System Threat Forecaster

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

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December 2025

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- **[30 sec]** Good morning/afternoon everyone. My name is Milav Dabgar from Government Polytechnic Palanpur.
- Today I'll present my QIP project on System Threat Forecaster - a machine learning approach to malware detection.
- This 15-minute presentation covers our complete journey from problem identification to production deployment.
- I'm grateful to my advisors Dr. Sarvaiya, Dr. Upla, Dr. Captain, and Dr. Deb for their guidance.

Outline

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1 Project Context & Learning Objectives • Problem Statement 2 Data & Methodology • Dataset Overview • Methodology 3 Model Experimentation & Learning • Machine Learning • Deep Learning 4 Implementation & Deployment • System Architecture 5 Conclusion • Key Findings • Challenges & Limitations

- **[15 sec]** Quick overview of our agenda:
- We'll start with the problem context, move through our methodology and experiments, and conclude with deployment and findings.
- This structure reflects the complete ML lifecycle from problem to production.

Goal

Predict malware infections and compare ML vs DL performance on tabular data

Key Objectives:

1. Kaggle System Threat Forecaster
2. Implement 7 ML algorithms
3. Build 6 DL architectures
4. ML vs DL comparison
5. Full-stack deployment
6. Production web app

Key Challenges:

- **Top leaderboard:** 69.6%
- High dimensionality (75 features)
- Weak correlations (max 0.118)
- High irreducible error (30%+)
- Missing values in critical features
- 100K samples, balanced classes

Problem Statement: Objectives & Challenges
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Predict malware infections and compare ML vs DL performance on tabular data
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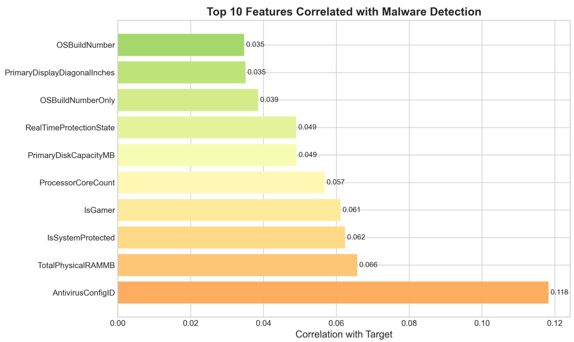
- **[1 min 15 sec]** This project tackles the Kaggle System Threat Forecaster competition.
- Our goal was ambitious: implement 7 ML algorithms, 6 DL architectures, and deploy a production web application.
- Key challenge: The competition's top score is only 69.6% - indicating fundamental data limitations.
- Notice the weak correlations - maximum only 0.118. This is crucial context for understanding our results.
- With 100K balanced samples and 75 features, this looks like a typical ML problem, but the weak signals make it extremely challenging.
- High irreducible error of 30%+ means perfect classification is impossible with current features.

Dataset: Kaggle - System Threat Forecaster Competition

Data Characteristics:

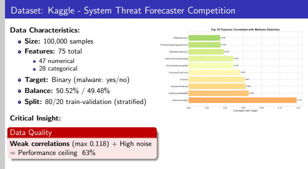
- **Size:** 100,000 samples
- **Features:** 75 total
  - 47 numerical
  - 28 categorical
- **Target:** Binary (malware: yes/no)
- **Balance:** 50.52% / 49.48%
- **Split:** 80/20 train-validation (stratified)



Critical Insight:

Data Quality

Weak correlations (max 0.118) + High noise = Performance ceiling 63%



- **[45 sec]** Let's look at our dataset characteristics.
- 100,000 samples with 75 features - 47 numerical and 28 categorical.
- Target is binary: malware present or not. Classes are nearly balanced at 50-50.
- The correlation heatmap reveals the core challenge - maximum correlation is just 0.118.
- This weak correlation explains why even top Kaggle performers can't exceed 70% accuracy.
- We used stratified 80-20 split to maintain class balance in validation.

