System Threat Forecaster

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

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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

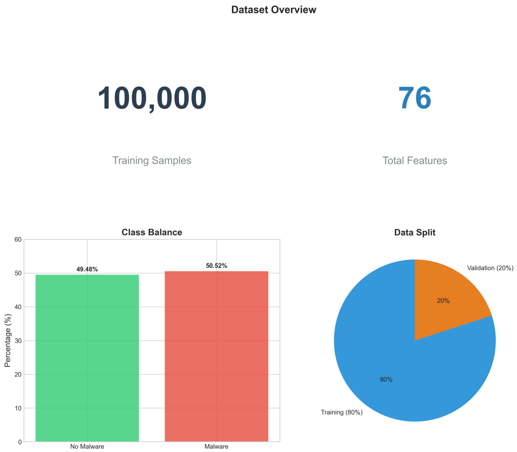
Primary Challenge

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

Dataset Overview



Dataset Overview

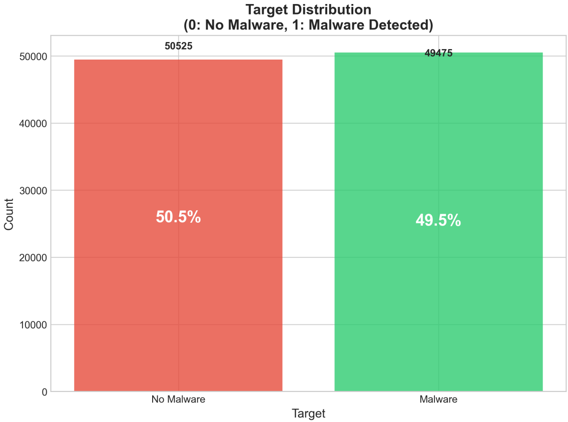
100,000

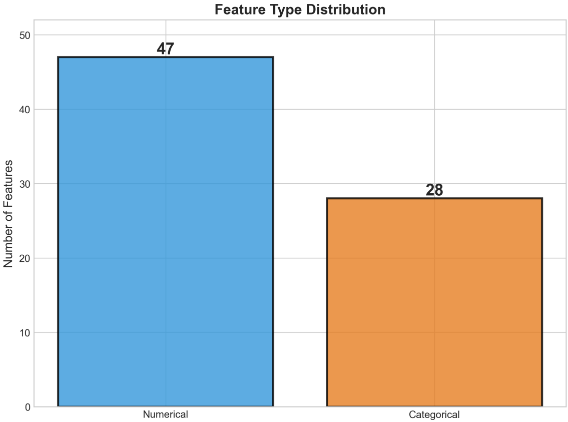
Training Samples

76

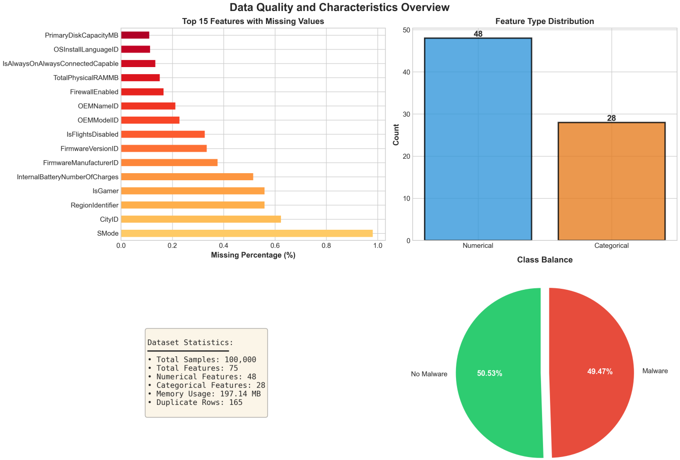
Total Features

Dataset Characteristics





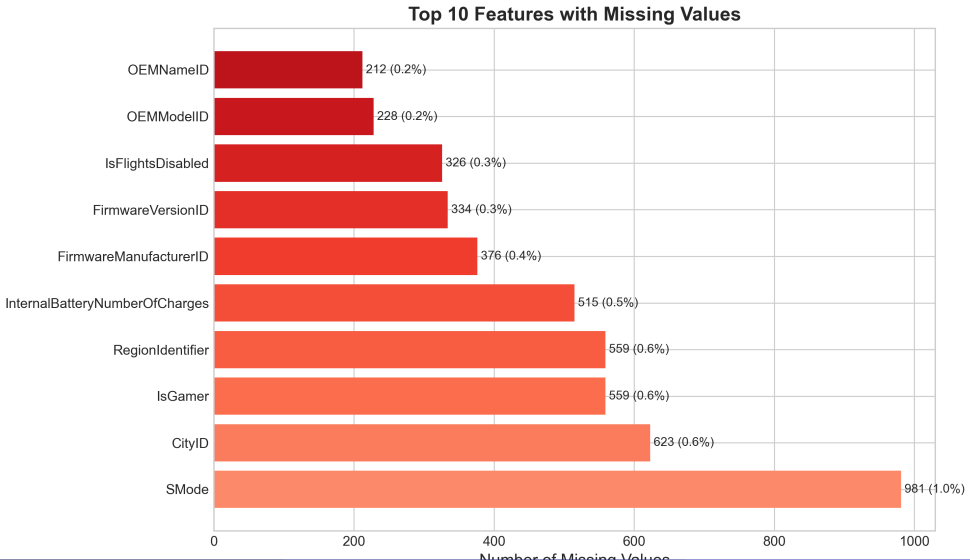
Data Quality Overview



Dataset Statistics:

- Total Samples: 100,000
- Total Features: 75
- Numerical Features: 48
- Categorical Features: 28
- Memory Usage: 197.14 MB
- Duplicate Rows: 165

Missing Values Analysis



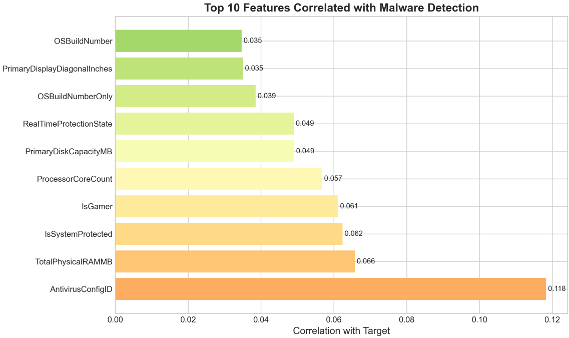
Key Features Analysis

Most Predictive Features:

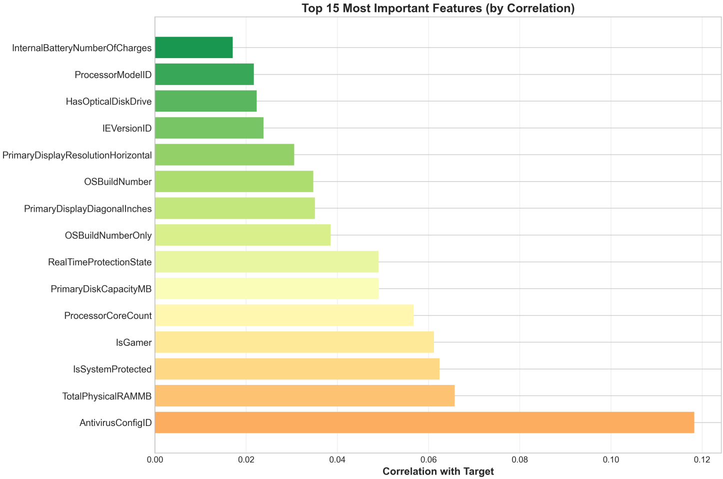
1. **AntivirusConfigID**
   Correlation: 0.118
2. **TotalPhysicalRAMMB**
   Correlation: 0.066
3. **IsSystemProtected**
   Correlation: 0.062
4. **IsGamer**
   Correlation: 0.061

Key Insight

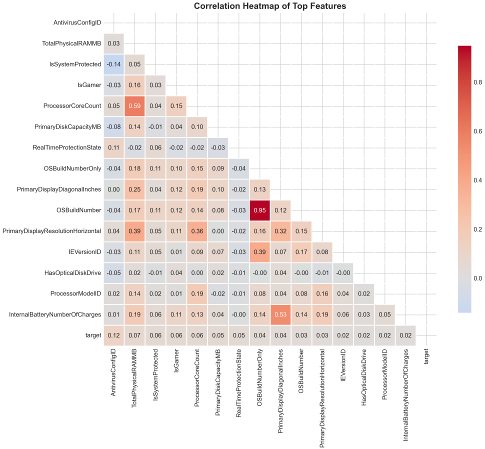
Security configuration has the highest predictive power



