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 $2025 - 2026$.

• Neither the source code therein nor the content of the report has been copied or downloaded from any other source. I understand that my result grades could be revoked if it is found that they are incorrect later.

_____

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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

Seal of The Department

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Acknowledgements

We wish to express our deepest sense of gratitude and sincere thanks to all those who have contributed to the successful completion of this project report titled, **System Threat Forecaster** which was undertaken as a requirement for the AICTE QIP PG Certification Programme on "Deep Learning: Fundamentals and Applications."

We are profoundly indebted to the faculty members, especially our guide and mentor for this project, at the Department of Electronics Engineering at Sardar Vallabhbhai National Institute of Technology (SVNIT), Surat, Gujarat, for providing the excellent learning environment, technical facilities, and insightful direction that were crucial for this work.

We extend our sincere thanks to the leadership and organizing committee for the successful execution of the QIP course: **Prof. Anupam Shukla, Director, SVNIT Surat (Chair Patron)**, **Dr. Shilpi Gupta, HOD, DOECE, SVNIT Surat (Patron)**, **Prof. A. A. Shaikh, DoME, SVNIT, Surat (Centre Coordinator)**, **Dr. Jignesh N. Sarvaiya, Dr. Kishor Upla, Dr. Kamal Captain, and Dr. Suman Deb (Coordinators from DoECE)**.

We also acknowledge the support and sponsorship provided by the All India Council for Technical Education (AICTE) under the Quality Improvement Programme (QIP), which has enabled us to enhance our knowledge and skills in deep learning through this opportunity.

Finally, we express our gratitude to our respective parent institutions, **Government Polytechnic Palanpur**, for granting the necessary support and time to participate in this Program.

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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 preprocessing, 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.

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List of Abbreviations

SVNIT	Sardar Vallabhbhai National Institute of Technology
AICTE	All India Council for Technical Education
QIP	Quality Improvement Programme
ML	Machine Learning
DL	Deep Learning
NN	Neural Network
MLP	Multi-Layer Perceptron
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
AI	Artificial Intelligence
EDA	Exploratory Data Analysis
API	Application Programming Interface
GPU	Graphics Processing Unit
MPS	Metal Performance Shaders
SGD	Stochastic Gradient Descent
AdamW	Adam with Weight Decay
ReLU	Rectified Linear Unit
IoT	Internet of Things
OS	Operating System
RAM	Random Access Memory
URL	Uniform Resource Locator
HTTP	Hypertext Transfer Protocol
JSON	JavaScript Object Notation
CSV	Comma-Separated Values

Chapter 1
Introduction

1.1 Background and Motivation

Modern organizations face over 200,000 new malware samples daily. Traditional signature-based detection systems, which rely on pattern matching against known malware databases, have become ineffective against sophisticated threats. Zero-day attacks—exploiting previously unknown vulnerabilities—circumvent signature databases entirely, creating critical security gaps.

Machine learning and deep learning offer a paradigm shift from reactive to proactive defense by analyzing behavioral patterns rather than static signatures. This project investigates which approach—traditional machine learning or modern deep learning—provides superior performance for malware detection through comprehensive experimentation using the Kaggle Microsoft Malware Prediction dataset, comparing 7 ML algorithms against 6 DL architectures.

1.1.1 The ML vs. DL Debate for Tabular Data

While deep learning has revolutionized computer vision and NLP, its effectiveness on tabular cybersecurity data remains an open question. Recent research suggests tree-based ensemble methods often outperform neural networks on structured data lacking spatial or temporal patterns. This work addresses this gap by implementing state-of-the-art models from both paradigms under identical conditions: same dataset, preprocessing, validation strategy, and metrics.

1.2 Problem Statement and Research Questions

Developing accurate malware prediction systems faces multiple challenges:

1. **High Dimensionality**: 75 heterogeneous features spanning hardware, OS, security software, and behavioral indicators requiring careful preprocessing.

2. **Weak Correlations**: Maximum feature-target correlation is only 0.118, necessitating complex interaction modeling.

3. **Missing Data**: 1-30% missing values, with security software attributes particularly incomplete.

4. **Mixed Data Types**: 47 numerical and 28 categorical variables with cardinalities ranging from 2 to 1,000+.