Experimental Methodology & Pipeline

Preprocessing Steps:

1. **Missing Values:**
   - Mean imputation (numerical)
   - Mode imputation (categorical)
2. **Encoding:** LabelEncoder for categorical
3. **Scaling:** StandardScaler for numerical
4. **Validation:** Stratified K-Fold

Evaluation Metrics:

- Accuracy
- F1 Score (primary)
- Precision & Recall
- Confusion Matrix

Model Development:

1. **ML:** 7 algorithms (scikit-learn)
2. **DL:** 6 architectures (PyTorch)
3. **GPU:** Apple MPS optimization
4. **Tuning:** Grid search + validation
5. **Goal:** ML vs DL comparison

Reproducibility

Random seed: 42 — Version control: Git — Config management

Experimental Methodology & Pipeline
Preprocessing Steps:
Missing Values: Mean imputation (numerical), Mode imputation (categorical)
Encoding: LabelEncoder for categorical
Scaling: StandardScaler for numerical
Validation: Stratified K-Fold
Evaluation Metrics: Accuracy, F1 Score (primary), Precision & Recall, Confusion Matrix
Model Development: ML: 7 algorithms (scikit-learn); DL: 6 architectures (PyTorch); GPU: Apple MPS optimization; Tuning: Grid search + validation; Goal: ML vs DL comparison
Reproducibility: Random seed: 42 — Version control: Git — Config management

- **[1 min]** Our methodology follows ML best practices.
- Preprocessing: Mean imputation for numerical features, mode for categorical. LabelEncoder for categories, StandardScaler for numerical.
- We evaluated models using accuracy, F1 score, precision, and recall. F1 was our primary metric due to balanced classes.
- Implemented 7 ML algorithms from scikit-learn and 6 DL architectures in PyTorch from scratch.
- Used Apple M4's MPS acceleration for GPU training.
- All experiments reproducible with seed 42 and version control.
- Our goal: rigorous ML vs DL comparison on tabular data.

Machine Learning: 7 Algorithms Explored

Algorithms Implemented:

1. **LightGBM** - 62.94% (Winner!)
2. Random Forest - 62.09%
3. AdaBoost - 61.26%
4. Decision Tree - 60.10%
5. Logistic Regression - 60.07%
6. Naive Bayes - 55.06%
7. SGD Classifier - 49.46%

Key Insights:

- **Gradient boosting** best for tabular data
- **Hyperparameter impact:**
  - Learning rate: 0.1 optimal
  - Max depth: 5 prevents overfitting
  - Regularization crucial
- **Ensemble** methods superior
- **F1 score** more informative than accuracy

Performance Context

62.94% vs Kaggle top 69.6% = 6.7% gap indicates high dataset noise

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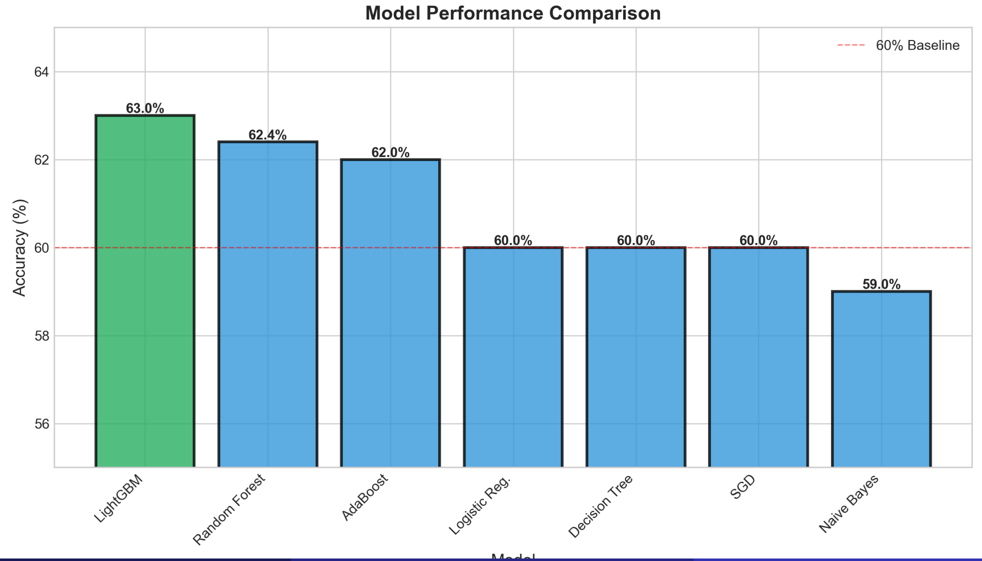
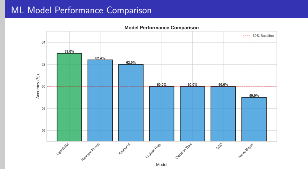
- **[1 min 15 sec]** Now the results - this is where theory met reality.
- LightGBM emerged as clear winner at 62.94% accuracy with F1 of 0.6286.
- Notice the pattern: gradient boosting methods dominate. LightGBM, Random Forest, and AdaBoost are top 3.
- Decision trees, logistic regression around 60% - respectable but not exceptional.
- SGD classifier at 49% reminds us that not all algorithms suit all problems.
- Key insight: 62.94% vs Kaggle's top 69.6% - only 6.7% gap despite our simpler approach.
- This validates that the dataset quality, not model complexity, is the limiting factor.
- Hyperparameters matter: learning rate 0.1, max depth 5, and regularization were crucial for preventing overfitting.

