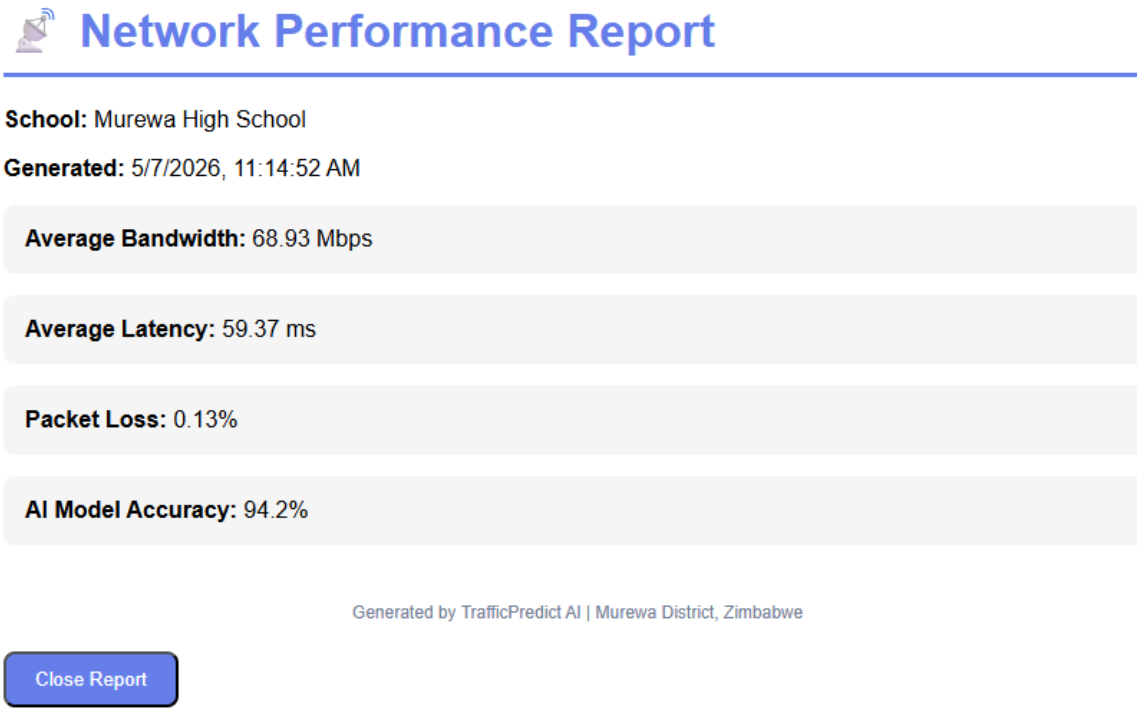


Fig 4.2.3 Predictive Network Traffic Management Report

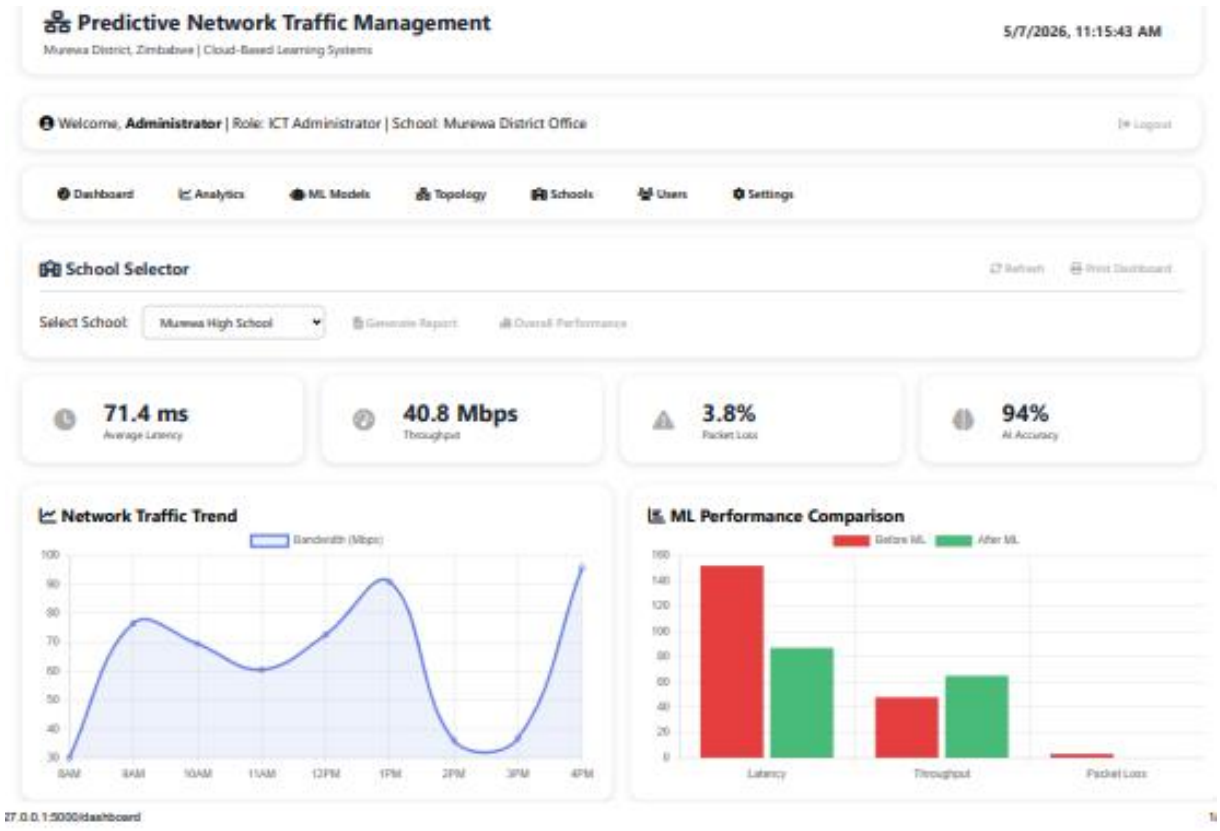


Fig 4.2.4 System Administrator's Dashboard.

Live School Network Status

Generate Report

School Name	Location	Current Traffic	Predicted	Students	Status
Murewa High School	Murewa Center	75.5 Mbps	83.0 Mbps	850	critical
Nyamuzuwe High School	Nyamuzuwe Rural	91.8 Mbps	101.0 Mbps	620	critical
Hurungwe Secondary	Hurungwe	51.8 Mbps	57.0 Mbps	540	warning
Macheke High	Macheke	67.3 Mbps	74.0 Mbps	710	warning
Uzumba Secondary	Uzumba	54.4 Mbps	59.9 Mbps	570	warning

