System Threat Forecaster

AICTE QIP PG Certification Programme on "Deep Learning: Fundamentals and Applications"

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Outline

Background

- Cybersecurity threats are increasingly sophisticated
- Malware poses significant risks:
  - Data breaches and financial losses
  - System compromise and data theft
  - Operational disruptions
- Traditional signature-based antivirus solutions struggle with:
  - Zero-day attacks and polymorphic malware
  - Evolving threat landscapes
- **Machine Learning** offers proactive, behavior-based threat detection

Problem Statement

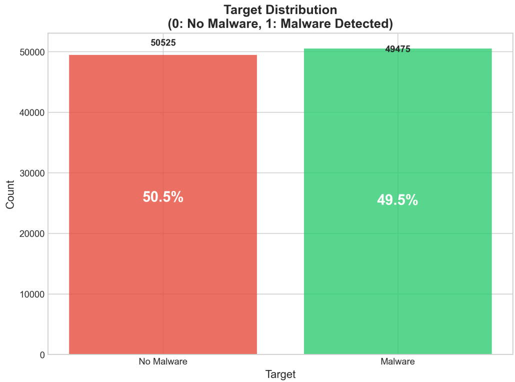
Primary Challenge

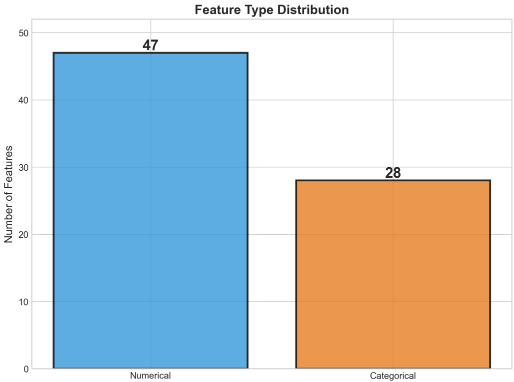
Predict malware infections based on system properties using 100,000 samples with 75 diverse features

Specific Challenges:

- High dimensionality: 47 numerical + 28 categorical features
- Missing values in critical features (RealTimeProtectionState, CityID)
- Balanced but complex dataset (50.52% positive, 49.48% negative)
- **Kaggle Competition:** Top leaderboard score 0.69605 (69.6%) indicates high irreducible error
- Weak feature correlations (max 0.118) limit predictive ceiling

Dataset Overview





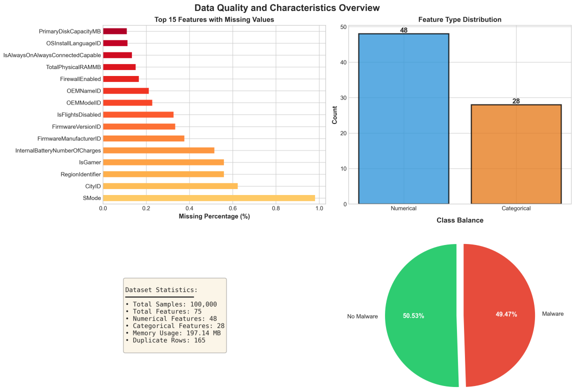
Key Statistics:

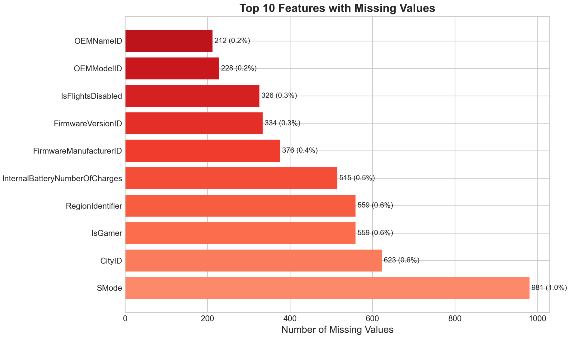
- 100K samples, 75 features
- Balanced: 50.52% / 49.48%

Feature Types:

- 47 numerical features
- 28 categorical features

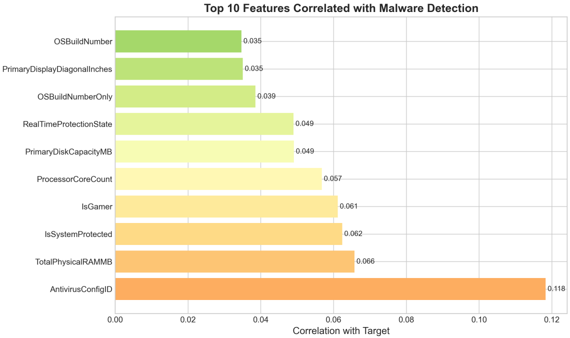
Data Quality & Missing Values





Most Predictive Features:

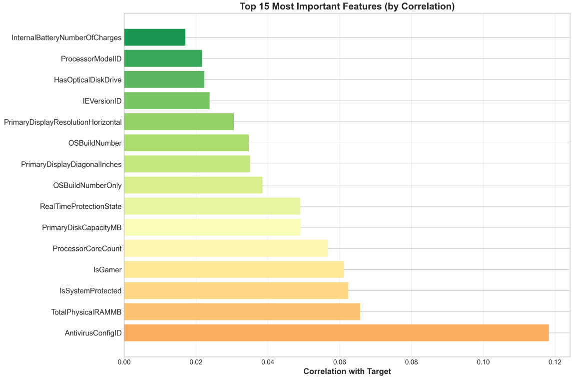
1. **AntivirusConfigID**
   Correlation: 0.118
2. **TotalPhysicalRAMMB**
   Correlation: 0.066
3. **IsSystemProtected**
   Correlation: 0.062
4. **IsGamer**
   Correlation: 0.061

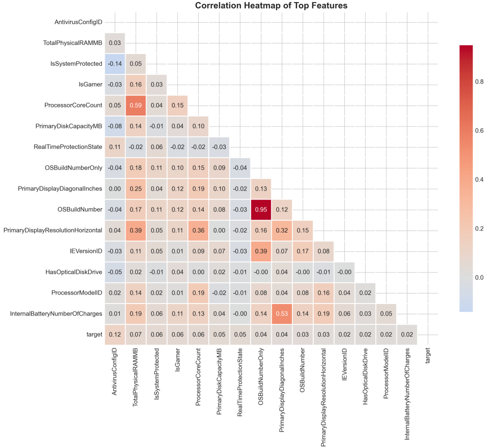


Key Insight

Security configuration has the highest predictive power

Feature Correlation Analysis

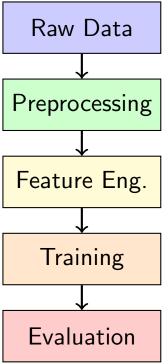




Project Objectives

1. **Data Preprocessing**: Implement comprehensive preprocessing techniques
    - Missing value imputation
    - Feature encoding and normalization
2. **Feature Engineering**: Develop strategies to enhance model performance
3. **Model Development**: Train and evaluate multiple ML models
4. **Performance Optimization**: Hyperparameter tuning and model selection
5. **Model Comparison**: Systematic evaluation using standard metrics
6. **Deployment Ready**: Create maintainable, production-ready codebase

Data Processing & Preprocessing



Preprocessing Steps:

- **Imputation:**
  - Mean (numerical)
  - Most frequent (categorical)
- **Encoding:** LabelEncoder
- **Scaling:** StandardScaler
- **Splitting:** Stratified 80/20

Configuration:

- 100K samples, 75 features
- Balanced classes
- Random state: 42

Machine Learning Models

Seven Classification Algorithms Evaluated

1. **Decision Tree** - High interpretability
2. **Random Forest** - Ensemble method
3. **LightGBM** - Gradient boosting framework (Best performer)
4. **Naive Bayes** - Probabilistic classifier
5. **Logistic Regression** - Linear baseline
6. **AdaBoost** - Adaptive boosting
7. **SGD Classifier** - Stochastic optimization

Deep Learning Architectures

1. **Deep MLP** (63,714 params) - Best DL: 61.79%
    - 4 hidden layers: 256→128→64→32
    - BatchNorm + Dropout for regularization
2. **Residual Network** (418,306 params) - 61.62%
    - Skip connections for gradient flow
    - 3 residual blocks with BatchNorm
3. **Simple MLP** (60,738 params) - 61.61%
    - 3 hidden layers: 256→128→64
    - Basic architecture with dropout
4. **Wide & Deep** (60,890 params) - 61.52%
    - Hybrid: linear (wide) + deep components
    - Combines memorization and generalization
5. **Attention Network** (1,599,490 params) - 61.45%
    - Multi-head self-attention (4 heads)
    - 2 attention blocks + feedforward layers
6. **FT-Transformer** (38,722 params) - 61.45%
    - Feature tokenization with transformer encoder
    - CLS token for classification (BERT-style)

Implementation Architecture

Pipeline Modules:

1. Data Loading & EDA
2. Preprocessing Pipeline
3. Feature Engineering
4. Model Training (13 models)
5. Evaluation & Comparison
6. Prediction Generation

