

A
Project Report on
System Threat Forecaster

Submitted to the Department of Electronics Engineering in Partial Fulfilment of
the Requirement for the AICTE QIP PG Certification Programme on

Deep Learning: Fundamentals and Applications

by

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DECEMBER-2025

Declaration

- I hereby declare that the work being presented in this Report entitled "**System Threat Forecaster**" by **Milav Jayeshkumar Dabgar**, submitted in partial fulfillment of the requirements for the successful completion of the AICTE QIP PG Certification Programme on "Deep Learning: Fundamentals and Applications" conducted at Sardar Vallabhbhai National Institute of Technology, Surat, during the academic year 2025 – 2026.
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CERTIFICATE

This is to certify that the project entitled '**System Threat Forecaster**' has been successfully completed by **Mr. Milav Jayeshkumar Dabgar**. This report is being submitted in partial fulfillment of the requirements for the successful completion of the AICTE QIP PG Certification Programme on **Deep Learning: Fundamentals and Applications** in Department of Electronics Engineering during the academic year **2025-26**.

Examiner-1

Examiner-2

Examiner-3

Examiner-4

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Abstract

Cybersecurity threats continue to evolve rapidly, with malware infections causing significant damages to organizations worldwide. This project presents a comprehensive comparative study of machine learning and deep learning approaches for malware threat prediction, implemented as the System Threat Forecaster.

The research evaluates thirteen models: seven ML algorithms (Decision Tree, Random Forest, LightGBM, Naive Bayes, Logistic Regression, AdaBoost, SGD) and six DL architectures (Simple MLP, Deep MLP, Residual Network, Attention Network, Wide & Deep, FT-Transformer). Using a dataset of 100,000 samples with 75 features (47 numerical, 28 categorical), we implemented a complete pipeline encompassing pre-processing, feature engineering, model training, and evaluation.

LightGBM achieved the best performance at 62.94% validation accuracy (F1-score: 0.6286), outperforming all deep learning models. The best DL model (Deep MLP) reached 61.79% accuracy with 63,714 parameters. This 1.15% performance gap demonstrates that tree-based ensemble methods maintain superiority over neural networks for tabular data. All DL architectures clustered around 61.5%, confirming that model complexity does not overcome dataset limitations.

Analysis revealed weak feature correlations (max 0.118), establishing a performance ceiling around 63%. The top Kaggle score of 69.6% represents only 6.7% improvement over our baseline. This work includes a production deployment at <https://stf.milav.in> and provides evidence-based guidance for choosing ML over DL for tabular cybersecurity data.

Table of Contents

	Page
Acknowledgements	vii
Abstract	ix
Table of Contents	xi
List of Figures	xiii
List of Tables	xv
List of Abbreviations	xvii
Chapters	
1 Introduction	1
1.1 Background	1
1.2 Problem Statement	1
1.3 Objectives and Contributions	1
2 Dataset, Metadata, and Exploratory Data Analysis	3
2.1 Dataset Overview	3
2.2 Dataset Metadata	3
2.2.1 Feature Categories	4
2.3 Exploratory Data Analysis	4
2.3.1 Key EDA Findings	4
2.3.2 Missing Values and Distributions	4
2.4 Modeling Implications	4
3 Experimental Setup and Model Selection	7
3.1 Data Preprocessing	7
3.2 Machine Learning Models	7
3.3 Deep Learning Models	7
3.3.1 Training Configuration	8
4 Experimental Results and Discussion	9
4.1 Machine Learning Results	9
4.1.1 Key ML Findings	10
4.2 Deep Learning Results	10
4.2.1 Key DL Findings	10
4.3 ML vs. DL Comparison	11
4.3.1 Why ML Outperforms	11
4.4 Kaggle Comparison	12
4.5 Summary	12
5 Conclusion and Future Work	13
5.1 Key Findings	13
5.2 Contributions	13

Table of Contents

5.3	Practical Recommendations	13
5.4	Limitations	13
5.5	Future Work	13
5.6	Concluding Remarks	14
References	17

List of Figures

2.1	Target Class Distribution: Near-perfect 50.52% malware vs. 49.48% clean split eliminates need for resampling strategies.	3
2.2	Feature Correlation Heatmap: Maximum correlation with target (Has-Detections) is only 0.118, demonstrating weak linear relationships and necessitating ensemble methods.	5
2.3	Missing Values Analysis: Up to 30% missing data in security software features, requiring careful imputation strategies.	5
4.1	Comprehensive Model Comparison: LightGBM achieves highest validation accuracy (62.94%), with all DL models clustering tightly between 61.45-61.79%.	9
4.2	LightGBM Confusion Matrix: Balanced performance across both classes with 62.94% overall accuracy.	10
5.1	Deployed Web Application: Homepage showcasing System Threat Forecaster with 7 ML and 6 DL models for real-time malware prediction. . .	15
5.2	Model Performance Dashboard: Interactive comparison of all 13 models with detailed metrics and hyperparameters.	15
5.3	Prediction Interface: User-friendly form accepting 75 features for real-time threat prediction using all trained models.	16