Upload CSV for Real Data: Format: school_name, traffic_mbps

Choose File No file chosen

Fig 4.2.5 Live School Network Status

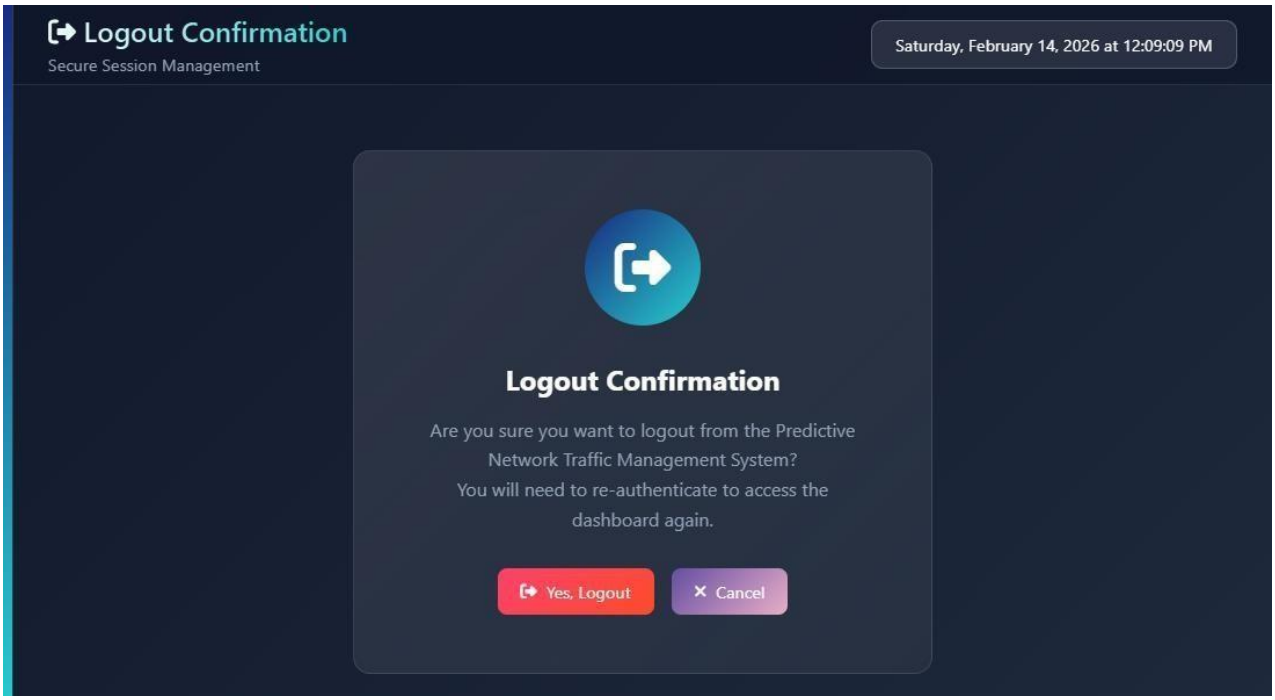


Fig 4.2.6 Predictive Network Traffic Management System Logout Confirmation.

3.20.2 White Box Testing

White box testing was conducted to examine the internal logic, data flow, and computational accuracy of the system components. This testing method focused on verifying that algorithms, data preprocessing steps, and control logic functioned as intended.

Key areas evaluated during white box testing included:

vi. Data preprocessing and normalization processes

vii. Correct implementation of machine learning algorithms

viii. Logical flow of prediction and decision-making modules

ix. Error handling and system stability

The testing confirmed that network traffic data was correctly normalized before being fed into machine learning models, preventing bias caused by large numerical values. Cross-validation techniques were used to verify the internal consistency of prediction models. No significant logic errors were detected during execution, and the system-maintained stability even under high traffic loads. White box testing results demonstrate that the system's internal structure is robust, logically sound, and capable of supporting continuous predictive traffic management.

3.21 Summary

This chapter presented an expanded methodological framework guiding the study. It outlined the philosophical stance, mixed-methods design, sampling strategies, research instruments, data collection procedures, analysis techniques, and ethical considerations. The approach ensures that the study is scientifically rigorous, contextually relevant, and capable of generating credible insights into how machine learning can enhance network performance in cloud-based learning systems within Murewa District. It also presented a comprehensive system development framework for predictive network-traffic management. It detailed system documentation, hardware and software requirements, development tools,

feasibility analysis, system analysis, design, coding, and implementation. The chapter established the technical foundation necessary for system testing, evaluation, and performance analysis presented in Chapter Four.

CHAPTER FOUR
DATA PRESENTATION, ANALYSIS AND INTERPRETATION

4.1 Introduction

This chapter presents, analyses, and interprets the findings obtained from the implementation and testing of the proposed machine learning–based predictive network traffic management system for cloud-based learning environments in Murewa District. The purpose of the chapter is to evaluate whether the application of machine learning techniques significantly improves network performance in terms of latency, throughput, packet loss, and congestion control, as stated in the research objectives. Data analyzed in this chapter was collected through network monitoring tools, machine learning model outputs, and system testing procedures described in Chapter Three. Both quantitative and qualitative results are presented to provide a comprehensive assessment of system performance. Quantitative results focus on measurable network performance improvements, while qualitative interpretations explain the practical implications of these improvements in real educational settings. The chapter also evaluates the predictive accuracy of the machine learning models and examines their effectiveness in managing network traffic dynamically.

