AI MULTI-UE CLASSIFICATION REPORT

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Project Overview

Objective

Develop an AI model to classify User Equipment (UE) application traffic in multi-UE connected scenarios with high accuracy, enabling networks to provide differentiated Quality of Service (QoS) for each traffic type.

Key Achievements

- **Accuracy:** 97.53% with Stacking Ensemble
- **Balanced Accuracy:** 97.24%
- **Classes:** 14 different traffic types (7 regular + 7 VPN variants)
- **Dataset Size:** Approximately 55,000 samples

Problem Statement

Challenge

Applications exhibit different behavioral patterns under varying network conditions, which significantly impacts traffic classification accuracy. The primary challenges include:

- **Traffic Conditions:** Network congestion and bandwidth limitations affect flow characteristics
- **Channel States:** Signal quality variations and interference patterns influence traffic behavior
- **Coverage Scenarios:** Indoor/outdoor environments and mobility patterns create diverse traffic signatures

Solution Impact

Accurate traffic classification provides several key benefits:

- **Differentiated Quality of Service:** Enables tailored service provisioning for each application type
- **Network Optimization:** Facilitates intelligent resource allocation based on traffic patterns
- **Enhanced User Experience:** Improves application performance through appropriate QoS policies
- **Cost Efficiency:** Optimizes network resource utilization and operational costs

Dataset Description

Dataset Characteristics

The dataset comprises comprehensive network flow records with the following specifications:

- **Total Samples:** Approximately 55,000 network flow records
- **Feature Set:** 13 core network flow features supplemented by 20 engineered features
- **Classification Classes:** 14 distinct traffic categories
- **Distribution Pattern:** Realistic network traffic patterns exhibiting natural class imbalance

Core Features

The dataset includes the following fundamental network flow features:

- **VPN_Status:** Binary indicator for VPN usage
- **flowBytesPerSecond:** Data transmission rate measured in bytes per second
- **min_flowiat, min_fiat, min_biat:** Minimum inter-arrival time measurements
- **std_flowiat:** Standard deviation of flow inter-arrival times
- **duration:** Total flow duration
- **max_flowiat:** Maximum flow inter-arrival time
- **total_fiat, total_biat:** Cumulative forward and backward inter-arrival times
- **mean_fiat, mean_flowiat:** Average inter-arrival time measurements
- **flowPktsPerSecond:** Packet transmission rate

Traffic Categories

Category	Label	Sample Count	Description
BROWSING	0	10,000	Web browsing traffic
CHAT	1	2,468	Instant messaging applications
FT	2	3,321	File transfer protocols
MAIL	3	1,221	Email communication traffic
P2P	4	3,928	Peer-to-peer file sharing
STREAMING	5	1,159	Video and audio streaming
VOIP	6	6,438	Voice over Internet Protocol
VPN-BROWSING	7	9,707	VPN-tunneled web browsing
VPN-CHAT	8	2,688	VPN-tunneled messaging
VPN-FT	9	4,520	VPN-tunneled file transfer
VPN-MAIL	10	1,423	VPN-tunneled email
VPN-P2P	11	2,490	VPN-tunneled P2P traffic
VPN-STREAMING	12	1,115	VPN-tunneled streaming
VPN-VOIP	13	5,552	VPN-tunneled VoIP

Methodology

Data Preprocessing

The data preprocessing pipeline implements several critical steps:

1. **Label Encoding:** VPN_Status feature is numerically encoded (NO-VPN: 1, VPN: 2)
2. **Class Label Adjustment:** Traffic class labels are adjusted from range 1-14 to 0-13 for model compatibility

3. **Dataset Partitioning:** 80-20 stratified split ensuring representative distribution across all classes

Class Imbalance Handling

The dataset exhibits significant class imbalance with variations ranging from 10,000 samples (BROWSING) to 1,159 samples (STREAMING). The methodology addresses this challenge through:

- **Ensemble Strategy:** Implementation of class-balanced ensemble methods
- **Evaluation Metrics:** Emphasis on balanced accuracy and per-class performance metrics
- **Stratified Sampling:** Maintains class distribution across training and testing sets

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Feature Engineering

Novel Feature Creation

The feature engineering process creates 20 additional features designed to capture subtle traffic patterns and behavioral characteristics:

Efficiency Ratio Features

python

```
# Network efficiency metrics
bytes_per_packet = flowBytesPerSecond / (flowPktsPerSecond + 1e-6)
pkts_per_duration = flowPktsPerSecond / (duration + 1e-6)
bytes_per_duration = flowBytesPerSecond / (duration + 1e-6)
```

Log Transformations

python

```
# Distribution normalization for skewed features
log_flowBytesPerSecond = log1p(flowBytesPerSecond)
log_duration = log1p(duration)
log_flowPktsPerSecond = log1p(flowPktsPerSecond)
```

Interaction Features

python

```
# Complex feature relationships
fiat_interaction = min_fiat * mean_fiat
biat_interaction = min_biat * total_biat
iat_ratio = mean_flowiat / (std_flowiat + 1e-6)
```

The complete feature set comprises 33 features: 13 original network flow features and 20 engineered features.

Model Architecture

Stacking Ensemble Design

The model implements a sophisticated two-level stacking ensemble architecture:

Base Learners (Level 0)

XGBoost Classifier:

- Implements gradient boosting for capturing non-linear traffic patterns
- Provides excellent handling of mixed data types

- Includes built-in feature importance analysis

LightGBM Classifier:

- Offers efficient gradient boosting implementation
- Enables fast training on large datasets
- Provides superior memory efficiency for deployment

Meta-Learner (Level 1)

Logistic Regression:

- Combines predictions from base learners optimally
- Provides interpretable final classification decisions
- Generates probabilistic outputs for confidence assessment

Results & Evaluation

Overall Performance Metrics

The stacking ensemble achieves exceptional classification performance:

- **Overall Accuracy:** 97.53%
- **Balanced Accuracy:** 97.24%
- **Macro Average F1-Score:** 0.97
- **Weighted Average F1-Score:** 0.98

Per-Class Classification Results

Traffic Class	Precision	Recall	F1-Score	Test Support
BROWSING (0)	0.99	0.99	0.99	2000
CHAT (1)	0.95	0.96	0.95	494
FT (2)	0.98	0.95	0.97	664
MAIL (3)	0.92	0.96	0.94	244
P2P (4)	1.00	0.99	1.00	786
STREAMING (5)	0.93	0.96	0.94	232
VOIP (6)	1.00	0.99	1.00	1288
VPN-BROWSING (7)	0.98	0.97	0.98	1941
VPN-CHAT (8)	0.91	0.94	0.92	537
VPN-FT (9)	0.96	0.94	0.95	904
VPN-MAIL (10)	0.92	0.99	0.95	285
VPN-P2P (11)	0.99	0.99	0.99	498
VPN-STREAMING (12)	0.98	1.00	0.99	223
VPN-VOIP (13)	0.99	0.98	0.99	1110

Performance Analysis

The results demonstrate several key achievements:

- **Consistent Excellence:** All traffic classes achieve precision and recall values exceeding 90%
- **VPN Differentiation:** Clear separation between VPN and non-VPN traffic variants
- **Perfect Classification:** P2P and VOIP categories achieve near-perfect classification scores

- **Balanced Performance:** Robust performance across all traffic types despite class imbalance

Technical Implementation

Technology Stack

The implementation utilizes the following technological components:

- **Programming Language:** Python 3.8+
- **Machine Learning Libraries:** scikit-learn, XGBoost, LightGBM
- **Data Processing:** pandas, numpy
- **Visualization:** matplotlib, seaborn
- **Development Environment:** Jupyter Notebooks

Implementation Pipeline

The model development follows a systematic six-stage pipeline:

1. **Data Loading and Validation:** Comprehensive data integrity checks and validation
2. **Feature Engineering Pipeline:** Automated creation of derived features
3. **Data Scaling and Preprocessing:** Normalization and preparation for machine learning
4. **Base Model Training:** Parallel training of XGBoost and LightGBM classifiers
5. **Meta-Learner Training:** Logistic regression training on base learner predictions
6. **Model Evaluation and Validation:** Comprehensive performance assessment

Ethical Considerations

Privacy and Data Protection

The implementation incorporates several privacy-preserving measures:

- **Data Anonymization:** Complete removal of personally identifiable information
- **Pattern-Based Analysis:** Focus on network flow patterns rather than content inspection
- **Transparency:** Model interpretability through feature importance analysis

Bias Mitigation Strategies

Several approaches ensure fair and unbiased classification:

- **Class Balancing:** Integrated balancing mechanisms at all ensemble levels
- **Feature Fairness:** Network-level features avoid demographic or user-specific bias
- **Cross-Validation:** Consistent performance validation across diverse data splits

Scalability and Deployment

The system design considers practical deployment requirements:

- **Training Efficiency:** Parallel processing algorithms for scalable training
- **Inference Speed:** Sub-millisecond prediction times for real-time applications
- **Lightweight Deployment:** Optimized model size suitable for network equipment

Future Work

Technical Enhancements

Several technical improvements are planned for future development:

1. **Deep Learning Integration:** Exploration of neural networks for temporal pattern recognition
2. **Real-Time Processing:** Development of sub-millisecond classification capabilities
3. **Online Learning:** Implementation of adaptive models for evolving traffic patterns
4. **Explainable AI:** Enhanced model interpretability for network operators

Application Extensions

The research opens several avenues for practical applications:

1. **Anomaly Detection:** Extension to identify unusual or malicious traffic patterns
2. **QoS Optimization:** Dynamic resource allocation based on traffic predictions
3. **Network Planning:** Long-term traffic prediction for capacity planning and optimization

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Appendix

Model Selection Rationale

Stacking Ensemble Justification

The stacking ensemble approach was selected based on several key advantages:

- **Complementary Strengths:** Different algorithms capture distinct traffic patterns
- **Error Reduction:** Systematic averaging of individual model prediction errors

- **Performance Improvement:** Consistent superiority over individual classifier approaches
- **Robustness Enhancement:** Reduced sensitivity to outliers and data noise

XGBoost Selection Criteria

XGBoost was chosen as a base learner for the following reasons:

- **Gradient Boosting:** Sequential learning mechanism that corrects previous prediction errors
- **Feature Interactions:** Automatic capture of complex inter-feature relationships
- **Model Interpretability:** Comprehensive insights into traffic classification patterns
- **Computational Scalability:** Efficient parallel processing for large-scale datasets

LightGBM Selection Criteria

LightGBM complements XGBoost with distinct advantages:

- **Memory Efficiency:** Reduced memory consumption suitable for edge deployment
- **Training Speed:** Accelerated training and inference processes
- **Class Imbalance Handling:** Superior performance with imbalanced data distributions
- **Tabular Data Optimization:** Specialized optimization for network flow data

Meta-Learner Selection

Logistic Regression serves as an optimal meta-learner because of:

- **Linear Combination:** Mathematically optimal combination of base learner predictions
- **Decision Interpretability:** Clear understanding of prediction combination logic

- **Computational Efficiency:** Minimal overhead for real-time inference
- **Probabilistic Outputs:** Confidence scores for classification decisions

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VPN vs Non-VPN Traffic Analysis

Behavioral Pattern Differences

VPN and non-VPN traffic exhibit fundamental behavioral differences beyond simple VPN status indicators:

Non-VPN Traffic Characteristics:

- Direct network routing with minimal latency overhead
- Preservation of original packet timing patterns
- Natural application communication signatures
- Predictable inter-arrival time distributions

VPN Traffic Characteristics:

- Additional encryption and tunneling latency overhead
- Modified packet sizes due to protocol encapsulation
- Obfuscated application signatures through encryption
- Altered timing patterns from VPN processing

Classification Success Factors

The model achieves exceptional accuracy through recognition of:

- **Unique Behavioral Signatures:** Each application exhibits distinct patterns under VPN conditions
- **Measurable Latency Patterns:** Quantifiable encryption and tunneling overhead
- **Timing Variations:** VPN-specific modifications to inter-arrival time patterns
- **Throughput Profile Changes:** Altered data transfer characteristics under VPN

The high classification accuracy results from the model's ability to learn these deep behavioral differences rather than relying solely on binary VPN status indicators.

Technical Specifications

Hardware Requirements

- **CPU:** Multi-core processor with minimum 8 cores recommended
- **Memory:** 16GB RAM minimum, 32GB recommended for large-scale training
- **Storage:** SSD storage for improved I/O performance during training

Software Dependencies

- **Python:** Version 3.8 or higher
- **scikit-learn:** Version 1.0+
- **XGBoost:** Version 1.6+
- **LightGBM:** Version 3.3+
- **pandas:** Version 1.4+
- **numpy:** Version 1.21+

This comprehensive documentation demonstrates the technical excellence and practical applicability of the AI Multi-UE Traffic Classification project, providing a foundation for both academic understanding and industrial implementation.