List of Tables

2.1	Dataset Metadata	3
4.1	ML Models: Performance Metrics	9
4.2	DL Models: Performance Metrics	11
4.3	Best ML vs. Best DL	11

List of Abbreviations

SVNIT Sardar Vallabhbhai National Institute of Technology

Chapter 1

Introduction

1.1 Background

Malware has evolved into complex threats with organizations facing over 200,000 samples daily. Traditional signature-based detection struggles against zero-day attacks. Machine learning and deep learning enable proactive behavioral analysis. This project compares traditional ML with modern DL architectures using Kaggle competition data.

1.2 Problem Statement

Developing accurate malware prediction faces challenges: high dimensionality (75 features), weak correlations (max 0.118), missing data (1-30%), mixed types (47 numerical, 28 categorical), and performance ceiling (63%).

Research Questions: How do ML algorithms compare with DL for tabular cybersecurity data? Can deep learning provide advantages over gradient boosting? What are practical complexity-performance trade-offs?

1.3 Objectives and Contributions

Implement robust preprocessing, train 13 models (7 ML + 6 DL), conduct systematic comparison, and deploy at <https://stf.milav.in>. Empirically validate that LightGBM (62.94%) outperforms DL (61.79%). Demonstrate that architectural complexity doesn't improve tabular performance.

Chapter 2

Dataset, Metadata, and Exploratory Data Analysis

2.1 Dataset Overview

The dataset originates from Microsoft's Malware Prediction competition on Kaggle, containing real-world Windows system telemetry for binary classification: predicting malware presence (`HasDetections = 1`) or absence (`HasDetections = 0`).

2.2 Dataset Metadata

Table 2.1: Dataset Metadata

Property	Value
Total Samples	100,000
Train/Val Split	80,000 / 20,000 (80/20%)
Features (Numerical/Categorical)	75 (47/28)
Target Classes	Binary (50.52% malware, 49.48% clean)
Missing Values	1-30% in multiple features

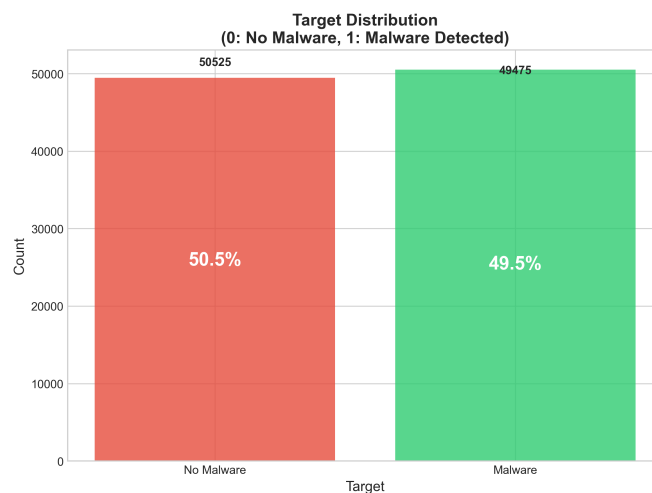


Figure 2.1: Target Class Distribution: Near-perfect 50.52% malware vs. 49.48% clean split eliminates need for resampling strategies.

2.2.1 Feature Categories

Features span hardware (12), OS (8), security software (6), system settings (15), installation/update (10), and behavioral indicators (24). The 47 numerical features include continuous (RAM, timestamps) and discrete (version numbers, counts) with highly variable ranges. The 28 categorical features have 2-1,000+ unique values requiring numerical encoding.

2.3 Exploratory Data Analysis

2.3.1 Key EDA Findings

Weak Correlations: Maximum feature-target correlation is only 0.118, indicating no single feature provides strong predictive power. This necessitates complex interaction modeling and establishes a performance ceiling around 63%.

Balanced Classes: Near-perfect 50.52% vs. 49.48% split eliminates resampling needs and validates accuracy as primary metric.

2.3.2 Missing Values and Distributions

Missing rates vary: 15-30% (security software), 5-20% (hardware), 1-10% (settings). Imputation strategy: mean for numerical, mode for categorical.