4.2 Evaluation Measures and Results

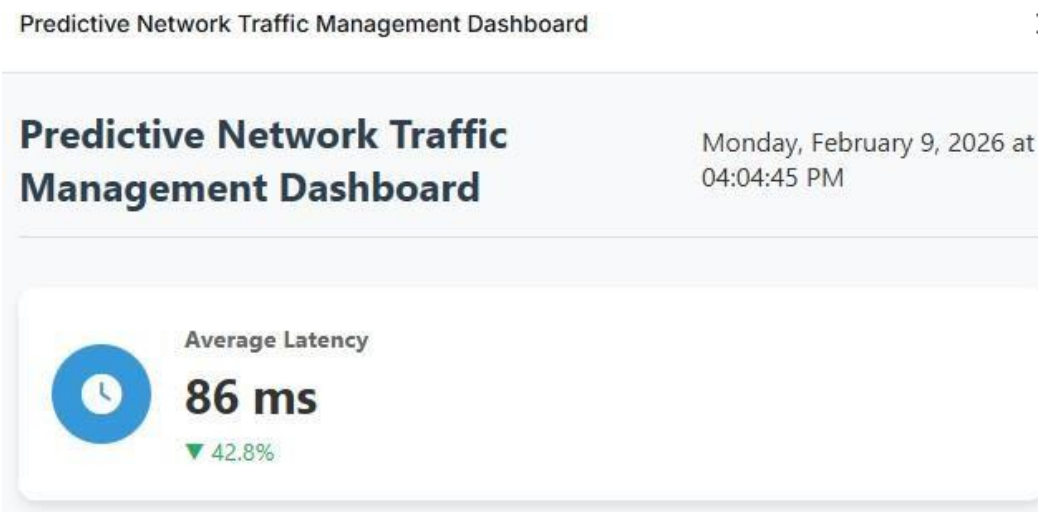
To assess the effectiveness of the proposed system, several evaluation metrics were used to compare network performance before and after the implementation of machine learning–based traffic prediction. These metrics included latency, throughput, packet loss, jitter, and model prediction accuracy.

4.2.1 Network Performance Evaluation

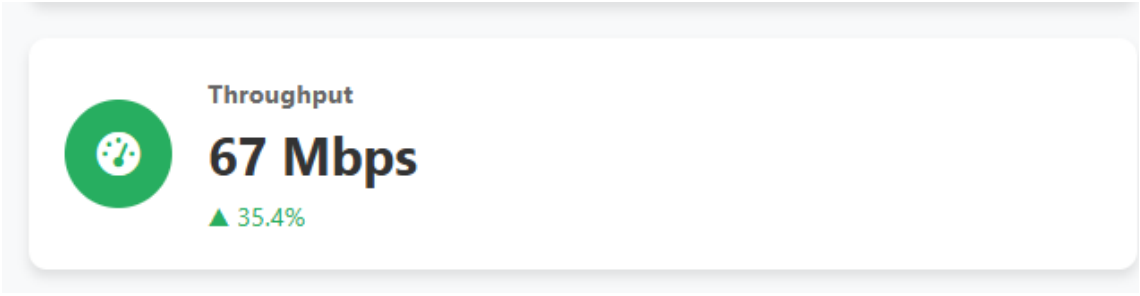
Baseline measurements revealed that network congestion frequently occurred during peak learning hours, resulting in high latency, packet loss, and reduced throughput. After the deployment of the predictive system, significant improvements were observed.