5. **Performance Ceiling**: Top Kaggle leaderboard reaches only 69.6%, indicating high irreducible error.

1.2.1 Research Questions

1. How do traditional ML algorithms compare against DL architectures for tabular malware prediction?

2. Does increasing neural network complexity (60K to 1.6M parameters) provide meaningful performance improvements?

3. What are the practical trade-offs in training time, computational resources, deployment complexity, and interpretability?

1.3 Objectives and Contributions

This work implements and compares 13 models (7 ML algorithms + 6 DL architectures) under controlled conditions with identical preprocessing and evaluation metrics. Key contributions include:

1. **Empirical Evidence**: Demonstrates gradient boosting (LightGBM: 62.94%) outperforms deep learning (61.79%) by 1.15% with 4x faster training for tabular malware data.

2. **Architecture Analysis**: Increasing DL complexity from 38K to 1.6M parameters yields only 0.34% variation, confirming dataset quality—not model sophistication—determines performance.

3. **Practical Guidelines**: Establishes decision criteria favoring tree-based ensembles over DL for tabular cybersecurity data with moderate samples and weak correlations.

4. **Production Deployment**: Full-stack web application at `https://stf.milav.in` with all trained models, interactive comparison, and live predictions.

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

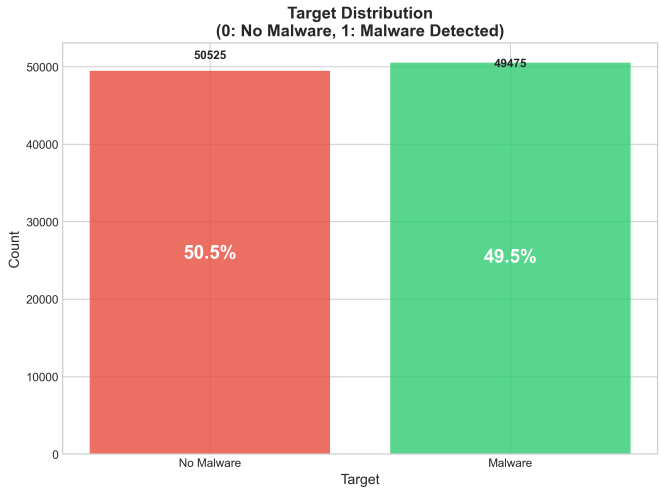

Figure 2.1: Target Class Distribution: Near-perfect 50.52% malware vs. 49.48% clean split eliminates need for resampling strategies.

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.