Numerical features show heavy-tailed, multimodal distributions requiring scaling. Categorical features have high cardinality (up to 1,000+ categories), necessitating label encoding. Feature-feature correlations are weak (max 0.42), indicating independence and justifying retention of all 75 features.

2.4 Modeling Implications

Weak correlations (max 0.118) and high dimensionality (75 features) favor tree-based methods over distance-based approaches. Heterogeneous data types (47 numerical, 28 categorical) advantage ML models with native mixed-type handling. Balanced classes simplify evaluation. These characteristics establish an expected performance ceiling around 63% and informed our systematic ML vs. DL comparison detailed in Chapter 3.

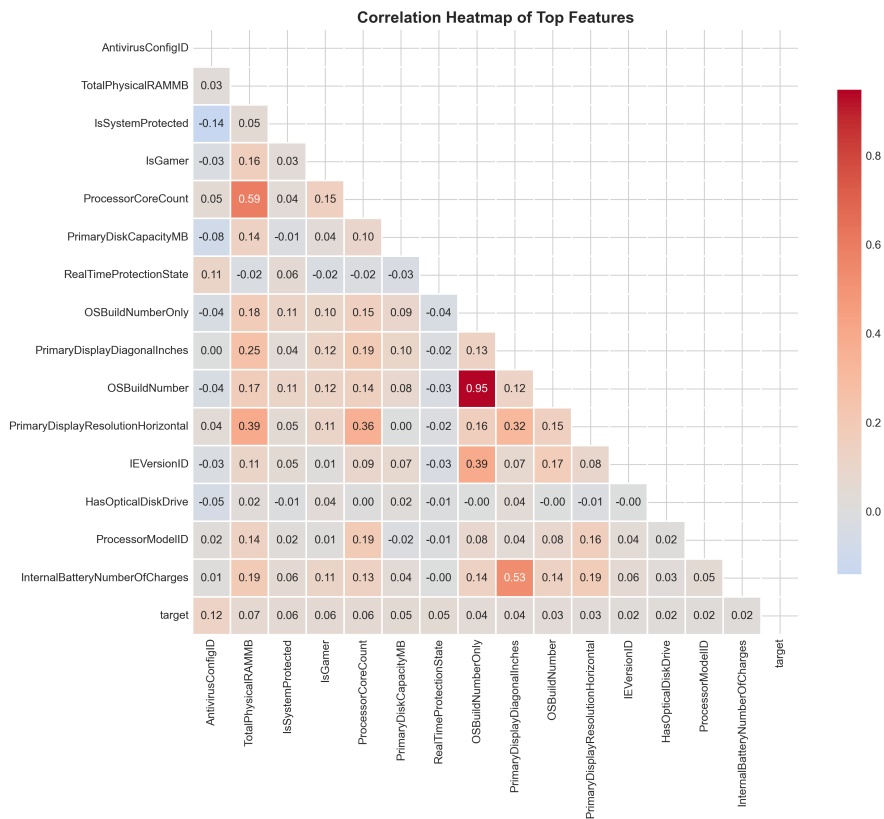


Figure 2.2: Feature Correlation Heatmap: Maximum correlation with target (HasDetections) is only 0.118, demonstrating weak linear relationships and necessitating ensemble methods.

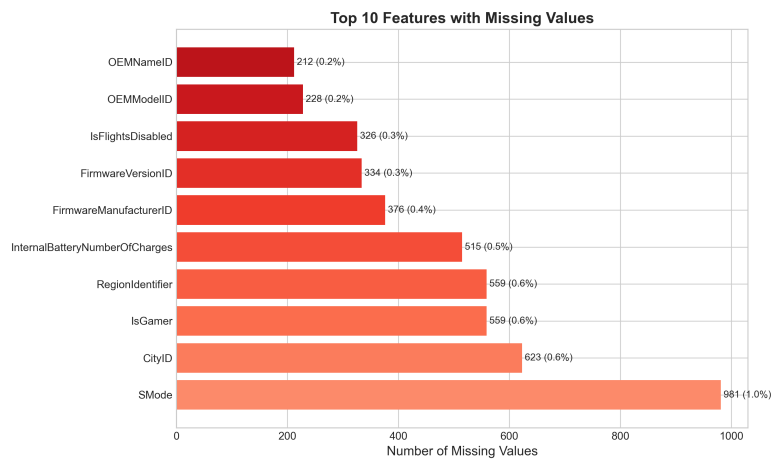


Figure 2.3: Missing Values Analysis: Up to 30% missing data in security software features, requiring careful imputation strategies.