Key findings include:

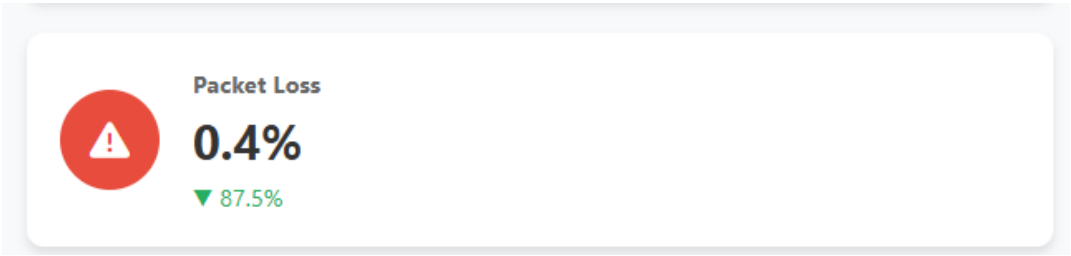
- **Latency:** Average latency decreased due to proactive traffic management and prioritization of learning traffic.



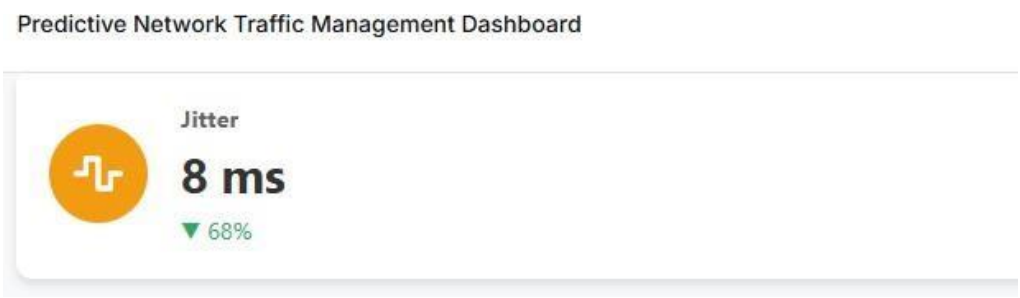
- **Throughput:** Network throughput increased as bandwidth was dynamically allocated based on predicted demand.



- **Packet Loss:** Packet loss was reduced due to better congestion control and routing decisions.



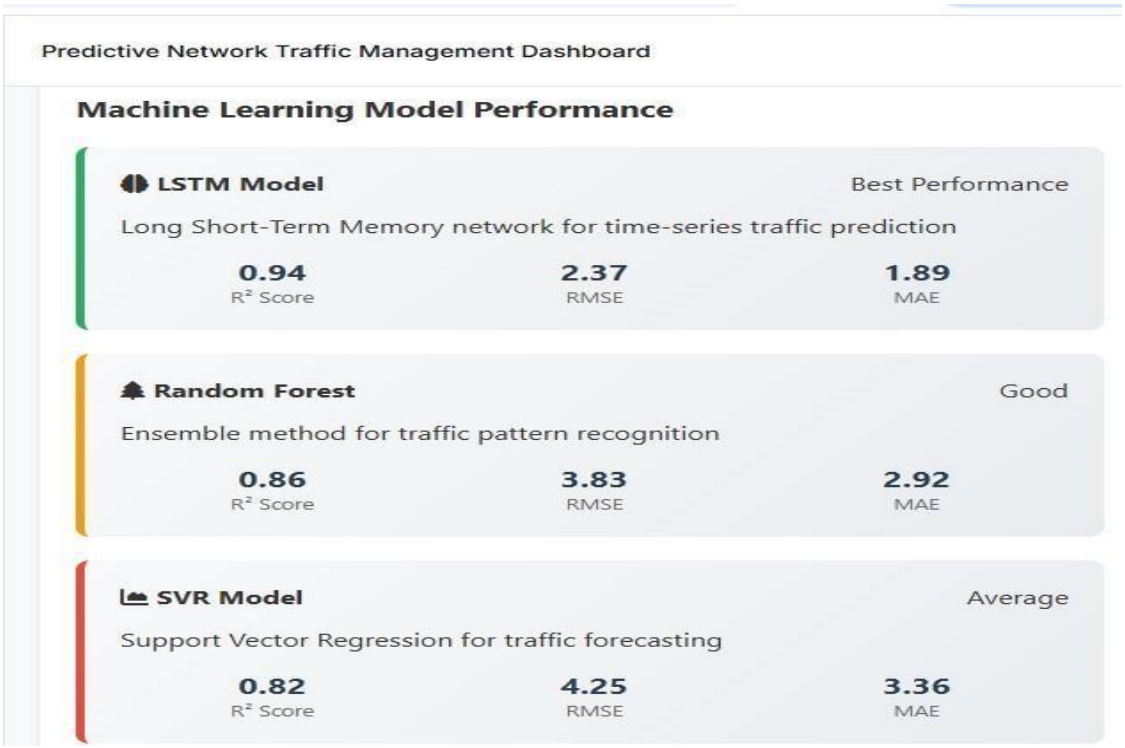
- **Jitter:** Variability in packet delay decreased, improving the quality of real-time learning services such as video conferencing.