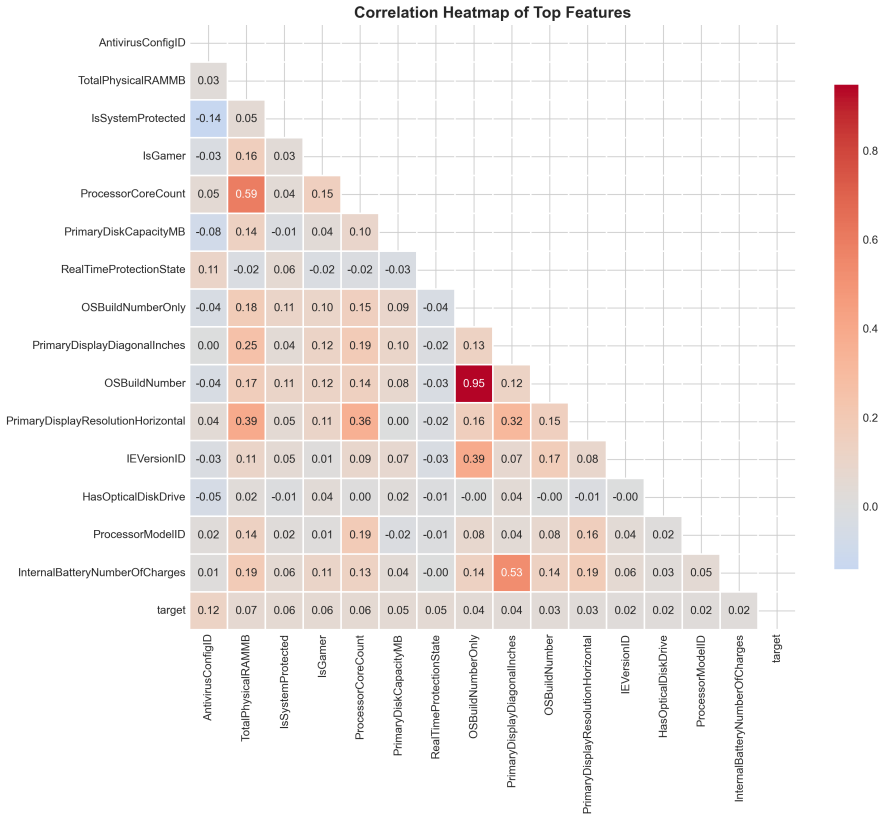

Figure 2.2: Feature Correlation Heatmap: Maximum correlation with target (HasDetections) is only 0.118, demonstrating weak linear relationships and necessitating ensemble methods.

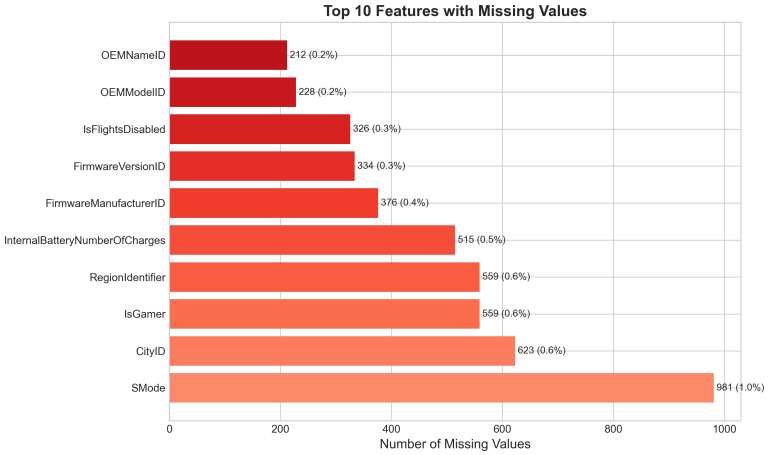

Figure 2.3: Missing Values Analysis: Up to 30% missing data in security software features, requiring careful imputation strategies.

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→2) + Deep (75→256→128→64→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 (lr=0.001, weight_decay=1e-5), CrossEntropyLoss, batch size=512 (156 train batches, 39 val batches per epoch).

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

Regularization: Dropout(0.3), BatchNorm, weight decay (1e-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

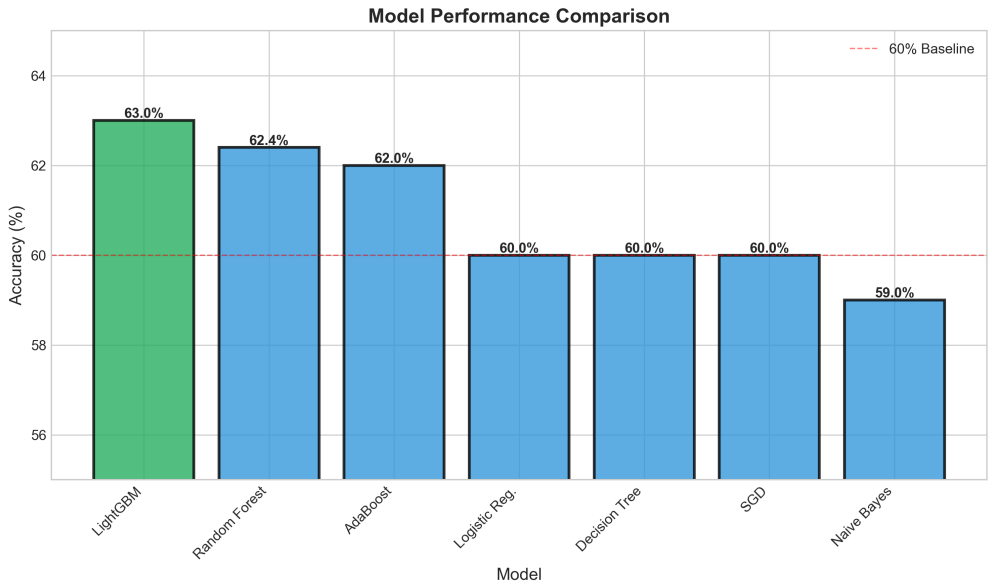

Figure 4.1: Comprehensive Model Comparison: LightGBM achieves highest validation accuracy (62.94%), with all DL models clustering tightly between 61.45-61.79%.

