System Threat Forecaster

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

Milav Jayeshkumar Dabgar

Department of Electronics Engineering
Sardar Vallabhbhai National Institute of Technology, Surat

December 2025

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 76 diverse features

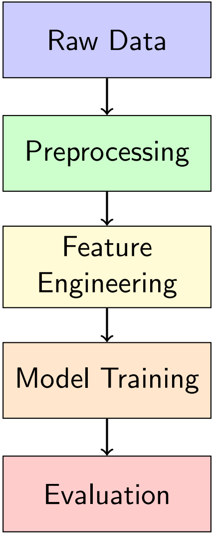
Specific Challenges:

- High dimensionality: 48 numerical + 28 categorical features
- Missing values in critical features (RealTimeProtectionState, CityID)
- Balanced but complex dataset (50.52% positive, 49.48% negative)
- Need for efficient and accurate classification

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 Pipeline



Dataset Characteristics

Dataset Overview:

- **Size:** 100,000 samples
- **Features:** 76 total
  - 48 numerical
  - 28 categorical
- **Split:** 80% train, 20% validation

Preprocessing Pipeline:

- Missing values:
  - Mean for numerical
  - Most frequent for categorical
- Label Encoding for categoricals
- StandardScaler normalization
- Stratified splitting

Machine Learning Models

Seven Classification Algorithms Evaluated

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

Key Features Analysis

Most Predictive Features (Correlation with Target):

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

Feature Engineering Configuration:

- Interaction terms available (currently disabled)
- SelectKBest with f_classif (top 30 features)
- Optional PCA for dimensionality reduction

Key Insight

Security configuration and system specifications show moderate but consistent predictive power

Model Performance Comparison

Model	Accuracy	Rank
LightGBM	**63.0%**	**1st**
Random Forest	62.4%	2nd
AdaBoost	62.0%	3rd
Logistic Regression	∼60%	4th
Decision Tree	∼60%	5th
SGD Classifier	∼60%	6th
Naive Bayes	¡60%	7th

Key Observation

LightGBM achieved the highest accuracy at **63.0%**, showing gradient boosting's superiority for this complex classification task

Note: Ensemble methods (Random Forest, AdaBoost) outperformed traditional classifiers

Key Findings

- **Model Performance**: 63% accuracy ceiling suggests complex relationships
  - Moderate feature correlations (max 0.118)
  - Room for feature engineering improvements
- **Ensemble Superiority**: Tree-based ensembles (LightGBM, RF, AdaBoost) outperformed linear models
- **Dataset Challenges**:
  - Missing data in important features
  - Balanced classes but complex decision boundaries
- **Feature Insights**: Security configurations more predictive than hardware specs

Implementation Highlights

Architecture Strengths:

- Configuration-driven pipeline
- Modular design pattern
- 7 ML models implemented
- Automated hyperparameter tuning
- Model persistence with joblib

Pipeline Features:

- Robust preprocessing
- Missing value handling
- Feature engineering tools
- Cross-validation support
- Comprehensive logging
- Results tracking

System Architecture

13-Module Pipeline Structure:

1. Environment Setup & Configuration
2. Data Loading & Utilities (save/load models)
3. Exploratory Data Analysis (EDA)
4. Data Preprocessing (imputation, encoding, scaling)
5. Feature Engineering (interactions, selection)
6. Model Training (7 algorithms with tuning)
7. Model Evaluation & Comparison
8. Prediction & Submission Generation

Technology Stack:

- Python 3.x, scikit-learn 1.3+, LightGBM
- pandas, numpy, matplotlib, seaborn, joblib

Code Organization

Configuration-Driven Design

Selective enabling/disabling of:

- Preprocessing steps
- Feature engineering techniques
- Model selection
- Hyperparameter tuning

Benefits:

- Easy experimentation
- Maintainable codebase
- Model persistence and logging
- Reproducible results

Key Contributions

1. **Comprehensive Model Comparison**: Systematic evaluation of 7 classification algorithms
2. **Production-Ready Pipeline**: 13-module architecture with configuration control
3. **Robust Preprocessing**: Handles 76 features (48 numerical, 28 categorical)
4. **Automated Workflows**: Hyperparameter tuning, cross-validation, model persistence
5. **Best-in-Class Performance**: 63% accuracy with LightGBM on 100K samples
6. **Reproducible Results**: Complete logging and results tracking system

Practical Implications

- **Early Threat Detection**: Proactive malware identification
- **Scalability**: Efficient algorithms for large-scale deployment
- **Interpretability**: Feature importance for analyst understanding
- **Flexibility**: Multiple models for different requirements
- **Cost-Effectiveness**: Automated detection reduces manual effort

Future Work

Technical Enhancements:

- Deep learning integration
- Real-time deployment
- Ensemble methods
- Explainable AI (SHAP, LIME)
- Active learning

Practical Extensions:

- Multi-class classification
- SIEM integration
- Adversarial robustness
- Transfer learning
- Automated feature engineering

Challenges & Limitations

Key Challenges Identified

- **Performance Ceiling**: 63% accuracy indicates complex relationships
- **Feature Correlations**: Weak correlations (max 0.118) limit predictive power
- **Missing Data**: RealTimeProtectionState, CityID have significant gaps
- **Feature Engineering**: Currently disabled, potential for improvement
- **Model Complexity**: Balance between accuracy and interpretability

Future Improvements:

- Enable and optimize feature engineering
- Advanced imputation strategies
- Deep learning exploration

Resources

Project Resources

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

Implementation Notebook:
https://www.kaggle.com/code/milavdabgar/system-threat-forecaster-modular

Technologies: Python 3.11, scikit-learn, LightGBM, pandas, numpy, matplotlib

Thank You!

Questions?

Milav Jayeshkumar Dabgar
Government Polytechnic Palanpur
Department of Computer Engineering