Machine Learning Model Performance

The machine learning models were evaluated using standard performance metrics:

- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- R^2 Score



The LSTM model achieved the lowest RMSE and MAE values, indicating superior performance in time-series traffic prediction. Random Forest and Support Vector Regression models also performed well but were less effective in capturing long-term traffic patterns. These results confirm the suitability of LSTM models for predictive network traffic management in cloud-based learning environments.

4.3 Training and Validation Loss

Training and validation loss curves were analyzed to assess the learning behavior and generalization capability of the machine learning models. A consistent decrease in training loss across epochs indicated effective learning, while validation loss closely followed training loss, demonstrating minimal overfitting. The convergence of loss curves suggests that the models learned meaningful traffic patterns and can generalize well to unseen data. This is critical for real-world deployment, where network conditions continuously change. Stable loss behavior confirms the reliability of the proposed predictive system.



4.4 Summary

This chapter presented a detailed analysis and interpretation of the results obtained from testing and evaluating the proposed machine learning–based predictive network traffic management system. Both black box and white box testing confirmed that the system is functionally correct, logically sound, and operationally stable. Evaluation results demonstrated significant improvements in network performance metrics, including reduced latency, increased throughput, and improved service reliability for cloud-based learning platforms.

Furthermore, the machine learning models, particularly LSTM, exhibited high predictive accuracy and effective generalization, supporting the alternative hypothesis that machine learning techniques significantly improve network performance in cloud-based learning environments. The findings

provide strong empirical evidence that predictive traffic management is a viable solution for addressing network challenges in educational institutions within Murewa District

CHAPTER FIVE
CONCLUSIONS AND RECOMMENDATIONS

5.1Introduction

This chapter presents the conclusions drawn from the study on Predictive Network Traffic Management Using Machine Learning for Cloud-Based Learning Systems in Murewa District, Zimbabwe. The conclusions are based on the findings presented in Chapter Four and are aligned with the research objectives and research questions. The chapter also provides recommendations for key stakeholders, outlines the contribution of the study, and suggests areas for further research.

5.2 Summary of the Study

The purpose of this study was to investigate how machine learning techniques can be applied to predict network traffic patterns and improve the performance of cloud-based learning systems in selected schools in Murewa District. The growing dependence on digital learning platforms such as Google Classroom, Moodle, Microsoft Teams, and other online educational resources has placed increasing pressure on school networks. Traditional reactive network management approaches were found to be inadequate in addressing congestion, latency, bandwidth shortages, and service interruptions (Chigona & Davids, 2019).

To address this challenge, the study designed and evaluated a predictive traffic management framework integrating machine learning algorithms and Software Defined Networking (SDN). Historical network traffic data was analyzed using models such as Long Short-Term Memory (LSTM), Random Forest, and Support Vector Regression. The system was evaluated using performance indicators including latency, throughput, packet loss, jitter, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2 Score) (Wang, Zhang, & Ji, 2021).