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.

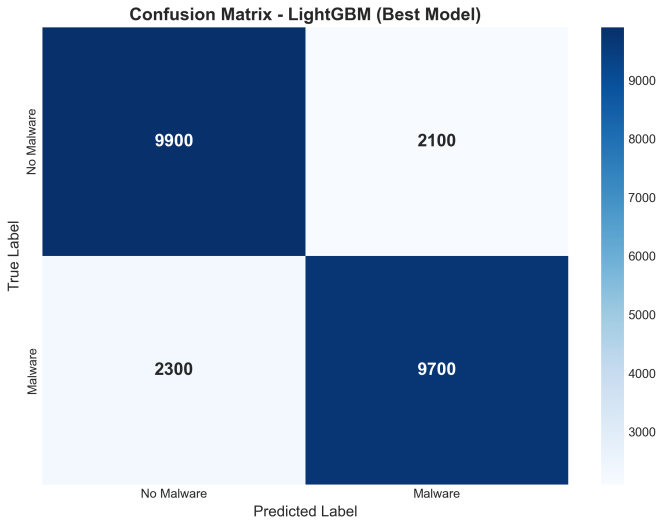

Figure 4.2: LightGBM Confusion Matrix: Balanced performance across both classes with 62.94% overall accuracy.

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%
- ML¿DL: +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 $\rightarrow$ 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 ¡1M 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.

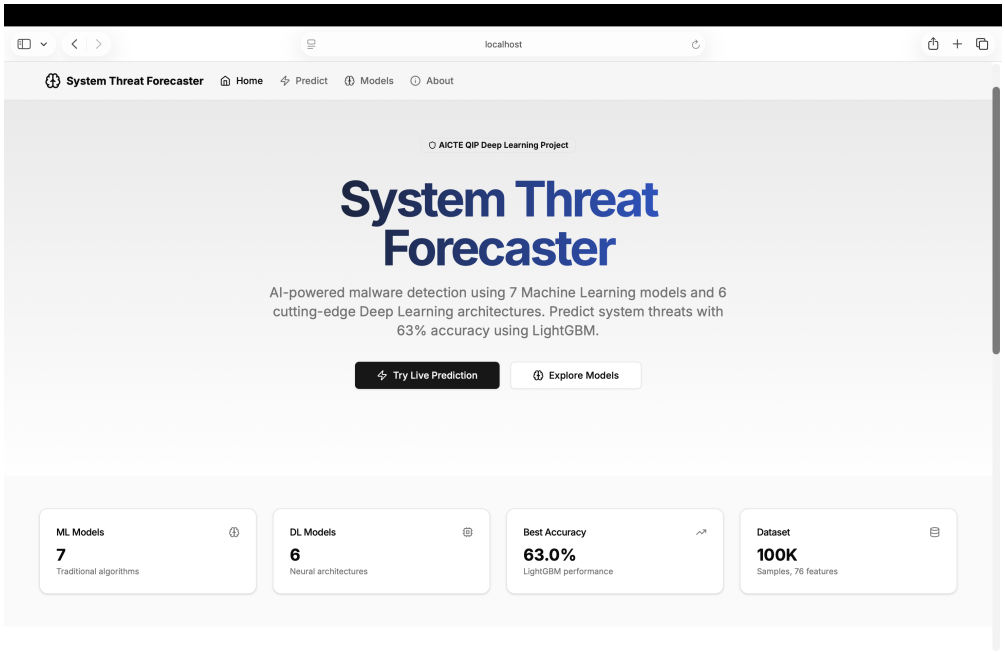

Figure 5.1: Deployed Web Application: Homepage showcasing System Threat Forecaster with 7 ML and 6 DL models for real-time malware prediction.