Feature Correlation Analysis



Feature Correlation Heatmap

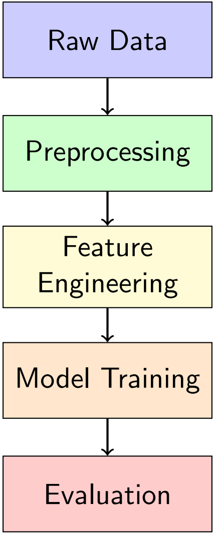


	AntivirusConfigID	TotalPhysicalRAMMB	IsSystemProtected	IsGamer	ProcessorCoreCount	PrimaryDiskCapacityMB	RealTimeProtectionState	OSBuildNumberOnly	PrimaryDisplayDiagonalInches	OSBuildNumber	PrimaryDisplayResolutionHorizontal	IEVersionID	HasOpticalDiskDrive	ProcessorModelID	InternalBatteryNumberOfCharges	target
AntivirusConfigID																
TotalPhysicalRAMMB	0.03															
IsSystemProtected	-0.14	0.05														
IsGamer	-0.03	0.16	0.03													
ProcessorCoreCount	0.05	0.59	0.04	0.15												
PrimaryDiskCapacityMB	-0.08	0.14	-0.01	0.04	0.10											
RealTimeProtectionState	0.11	-0.02	0.06	-0.02	-0.02	-0.03										
OSBuildNumberOnly	-0.04	0.18	0.11	0.10	0.15	0.09	-0.04									
PrimaryDisplayDiagonalInches	0.00	0.25	0.04	0.12	0.19	0.10	-0.02	0.13								
OSBuildNumber	-0.04	0.17	0.11	0.12	0.14	0.08	-0.03	0.95	0.12							
PrimaryDisplayResolutionHorizontal	0.04	0.39	0.05	0.11	0.36	0.00	-0.02	0.16	0.32	0.15						
IEVersionID	-0.03	0.11	0.05	0.01	0.09	0.07	-0.03	0.39	0.07	0.17	0.08					
HasOpticalDiskDrive	-0.05	0.02	-0.01	0.04	0.00	0.02	-0.01	-0.00	0.04	-0.00	-0.01	-0.00				
ProcessorModelID	0.02	0.14	0.02	0.01	0.19	-0.02	-0.01	0.08	0.04	0.08	0.16	0.04	0.02			
InternalBatteryNumberOfCharges	0.01	0.19	0.06	0.11	0.13	0.04	-0.00	0.14	0.53	0.14	0.19	0.06	0.03	0.05		
target	0.12	0.07	0.06	0.06	0.06	0.05	0.05	0.04	0.04	0.03	0.03	0.02	0.02	0.02	0.02	

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



Raw Data

Preprocessing

Feature Engineering

Model Training

Evaluation

Preprocessing Pipeline

Dataset Specifications:

- **Size:** 100,000 samples
- **Features:** 76 total
  - 48 numerical
  - 28 categorical
- **Split:** 80% train, 20% validation
- **Target:** Balanced (50.52% / 49.48%)

Preprocessing Steps:

- 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 (Best performer)
4. **Naive Bayes** - Probabilistic classifier
5. **Logistic Regression** - Linear baseline
6. **AdaBoost** - Adaptive boosting
7. **SGD Classifier** - Stochastic optimization

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

Implementation Highlights

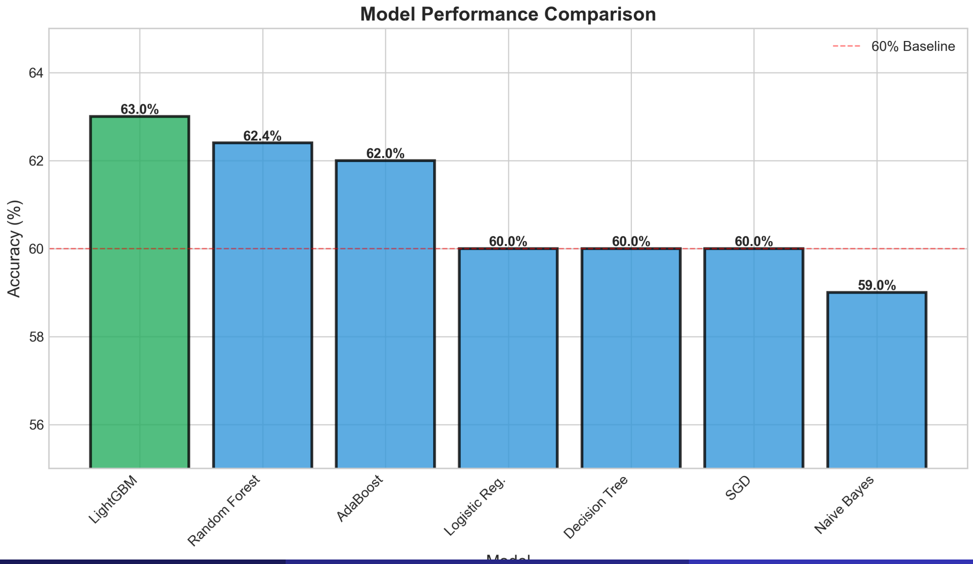
Architecture Strengths:

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

Pipeline Features:

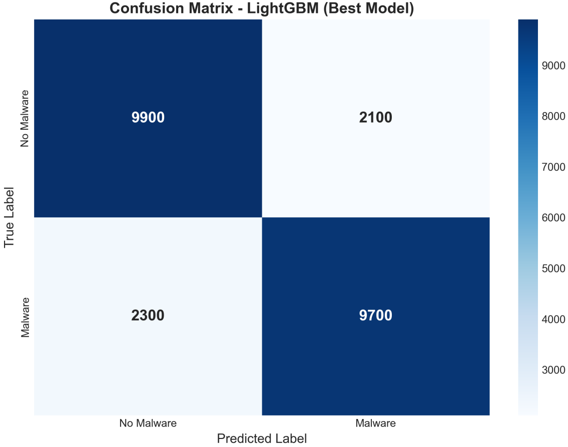
- Robust preprocessing
- Missing value handling
- Feature engineering tools
- Cross-validation support
- Comprehensive logging
- Results tracking

Model Performance Comparison



Best Model: LightGBM Performance

Confusion Matrix:



Confusion Matrix - LightGBM (Best Model)

True Label \ Predicted Label	No Malware	Malware
No Malware	9900	2100
Malware	2300	9700

Model Characteristics:

- **Accuracy:** 63.0%
- **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

- **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

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?

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