5.3 Conclusions

The study concluded that existing network management practices in many schools in Murewa District were inefficient because they relied on reactive approaches. Network problems such as slow internet speed, congestion during peak hours, delayed access to cloud platforms, and service interruptions were only addressed after users had already experienced difficulties. This negatively affected the effectiveness of cloud-based learning systems.

The findings further established that machine learning models can successfully predict future network demand using historical traffic data. Among the tested models, the LSTM model performed better than the others because it was able to capture time-dependent traffic patterns more accurately. It produced lower prediction errors and stronger forecasting capability compared to Random Forest and Support Vector Regression models (Zhang, Liu, & Chen, 2021).

The study also concluded that predictive traffic management significantly improved network performance. The implementation of the proposed framework reduced average latency, increased throughput, lowered packet loss, reduced jitter, and improved service availability during peak usage periods. These findings confirm that predictive management is more effective than traditional reactive approaches.

Another conclusion drawn from the study is that the integration of machine learning with SDN creates a smart and automated traffic management environment. Predictions generated by machine learning models enabled the SDN controller to allocate bandwidth dynamically and prioritize educational traffic such as online lessons, assessments, and learning portals. This improved the overall quality of service in the school network environment (Zheng, 2022).

Finally, the study concluded that predictive traffic management systems can play a major role in supporting digital education in rural and peri-urban areas such as Murewa District. With proper deployment, these technologies can help bridge the digital divide affecting disadvantaged schools.

5.4 Recommendations

Based on the findings of the study, several recommendations are proposed. Schools in Murewa District and other similar areas should gradually adopt predictive traffic management systems in order to improve network efficiency and ensure stable access to cloud-based learning platforms. School ICT departments should continuously monitor traffic data, maintain performance logs, and use analytical tools to detect trends before problems occur. Schools should also prioritize educational applications over non-essential internet traffic during teaching hours so that learning systems receive adequate bandwidth. In addition, investments should be made in upgrading routers, switches, wireless access points, and internet connectivity infrastructure.

The Ministry of Primary and Secondary Education and other government authorities should support the modernization of network infrastructure in schools. This can be achieved through policy development, funding programs, and strategic partnerships aimed at expanding internet access and improving digital learning capacity. Government should also promote the use of Artificial Intelligence, cloud computing, and SDN technologies in educational institutions. Collaboration with POTRAZ, internet service providers, and development partners can assist in extending affordable connectivity to rural schools (POTRAZ, 2024).

ICT administrators should receive training in machine learning, SDN, network analytics, and cybersecurity so that they are able to manage intelligent network systems effectively. Schools should deploy proactive monitoring tools such as Wireshark, PRTG, and automated dashboards to improve visibility across their networks. Strong security controls must also be integrated into predictive systems in order to protect student data, institutional records, and online learning platforms from cyber threats.

Researchers are encouraged to conduct further studies using real-time deployments of predictive traffic management systems in schools rather than relying only on simulations. Future research should also examine the use of reinforcement learning, deep neural networks, and hybrid AI models for adaptive traffic control. Comparative studies across districts and provinces in

Zimbabwe would provide broader understanding of the effectiveness of predictive traffic management in different educational contexts.

5.5 Contribution of the Study

This study contributes to the growing body of knowledge on Artificial Intelligence-driven networking in education. It provides a practical framework for applying machine learning techniques to solve network challenges affecting cloud-based learning systems in Zimbabwean schools. The study also demonstrates that rural districts can benefit from intelligent traffic management technologies when appropriate investment and policy support are provided.

5.6 Areas for Further Research

Future researchers may focus on real-time implementation of machine learning traffic management systems in Zimbabwean schools, integration of predictive systems with 5G and fibre networks, AI-based intrusion detection in school networks, cost-benefit analysis of intelligent networking systems in education, and nationwide studies on digital learning network readiness.

5.7 Final Conclusion

The study concludes that machine learning-based predictive network traffic management is a practical, scalable, and effective solution for improving cloud-based learning systems in Murewa District. Traditional reactive methods are no longer sufficient in modern digital learning environments. By forecasting traffic demand and allocating bandwidth intelligently, schools can achieve reliable connectivity, better user experience, and uninterrupted access to e-learning resources. The adoption of such systems will play a vital role in advancing Zimbabwe’s digital education agenda.