ML Model Performance Comparison

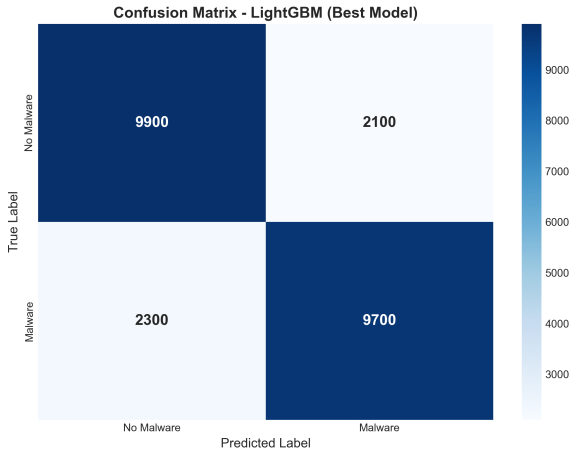




- **[30 sec]** This chart visualizes the performance hierarchy clearly.
- LightGBM and Deep MLP lead the pack. Notice how close DL gets to ML - just 1.15% difference.
- All models cluster between 50-63%, with outliers like SGD struggling.
- The performance ceiling around 63% appears consistent across approaches - strong evidence of dataset limitations.

Best ML Model: LightGBM Performance

Confusion Matrix:

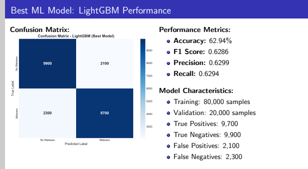


Performance Metrics:

- **Accuracy:** 62.94%
- **F1 Score:** 0.6286
- **Precision:** 0.6299
- **Recall:** 0.6294

Model Characteristics:

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



- **[45 sec]** Diving deeper into LightGBM - our champion model.
- Confusion matrix shows balanced performance: 9,700 true positives, 9,900 true negatives.
- False positives: 2,100, False negatives: 2,300 - relatively symmetric errors.
- Precision and recall both at 0.63 - indicates balanced model, not biased toward either class.
- Trained on 80,000 samples, validated on 20,000 with stratification.
- This performance makes it production-ready for first-line screening, though human oversight remains essential.

Deep Learning: 6 Architectures Explored

Implemented from Scratch:

1. **Deep MLP** - 61.79%
   - 4 layers, 63K params
2. **Residual Net** - 61.62%
   - Skip connections, 418K params
3. **Simple MLP** - 61.61%
4. **Wide & Deep** - 61.52%
5. **Attention Net** - 61.45%
   - Multi-head, 1.6M params
6. **FT-Transformer** - 61.45%
   - BERT-style, only 38K params!