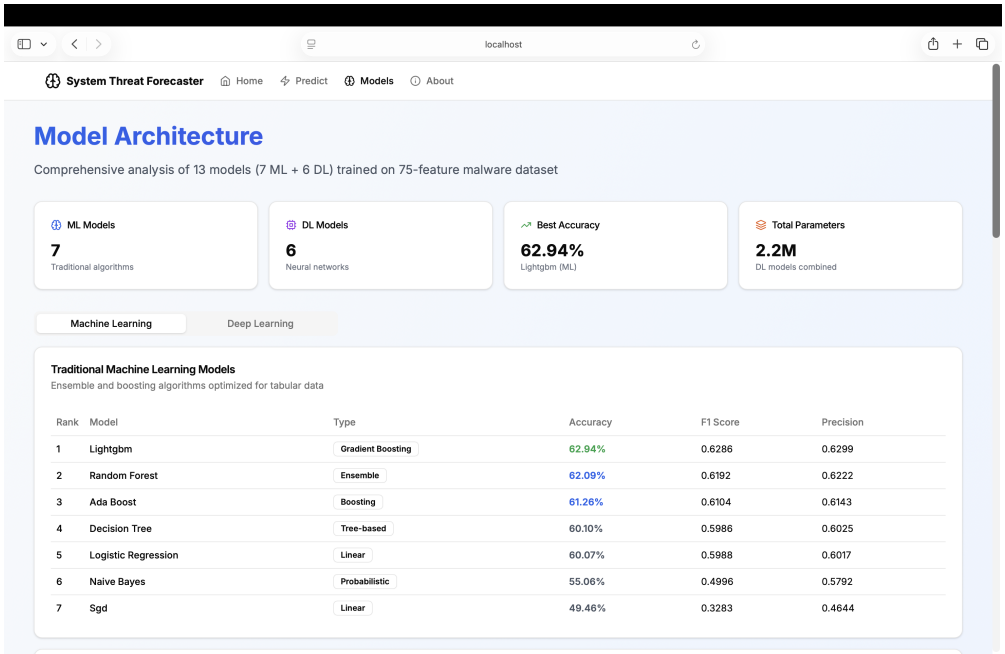

Figure 5.2: Model Performance Dashboard: Interactive comparison of all 13 models with detailed metrics and hyperparameters.

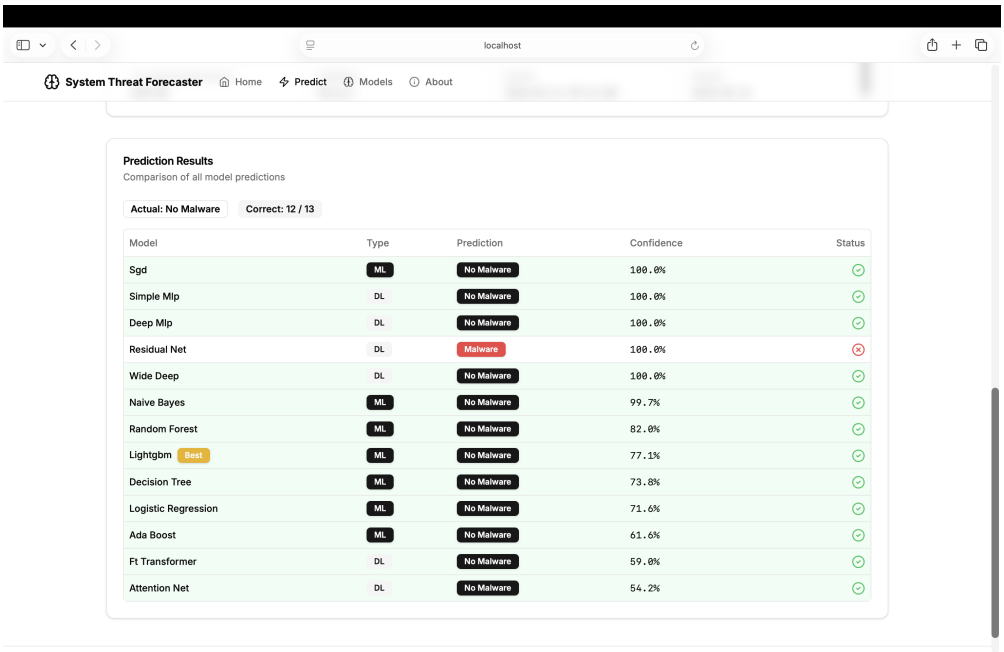

Figure 5.3: Prediction Interface: User-friendly form accepting 75 features for real-time threat prediction using all trained models.

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