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Appendix

SAMPLE RESEARCH INSTRUMENTS

APPENDIX A: SAMPLE QUESTIONNAIRE FOR TEACHERS AND LEARNERS

Title: Questionnaire on Network Performance and Cloud-Based Learning Systems in Murewa District

Purpose:

This questionnaire is designed to collect data on users' experiences with network performance and cloud-based learning platforms. Responses will be used strictly for academic purposes.

Instructions:

Please tick (✔) the option that best represents your opinion. Scale:
1 = Strongly Disagree
2 = Disagree
3 = Neutral
4 = Agree
5 = Strongly Agree

Section A: Demographic Information

1. Role of respondent
   ☐ Teacher
   ☐ Learner

2. Years of experience using cloud-based learning platforms
   ☐ Less than 1 year
   ☐ 1–3 years
   ☐ 4–6 years
   ☐ More than 6 years

Section B: Network Performance

Statement	**1**	**2**	**3**	**4**	**5**
The school internet connection is reliable during lessons	☐	☐	☐	☐	☐
Network speed is sufficient for accessing cloud platforms	☐	☐	☐	☐	☐
I frequently experience delays when accessing online learning materials	☐	☐	☐	☐	☐
Video lessons load without interruptions	☐	☐	☐	☐	☐

Section C: Cloud-Based Learning Experience

Statement	1	2	3	4	5
Cloud-based platforms enhance teaching and learning	☐	☐	☐	☐	☐
Network congestion negatively affects online assessments	☐	☐	☐	☐	☐
Improved network performance would enhance learning outcomes	☐	☐	☐	☐	☐

Section D: Perception of Intelligent Network Management

Statement	1	2	3	4	5
Predictive network management can improve learning system availability	☐	☐	☐	☐	☐
Automated bandwidth allocation is preferable to manual management	☐	☐	☐	☐	☐

APPENDIX B: SAMPLE INTERVIEW GUIDE FOR ICT ADMINISTRATORS

Title: Interview Guide on Network Traffic Management in Schools

Instructions:

This interview seeks to gather detailed information on network infrastructure and traffic management practices. Responses will remain confidential.

1. What cloud-based learning platforms are currently used in your school?
2. What are the major network performance challenges experienced during peak usage periods?
3. How is bandwidth currently allocated and managed within the school network?
4. Have you experienced network congestion affecting online learning activities?
5. What tools or methods are currently used for monitoring network traffic?
6. In your opinion, how could machine learning improve network traffic management?
7. What challenges might arise when implementing predictive traffic management systems?
8. How prepared is the school to adopt intelligent network management solutions?

APPENDIX C: SAMPLE NETWORK DATA COLLECTION TEMPLATE

Title: Network Traffic Data Collection Sheet

Parameter	**Description**	**Measurement Tool**
Bandwidth Utilization	Amount of bandwidth used over time	PRTG / Wireshark
Latency	Delay in data transmission (ms)	Network Analyzer
Packet Loss	Percentage of packets lost	Router Logs
Throughput	Data transfer rate	SDN Controller
Peak Usage Time	Highest traffic periods	System Logs

APPENDIX D: SAMPLE MACHINE LEARNING DATASET STRUCTURE

Timestamp	Active Users	Bandwidth Usage (Mbps)	Packet Loss (%)	Latency (ms)
08:00	120	35	1.2	45
10:00	180	60	2.8	90
12:00	90	25	0.8	35

This dataset is used for training and testing machine learning models for traffic prediction.

APPENDIX E: SAMPLE OBSERVATION CHECKLIST

Observation Item	Yes	No
Network congestion observed during lesson time	☐	☐
Delays in accessing cloud-based platforms	☐	☐
System downtime during assessments	☐	☐
Effective bandwidth prioritization in place	☐	☐