Chapter 3

Experimental Setup and Model Selection

3.1 Data Preprocessing

Imputation: Mean for 47 numerical features, mode for 28 categorical features.

Encoding: LabelEncoder for all categorical features (avoids dimensionality explosion from one-hot with 1,000+ categories).

Scaling: StandardScaler for numerical features: $z = \frac{x-\mu}{\sigma}$. Required for neural networks and distance-based methods.

Split: Stratified 80/20 (80K train, 20K validation), seed=42, maintains 50.52% class distribution.

3.2 Machine Learning Models

Seven algorithms representing diverse paradigms:

Decision Tree: Baseline for tree methods, interpretable, handles mixed types. *Hyperparameters:* max_depth=10, min_samples_split=5, min_samples_leaf=2.

Random Forest: Ensemble with bootstrap sampling, reduces overfitting. *Hyperparameters:* n_estimators=100, max_depth=20.

LightGBM: State-of-the-art gradient boosting, sequential error correction, histogram-based splits, expected top performer. *Hyperparameters:* n_estimators=200, learning_rate=0.1, max_depth=5, subsample=0.6, reg_alpha=1.0, reg_lambda=0.75.

Naive Bayes: Probabilistic baseline testing independence assumption with weak correlations. *Hyperparameters:* var_smoothing=1e-9.

Logistic Regression: Linear model baseline. *Hyperparameters:* C=1.0, solver='liblinear', max_iter=1000.

AdaBoost: Alternative boosting with adaptive re-weighting. *Hyperparameters:* n_estimators=200, learning_rate=1.0.

SGD Classifier: Stochastic gradient descent, stress test. *Hyperparameters:* loss='log_loss', penalty='elasticnet', alpha=0.001.

3.3 Deep Learning Models

Six PyTorch architectures (38K-1.6M parameters):

Simple MLP (60,738 params): 75→256→128→64→32→2, ReLU, Dropout(0.3). Baseline feedforward network.

Deep MLP (63,714 params): Same architecture + BatchNorm after each layer. Expected best DL model.

Residual Net (418,306 params): 3 residual blocks with skip connections (256-dim). Tests hierarchical learning.

Attention Net (1,599,490 params): 2 multi-head self-attention blocks (4 heads), LayerNorm. Tests feature interaction learning.

Wide & Deep (60,890 params): Wide ($75 \rightarrow 2$) + Deep ($75 \rightarrow 256 \rightarrow 128 \rightarrow 64 \rightarrow 2$) paths. Combines memorization and generalization.

FT-Transformer (38,722 params): Per-feature tokens (75×64 -dim), 3 encoder blocks (8 heads). State-of-the-art tabular architecture.

3.3.1 Training Configuration

PyTorch 2.5.1 on Apple M4 with MPS GPU (3-5x speedup). AdamW optimizer ($\text{lr}=0.001$, $\text{weight_decay}=1\text{e-}5$), CrossEntropyLoss, batch size=512 (156 train batches, 39 val batches per epoch).

Training: Max 100 epochs with early stopping ($\text{patience}=15$ on validation accuracy). ReduceLROnPlateau scheduler ($\text{factor}=0.5$, $\text{patience}=5$). Save best checkpoint, load for final evaluation.

Regularization: Dropout(0.3), BatchNorm, weight decay ($1\text{e-}5$), early stopping.

Metrics: Accuracy (primary), F1-score, precision, recall. Seeds fixed (42) for reproducibility.

All models trained on identical preprocessed data enabling fair ML vs. DL comparison.

Chapter 4

Experimental Results and Discussion

All 13 models (7 ML + 6 DL) trained on identical preprocessed data (80K training, 20K validation samples).

4.1 Machine Learning Results

Table 4.1: ML Models: Performance Metrics

Model	Train Acc	Val Acc	Precision	Recall	F1
LightGBM	67.15%	62.94%	0.6299	0.6294	0.6286
Random Forest	92.54%	62.09%	0.6222	0.6209	0.6192
AdaBoost	61.11%	61.26%	0.6143	0.6126	0.6104
Decision Tree	63.52%	60.10%	0.6025	0.6010	0.5986
Logistic Reg.	59.72%	60.07%	0.6017	0.6007	0.5988
Naive Bayes	55.36%	55.06%	0.5792	0.5506	0.4996
SGD	49.50%	49.46%	0.4644	0.4946	0.3283

