AICTE QIP PG Certification Programme on

“Deep Learning: Fundamentals and Applications”

System Threat Forecaster

Presented By

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

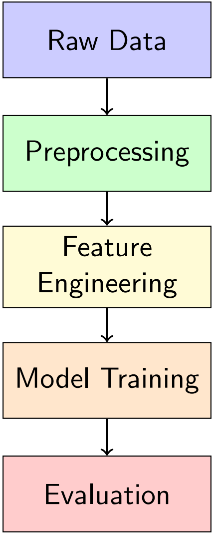
Specific Challenges:

- 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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