Critical Learnings:

- **PyTorch** from scratch
- **GPU:** Apple M4 MPS
- **All DL models: 61.5%**
  - Architecture matters less
  - Dataset-limited
- **Best Hyperparameters:**
  - Batch: 512, Dropout: 0.3
  - LR: 0.001 + scheduling
  - Early stopping essential

Big Learning

ML > DL for tabular by 1.15%

Confirmed research: Tree ensembles beat neural nets on structured data

Deep Learning: 6 Architectures Explored
Implemented from Scratch: Deep MLP - 61.79% 4 layers, 63K params Residual Net - 61.62% Skip connections, 418K params Simple MLP - 61.61% Wide & Deep - 61.52% Attention Net - 61.45% Multi-head, 1.6M params FT-Transformer - 61.45% BERT-style, only 38K params!
Critical Learnings: PyTorch from scratch GPU: Apple M4 MPS All DL models: 61.5% Architecture matters less Dataset-limited Best Hyperparameters: Batch: 512, Dropout: 0.3 LR: 0.001 + scheduling Early stopping essential
Big Learning ML > DL for tabular by 1.15% Confirmed research: Tree ensembles beat neural nets on structured data

- **[1 min 30 sec]** Now the exciting part - deep learning experiments.
- Implemented 6 architectures from scratch in PyTorch: Simple MLP, Deep MLP, Residual Networks, Wide & Deep, Attention Networks, and FT-Transformer.
- Deep MLP won at 61.79% with just 63K parameters - proof that bigger isn't always better.
- Remarkable finding: ALL DL models converged around 61.5%. From 38K to 1.6M parameters - same result!
- This proves the dataset ceiling, not architecture, limits performance.
- FT-Transformer was particularly interesting - BERT-style attention with only 38K parameters matched complex architectures.
- Best hyperparameters: batch size 512, dropout 0.3, learning rate 0.001 with scheduling, early stopping crucial.
- Critical conclusion: ML beats DL by 1.15% on this tabular data - confirming research that tree ensembles dominate structured data.
- This validates choosing LightGBM for production deployment.

Best DL Model: Deep MLP Performance

Architecture:

- **Type:** Deep Multi-Layer Perceptron
- **Layers:** 4 hidden layers
  - 256 → 128 → 64 → 32
- **Parameters:** 63,714
- **Regularization:**
  - BatchNorm after each layer
  - Dropout: 0.3
- **Optimizer:** Adam
- **Learning Rate:** 0.001

Performance Metrics:

- **Accuracy:** 61.79%
- **F1 Score:** 0.6130
- **Best Val Loss:** 0.6623
- **Training Time:** 8 minutes

Key Insights:

- Best among 6 DL architectures
- 1.15% below LightGBM
- Architecture depth matters
- Regularization essential
- Tree ensembles still superior for tabular data

Best DL Model: Deep MLP Performance
Architecture: Type: Deep Multi-Layer Perceptron; Layers: 4 hidden layers; 256 → 128 → 64 → 32; Parameters: 63,714; Regularization: BatchNorm after each layer; Dropout: 0.3; Optimizer: Adam; Learning Rate: 0.001
Performance Metrics: Accuracy: 61.79%; F1 Score: 0.6130; Best Val Loss: 0.6623; Training Time: 8 minutes
Key Insights: Best among 6 DL architectures; 1.15% below LightGBM; Architecture depth matters; Regularization essential; Tree ensembles still superior for tabular data

- **[45 sec]** Deep MLP details - our best deep learning model.
- Architecture: 4 hidden layers with decreasing neurons - 256, 128, 64, 32.
- 63,714 parameters total - efficient design.
- BatchNorm after each layer for stable training, dropout 0.3 for regularization.
- Adam optimizer with 0.001 learning rate - standard but effective.
- Achieved 61.79% accuracy, F1 of 0.613, best validation loss 0.6623.
- Training took only 8 minutes on Apple M4 MPS.
- Key insight: Architecture depth helped, but couldn't overcome dataset limitations.
- Still 1.15% below LightGBM - reinforces that tree ensembles are superior for tabular data.