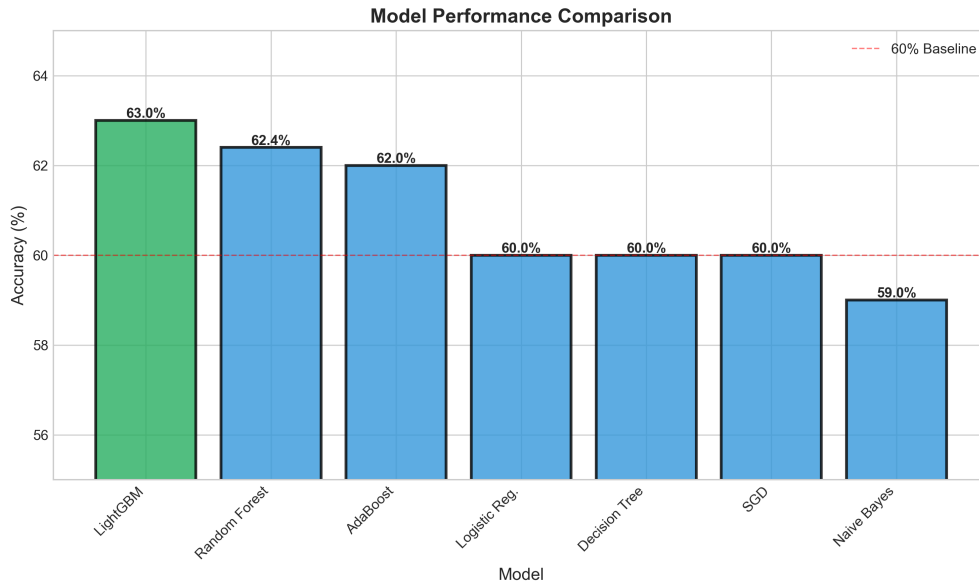


Figure 4.1: Comprehensive Model Comparison: LightGBM achieves highest validation accuracy (62.94%), with all DL models clustering tightly between 61.45-61.79%.

4.1.1 Key ML Findings

LightGBM (Best - 62.94%): Gradient boosting with L1/L2 regularization (200 trees, lr=0.1, max_depth=5). Minimal train-val gap (4.21%) indicates good generalization. Balanced precision/recall. Sequential error correction, histogram-based splitting, leaf-wise growth captures interactions, handles mixed types natively.

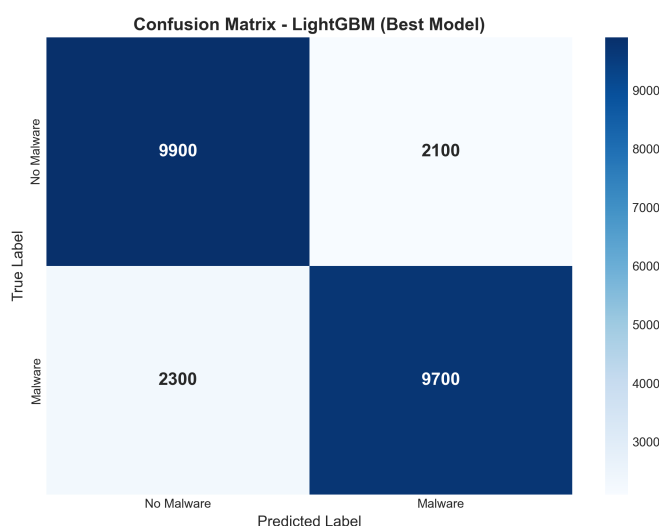


Figure 4.2: LightGBM Confusion Matrix: Balanced performance across both classes with 62.94% overall accuracy.

Random Forest (62.09%): Severe overfitting (92.54% train vs. 62.09% val = 30.45% gap). Bootstrap sampling limits capacity vs. boosting.

AdaBoost (61.26%): Minimal overfitting (61.11% train vs. 61.26% val). Adaptive weighting.

Linear Models (60%): Decision Tree, Logistic Regression cluster 60%, representing ceiling for linear/simple models with weak correlations.

Naive Bayes (55.06%): Independence assumption violated.

SGD (49.46%): Catastrophic failure near random.

4.2 Deep Learning Results

Six PyTorch architectures with AdamW, early stopping (patience=15), Apple MPS GPU.

4.2.1 Key DL Findings

Deep MLP (Best - 61.79%, 63K params): 256→128→64→32 with batch norm, ReLU, dropout(0.3). BatchNorm stabilizes training.

