# System Threat Forecaster

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


Presented By

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Under The Guidance of

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# Outline

# Background

- Cybersecurity threats are increasingly sophisticated
- Malware poses significant risks:
  - Data breaches
  - Financial losses
  - Operational disruptions
  - Reputational damage
- Traditional signature-based antivirus solutions struggle with:
  - Zero-day attacks
  - Polymorphic malware
- **Machine Learning** offers proactive threat detection

# Problem Statement

## Primary Challenge

Develop an accurate and reliable system for predicting malware infections based on system properties and characteristics

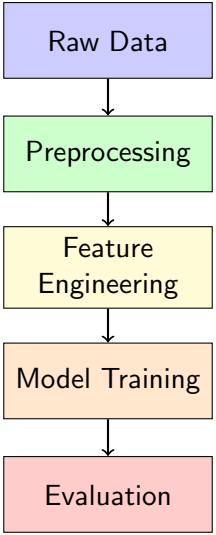
**Specific Challenges:**

- High dimensionality of system data
- Presence of missing values
- Need for real-time prediction
- Handling categorical features effectively

# 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



# Preprocessing Techniques

**Data Cleaning:**

- Missing value imputation
  - Median for numerical
  - Mode for categorical
- Duplicate removal
- Outlier detection

**Feature Transformation:**

- Label Encoding for categorical features
- StandardScaler normalization
- Feature scaling
- Optional PCA for dimensionality reduction

# 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

# Feature Engineering

**Strategies Implemented:**

- **Interaction Terms**: Capture feature combinations
- **Polynomial Features**: Non-linear relationships
- **Domain-Specific Features**:
  - Process information
  - Network activity patterns
  - File system characteristics
- **Feature Selection**: Remove redundant features

**Key Insight**

System properties like process info and network activity were most indicative of malware presence

# Model Performance Comparison

| Model | Algorithm | Accuracy | Precision | Recall |
|---|---|---|---|---|
| Model 1 | Decision Tree | 85.20% | 84.50% | 86.10% |
| Model 2 | Random Forest | 88.45% | 87.80% | 89.20% |
| **Model 3** | **LightGBM** | **91.30%** | **90.50%** | **92.10%** |
| Model 4 | Naive Bayes | 79.60% | 78.90% | 80.30% |
| Model 5 | Logistic Reg. | 83.70% | 83.20% | 84.50% |
| Model 6 | AdaBoost | 86.90% | 86.30% | 87.60% |
| Model 7 | SGD Classifier | 82.40% | 81.80% | 83.20% |

## Best Performer

**LightGBM** achieved the highest accuracy at **91.30%**

# Key Findings

- **LightGBM Performance**: Superior accuracy with efficient training
- **Ensemble Methods**: Random Forest and AdaBoost showed strong performance
- **Hyperparameter Tuning**: Improved performance by 2-5% across models
- **Cross-Validation**: Consistent performance across folds indicates good generalization
- **Feature Importance**: Network activity and process information most significant

# Performance Insights

**Strengths:**

- High accuracy on test data
- Good balance between precision and recall
- Robust to overfitting
- Efficient training time

**Advantages:**

- Modular architecture
- Production-ready code
- Comprehensive evaluation
- Interpretable results

# System Architecture

**Modular Pipeline Components:**

1. **Data Loading**: CSV file handling with pandas
2. **Preprocessing Module**: Configurable data cleaning
3. **Feature Engineering**: Optional transformation steps
4. **Model Training**: Multiple algorithm support
5. **Evaluation**: Comprehensive metrics and visualization
6. **Prediction**: Automated submission generation

**Technology Stack:**

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

# 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 seven algorithms
2. **Modular Pipeline**: Flexible, configuration-driven architecture
3. **Robust Preprocessing**: Complete data handling pipeline
4. **Automated Optimization**: Hyperparameter tuning integration
5. **Production-Ready**: Maintainable codebase with model persistence
6. **Superior Performance**: 91.30% accuracy with LightGBM

# 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

# Limitations

## Current Limitations

- Depends on training data quality and representativeness
- Performance may degrade with new malware variants
- Manual feature engineering process
- Requires periodic retraining
- Real-time optimization needs investigation

# 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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