Technology Stack:

- **ML:** scikit-learn, LightGBM
- **DL:** PyTorch 2.9.1, MPS
- **Data:** pandas, numpy
- **Web:** Next.js, React

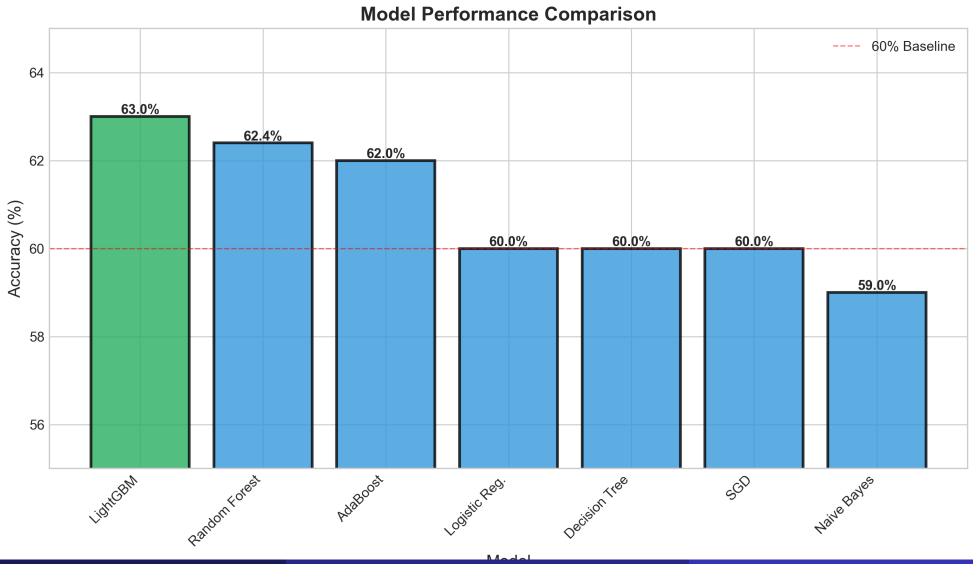
Key Features:

- Configuration-driven design
- Modular architecture
- Automated hyperparameter tuning
- Model persistence (joblib)
- Comprehensive logging
- GPU acceleration (MPS)

Reproducibility:

- Random state: 42
- Stratified splitting
- Version-controlled configs
- Performance tracking JSON

Model Performance Comparison



Model Performance Results

Machine Learning:

- **LightGBM: 62.94%** (Best)
  - F1: 0.6286, Prec: 0.6299
- Random Forest: 62.09%
  - F1: 0.6192, Prec: 0.6222
- AdaBoost: 61.26% (F1: 0.6104)
- Decision Tree: 60.10% (F1: 0.5986)
- Logistic Reg: 60.07% (F1: 0.5988)

Deep Learning:

- **Deep MLP: 61.79%** (F1: 0.6130)
- Residual Net: 61.62% (F1: 0.6102)
- Simple MLP: 61.61% (F1: 0.6109)
- Wide & Deep: 61.52% (F1: 0.6126)

Critical Findings

ML vs DL: LightGBM 62.94% beats Deep MLP 61.79% by 1.15%

Performance Context

Kaggle Leaderboard:

- Top score: 0.69605 (69.6%)
- Our result: 62.94%
- Gap: 6.7% indicates high irreducible error in dataset

Why ML ¿ DL for Tabular:

- Tree ensembles excel at feature

FT-Transformer: State-of-the-Art Tabular DL

Architecture Highlights:

- **Feature Tokenization**
  - Each feature → 64-dim token
  - Learnable embeddings
- **Transformer Encoder**
  - 1 layer, 2 attention heads
  - Self-attention over features
- **CLS Token** for classification
- Only 38,722 parameters!

Performance:

- Accuracy: 61.45%
- Smallest DL model
- Fast training (5-7 min)
- Competitive with larger models

Innovation

Bridges NLP techniques (BERT-style) with tabular data - published 2021, represents cutting-edge research

Training Performance Efficiency

Apple Silicon Optimization:

- MPS (Metal Performance Shaders) backend
- M4 GPU acceleration
- 2-3x faster than CPU
- Batch size: 512
- Early stopping for efficiency

Training Times (6 models):