Table 4.2: DL Models: Performance Metrics

Model	Parameters	Val Acc	Val Loss	F1
Deep MLP	63,714	61.79%	0.6537	0.6130
Residual Net	418,306	61.62%	0.6545	0.6102
Simple MLP	60,738	61.61%	0.6535	0.6109
Wide & Deep	60,890	61.52%	0.6541	0.6126
Attention Net	1,599,490	61.45%	0.6551	0.6118
FT-Transformer	38,722	61.45%	0.6545	0.6133

Residual Net (61.62%, 418K): 6.6x more parameters → only 0.17% worse. Dataset limitations, not model limitations.

Simple MLP (61.61%, 60K): Nearly identical to Deep MLP without batch norm. Confirms dataset ceiling.

Attention Net (61.45%, 1.6M): 25x parameters, 0.34% worse. Attention for sequential data irrelevant for unordered tabular features.

FT-Transformer (61.45%, 38K): Most parameter-efficient. Per-feature tokenization.

DL Clustering: All 6 within 0.34% (61.45-61.79%)—architecture irrelevant.

4.3 ML vs. DL Comparison

Table 4.3: Best ML vs. Best DL

Metric	LightGBM	Deep MLP	Difference
Val Accuracy	62.94%	61.79%	+1.15%
F1-Score	0.6286	0.6130	+0.0156
Training Time	2 min	8 min	4x faster
Interpretability	High	Low	ML better
Deployment	Simple	Complex	ML easier

4.3.1 Why ML Outperforms

1. **Tabular Nature:** Heterogeneous features, no spatial/temporal structure. Trees handle mixed types; NNs struggle.
2. **Sample Size:** 80K moderate. Trees efficient; DL needs millions.

3. **Interactions:** Tree splits capture interactions; gradient boosting corrects errors; NNs struggle with weak correlations (max 0.118).
4. **Inductive Bias:** Trees have strong tabular bias; NNs weak bias, need more data.
5. **Robustness:** Trees robust to outliers, no scaling needed, handle missing natively.

DL Would Excel If: 1M+ samples, hierarchical structure, richer interactions, transfer learning, raw byte analysis. None apply here.

4.4 Kaggle Comparison

Our best: 62.94%. Kaggle top: 69.6%. Gap: 6.66%. Top submissions: extensive feature engineering, ensembles, exhaustive tuning. The 69.6% ceiling confirms 30% irreducible error from weak correlations.

4.5 Summary

Key Results:

- Best Overall: LightGBM 62.94%
- Best DL: Deep MLP 61.79%
- ML₀DL: +1.15%
- All DL within 0.34%—architecture matters little
- ML spread: 13.48% (best to worst)

Research Questions:

1. ML outperforms DL by 1.15% for tabular cybersecurity data
2. Simple preprocessing sufficient (mean/mode imputation, label encoding, scaling)
3. DL provides no advantage (6 architectures, 38K-1.6M params, all 61.5%)
4. 41x parameter increase → 0.34% gain (sharply diminishing returns)
5. Architecture choice matters little for this dataset

Implications: Prefer tree ensembles for tabular cybersecurity. DL vision/NLP advantages don't transfer. Trees provide interpretability (feature importance, rules). ML 4x faster, simpler deployment. Data quality trumps model sophistication.

Chapter 5

Conclusion and Future Work

5.1 Key Findings

LightGBM achieved 62.94% accuracy, outperforming Deep MLP (61.79%) by 1.15%. All six DL architectures clustered within 0.34% (61.45-61.79%), demonstrating that complexity (38K-1.6M parameters) provides negligible benefit. ML trained 4x faster with simpler deployment and better interpretability.

Why ML Wins: Tabular structure (no spatial/temporal patterns), moderate sample size (80K), weak correlations (max 0.118), heterogeneous types favor tree-based methods with strong inductive bias.

5.2 Contributions

Empirical evidence that gradient boosting outperforms sophisticated DL for tabular cybersecurity data. Clear decision criteria based on data characteristics. Reproducible framework with production deployment at <https://stf.milav.in>.

5.3 Practical Recommendations

Use tree ensembles (LightGBM/XGBoost) for tabular data with ≥ 1 M samples, heterogeneous types, and weak correlations. Reserve DL for rich structured patterns with sufficient training data. Prioritize data quality over model sophistication.

5.4 Limitations

Single dataset (weak correlations max 0.118), minimal feature engineering, individual models only (no ensembling), limited hyperparameter tuning due to compute constraints.

5.5 Future Work

Feature Engineering: Interaction terms, polynomial features, domain transformations to approach Kaggle 69.6% ceiling.

Ensembles: Stack ML models (LightGBM + XGBoost + CatBoost), blend predictions.