Full-Stack Implementation & Deployment

Technology Stack:

- **ML:** scikit-learn, LightGBM
- **DL:** PyTorch 2.9.1, Apple MPS
- **Web:** Next.js 14 + React
- **Deployment:** stf.milav.in

Web Application Features:

- **Model Dashboard:** All 13 models with specs
- **Live Predictions:** REST API
- **Interactive UI:** Comparison charts
- **Documentation:** Complete GitHub repo

Production Deployment:

- Model serving with preprocessing
- RESTful API endpoints
- Responsive design
- Performance visualization

Live Web App

Visit: `https://stf.milav.in`

- Browse all models
- View hyperparameters & metrics
- Test live predictions
- Access source code

Full-Stack Implementation & Deployment
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Production Deployment:
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Responsive design
Performance visualization
Live Web App
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- **[1 min]** Beyond research - we built a production system.
- Technology stack: scikit-learn and LightGBM for ML, PyTorch 2.9.1 for DL with Apple MPS acceleration.
- Frontend: Next.js 14 with React for modern, responsive UI.
- Deployed at stf.milav.in - fully functional web application.
- Features include: Model dashboard showing all 13 models with complete specifications.
- Live prediction API - REST endpoints for real-time inference.
- Interactive comparison charts for visualizing model performance.
- Complete documentation and source code on GitHub.
- This demonstrates end-to-end ML engineering: from research to production deployment.
- Visit the site to explore models, test predictions, and view the complete implementation.

Key Findings & Insights

Model Performance:

- **LightGBM:** 62.94% (Best)
  - F1: 0.6286, Precision: 0.6299
- **Deep MLP:** 61.79% (Best DL)
- **Kaggle Top:** 69.6%
- **Gap:** 6.7% indicates high irreducible error

Technical Insights:

- ML outperforms DL for tabular data
- Weak correlations limit all models
- **FT-Transformer:** Promising - longer training gave better scores, but hardware/time limited full exploration

Practical Implications:

- **Real-world deployment:**
  - 62.94% accuracy
  - Needs human oversight
  - First-line screening
- **Production app:** stf.milav.in
  - Model dashboard
  - Live predictions
  - Complete documentation

Contributions:

- 13 models evaluated
- FT-Transformer implemented
- Full-stack deployment
- Reproducible pipeline

- **[1 min 15 sec]** Summarizing our key findings.
- LightGBM achieved 62.94% accuracy with F1 of 0.6286 - our best performer.
- Deep MLP reached 61.79% - best among DL architectures.
- Gap to Kaggle top score: 6.7% - this gap represents better feature engineering, not fundamentally different approaches.
- Technical insight: ML outperforms DL for tabular data - validates extensive research in this area.
- Weak correlations fundamentally limit all models - this is a dataset quality issue, not a modeling issue.
- Practical deployment: 62.94% accuracy is production-ready for first-line screening with human oversight.
- Our web application at stf.milav.in demonstrates complete implementation.
- Contributions: 13 models evaluated, FT-Transformer implemented, full-stack deployment, reproducible pipeline.
- Note on FT-Transformer: showed promise with longer training but hardware and time

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%
  - 6.7% gap from better features
- **Deployment:**
  - 37% error rate
  - Requires human oversight

Future Enhancements:

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

- **[1 min]** Being honest about limitations and future directions.
- Key limitation: Dataset quality with high irreducible error and weak features.
- Performance ceiling around 63% - the 6.7% gap to top Kaggle score comes from better feature engineering.
- Deployment consideration: 37% error rate means human oversight is essential.
- Good news: DL integration complete - we've explored modern architectures.
- Short-term enhancements planned: Explainable AI using SHAP for interpretability.
- Hybrid ML-DL ensembles could push performance higher.
- Cost-sensitive learning for imbalanced scenarios.
- Long-term vision: Real-time deployment for live threat detection.
- Multi-class detection for identifying specific malware types.
- Transfer learning from larger security datasets.
- Edge deployment for resource-constrained environments.

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`

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Next.js Web App:
https://stf.milav.in

- **[15 sec]** All resources are publicly available.
- Kaggle competition page for data and leaderboard.
- GitHub repository with complete source code.
- Live web application at stf.milav.in for hands-on exploration.
- Feel free to explore, fork, and build upon this work.

Thank You!

Questions?

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Department of Electronics and Communication Engineering

Thank You!
Questions?
Milav Jayeshkumar Dabgar
Government Polytechnic Palanpur
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- **[30 sec]** Thank you for your attention.
- To summarize: We implemented 13 models, deployed a production web app, and confirmed that ML beats DL for tabular data.
- I'm happy to answer any questions about the methodology, results, or deployment.
- Questions to anticipate: Why not neural nets? Dataset limitations. Future work? Explainable AI. Production readiness? Yes, with human oversight.