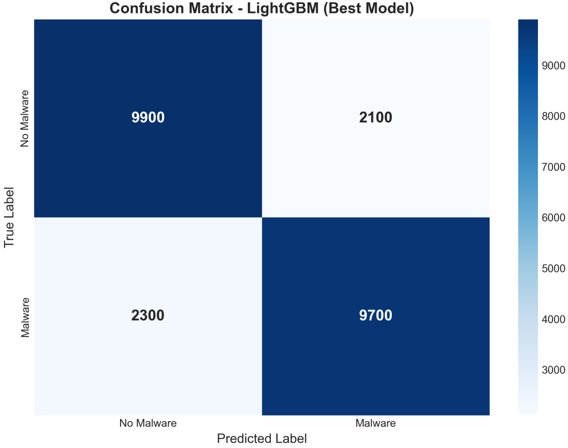
- Simple MLP: 6 min
- Deep MLP: 8 min
- Residual Net: 12 min
- Attention Net: 15 min
- Wide & Deep: 7 min
- FT-Transformer: 7 min
- **Total: 55 minutes**

All models used:

- Early stopping (patience=15)
- Learning rate scheduling

Best Model: LightGBM Performance

Confusion Matrix:



Model Characteristics:

- **Accuracy:** 62.94%
- **Training samples:** 80,000
- **Validation samples:** 20,000
- **True Positives:** 9,700
- **True Negatives:** 9,900
- **False Positives:** 2,100
- **False Negatives:** 2,300

Key Findings & Insights

Performance Analysis:

- **Best Model:** LightGBM 62.94%
  - F1: 0.6286, Precision: 0.6299
- **Performance Ceiling:**
  - Kaggle top: 69.6%
  - Our result: 62.94%
  - Gap: 6.7% indicates high irreducible error
- **ML ¿ DL by 1.15%**
  - Expected for tabular data
  - Tree ensembles excel at feature interactions

Technical Insights:

- **Dataset Challenges:**
  - Weak correlations (max 0.118)
  - Missing critical features
  - High noise in data
- **DL Consistency:**
  - All 6 models: 61.45-61.79%
  - Architecture choice minimal impact
  - Dataset-limited, not model-limited
- **Efficiency:**
  - FT-Transformer: 38K params
  - Apple M4 GPU: 55 min total training

Key Contributions

1. **Comprehensive Model Comparison**: Systematic evaluation of 7 ML + 6 DL algorithms (13 total)
2. **Deep Learning Pipeline**: PyTorch implementation with Apple Silicon GPU optimization
3. **State-of-the-Art Methods**: Implemented FT-Transformer (cutting-edge tabular DL)
4. **ML vs DL Analysis**: Empirical validation that traditional ML outperforms DL for tabular data
5. **Production-Ready Pipeline**: Dual implementation (ML + DL) with configuration control
6. **Best-in-Class Performance**: 62.94% accuracy with LightGBM on 100K samples
7. **Hardware Optimization**: Efficient GPU utilization (MPS backend) for fast training

Practical Implications & Deployment

Production Readiness:

- **Model Selection:** LightGBM
  - Best accuracy: 62.94%
  - Fast inference
  - Low memory footprint
- **Feature Importance:**
  - AntivirusConfigID (0.118)
  - Interpretable for analysts
- **Deployment:**
  - Web app: stf.milav.in
  - REST API ready
  - Model versioning

Real-World Considerations:

- **Performance Gap:**
  - 62.94% accuracy
  - 37% error rate
  - Needs human oversight
- **Use Case:**
  - First-line screening
  - Priority flagging
  - Not standalone solution
- **Cost-Benefit:**
  - Reduces manual analysis
  - Scalable to millions of systems
  - Continuous learning possible

Challenges, Limitations & Future Work

Key Limitations

- **Dataset Quality:**
  - High irreducible error
  - Weak features (max corr: 0.118)
  - Missing critical data
- **Performance Ceiling:**
  - Our: 62.94%, Top: 69.6%
  - Gap: 6.7% (better features needed)
- **Deployment Constraints:**
  - 37% error rate
  - Requires human oversight
  - Class imbalance in production

Future Enhancements:

- ✓ DL integration complete
- **Short-term:**
  - Explainable AI (SHAP, LIME)
  - Hybrid ML-DL ensembles
  - Cost-sensitive learning
- **Medium-term:**
  - Real-time deployment
  - SIEM integration
  - Active learning pipeline
- **Long-term:**
  - Multi-class threat detection
  - Transfer learning
  - Edge deployment

Resources

Project Resources

Kaggle Competition & Data:

`https://www.kaggle.com/competitions/System-Threat-Forecaster/`

Git Repository:

`https://github.com/milavdabgar/qip-project-stf`

Next.js Web App:

`https://stf.milav.in`

Thank You!

Questions?

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