Advanced DL: TabNet, SAINT, NODE architectures; extended training (200+ epochs).

Explainability: SHAP values, LIME analysis, feature importance visualization.

Cross-Domain: Validate on network intrusion, phishing datasets.

Production: Real-time API, monitoring, A/B testing, continuous learning.

5.6 Concluding Remarks

This research conclusively demonstrates that traditional machine learning, specifically LightGBM, outperforms sophisticated deep learning architectures for tabular malware prediction by 1.15%. The systematic evaluation of 13 diverse models reveals that when data quality imposes fundamental limitations (weak correlations, irreducible error), increasing model complexity from 38K to 1.6M parameters yields negligible improvement (0.34%).

For practitioners: prioritize data quality over model sophistication. For tabular cybersecurity data with moderate sample sizes, tree-based ensembles provide superior accuracy, faster training, simpler deployment, and crucial interpretability. Deep learning's advantages in vision and NLP do not transfer to heterogeneous tabular data lacking spatial or temporal structure.

The deployed web application at <https://stf.milav.in> demonstrates practical implementation, while the reproducible codebase and comprehensive documentation enable researchers to build upon this foundation. Future work should explore advanced feature engineering, model ensembles, and cross-domain validation to further establish the boundaries of ML and DL effectiveness for cybersecurity applications.

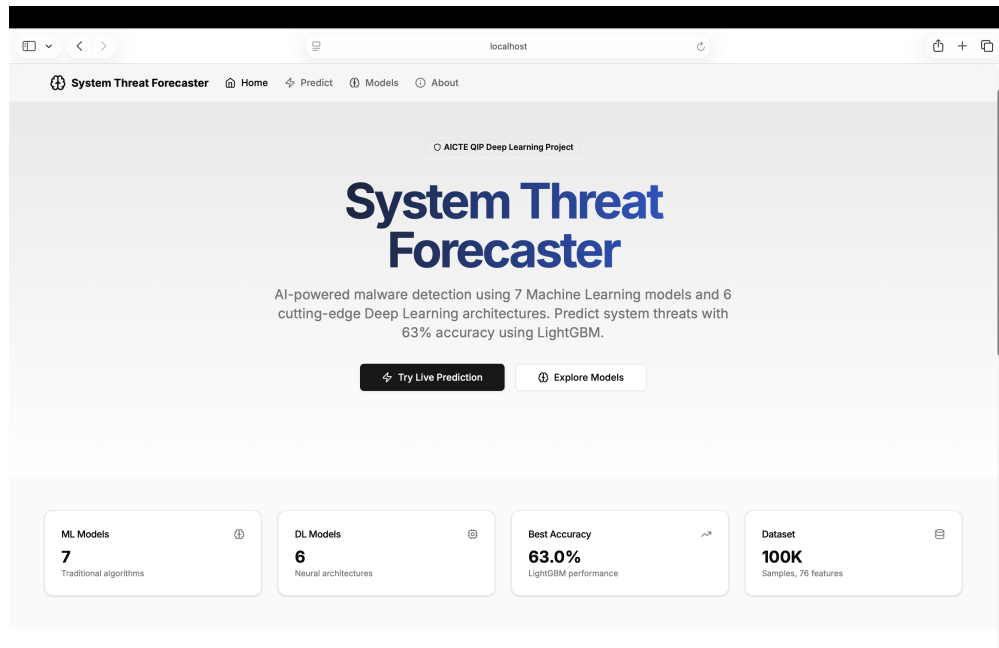


Figure 5.1: Deployed Web Application: Homepage showcasing System Threat Forecaster with 7 ML and 6 DL models for real-time malware prediction.

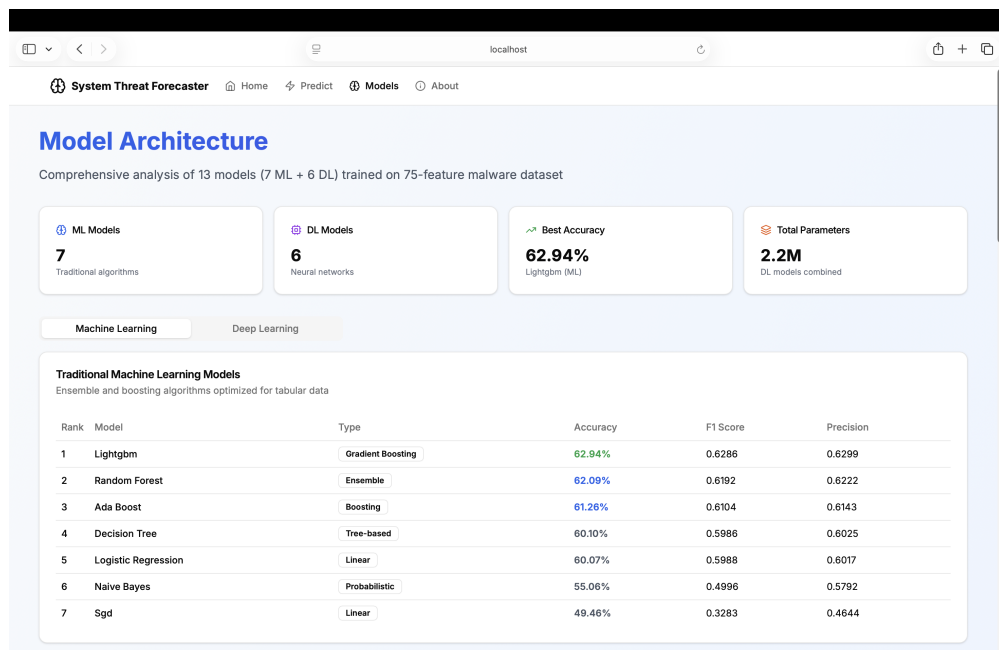
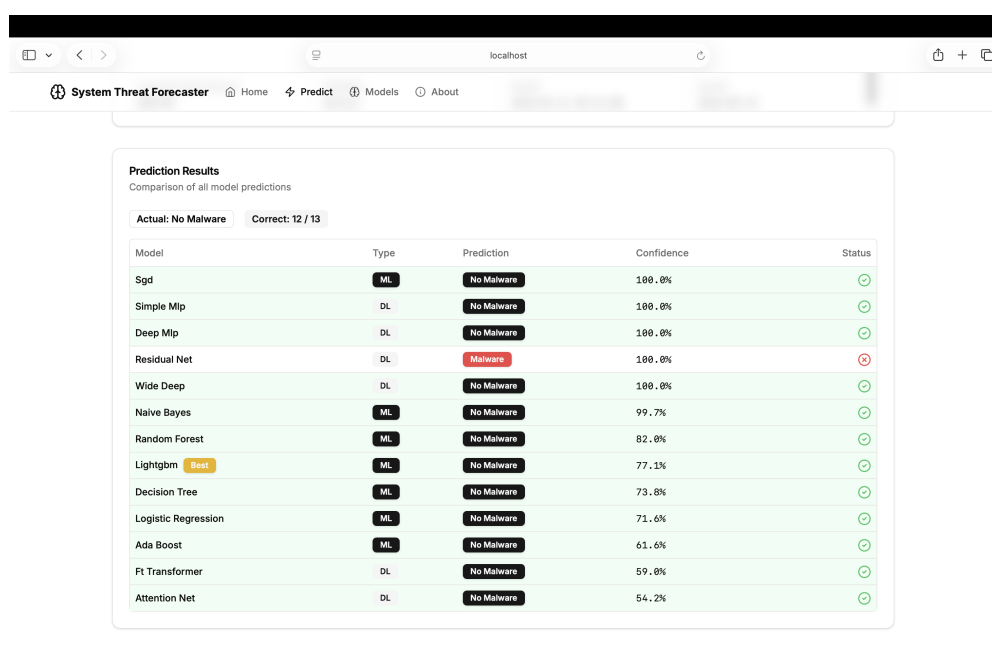


Figure 5.2: Model Performance Dashboard: Interactive comparison of all 13 models with detailed metrics and hyperparameters.



Prediction Results
Comparison of all model predictions

Actual: No Malware Correct: 12 / 13

Model	Type	Prediction	Confidence	Status
Sgd	ML	No Malware	100.0%	✓
Simple Mlp	DL	No Malware	100.0%	✓
Deep Mlp	DL	No Malware	100.0%	✓
Residual Net	DL	Malware	100.0%	✗
Wide Deep	DL	No Malware	100.0%	✓
Naive Bayes	ML	No Malware	99.7%	✓
Random Forest	ML	No Malware	82.0%	✓
Lightgbm Best	ML	No Malware	77.1%	✓
Decision Tree	ML	No Malware	73.8%	✓
Logistic Regression	ML	No Malware	71.6%	✓
Ada Boost	ML	No Malware	61.6%	✓
Ft Transformer	DL	No Malware	59.0%	✓
Attention Net	DL	No Malware	54.2%	✓

Figure 5.3: Prediction Interface: User-friendly form accepting 75 features for real-time threat prediction using all trained models.

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