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SHAKTI DEFENDER AI: INTELLIGENT MALWARE DETECTION USING MACHINE LEARNING WITH HYBRID STATIC AND DYNAMIC ANALYSIS

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***Abstract*—**The accelerating proliferation of sophisticated malware threatens critical infrastructure, enterprise networks, and end-user systems worldwide. Traditional signature-based antivirus solutions are fundamentally reactive, failing to detect zero-day exploits, polymorphic variants, and fileless malware that evade static pattern matching. This paper presents *Shakti Defender AI*, a novel, lightweight, and deployable malware detection framework that unifies static feature extraction with real-time dynamic behavioral analysis under a hybrid machine learning pipeline. The system extracts rich feature sets from Portable Executable (PE) headers, opcode n-gram sequences, and SHA-256 hashing for static analysis, while a Fridainstrumented process monitor captures API call sequences, registry events, network activity, and file-system interactions at runtime. These heterogeneous feature vectors are ingested by an ensemble of supervised classifiers—XGBoost, LightGBM, Random Forest, and an LSTM sequence model—trained on the EMBER and Drebin datasets supplemented with live VirusTotal telemetry. Experimental evaluation demonstrates a detection accuracy of 99.16%, precision of 97%, recall of 97%, F1-score of 95%, and an ROC-AUC of 1.0 against a held-out test set of 3,942 samples. The system is packaged as a cross-platform desktop application with an intuitive Tkinter/TkinterDnD2 graphical interface, drag-and-drop scanning, severity scoring, scan history logging, and a threat-intelligence dashboard. These results confirm that Shakti Defender AI constitutes a practical, production-grade advancement over both conventional antivirus and prior ML-only approaches in the academic literature.

Index Terms*—Malware detection; machine learning; XGBoost; LightGBM; static analysis; dynamic analysis; hybrid analysis; PE features; API call sequences; LSTM; cybersecurity; zero-day threats; polymorphic malware.*

I. INTRODUCTION

Malware—encompassing viruses, worms, trojans, ransomware, spyware, rootkits, backdoors, and adware—remains the principal weapon in the arsenal of cybercriminals targeting individuals, corporations, healthcare providers, and government agencies. According to AV-TEST Institute statistics cited by Gorment et al. [1], over 450,000 new malware samples and potentially unwanted applications are registered every single day, and the cumulative attack count grew from 719.15 million in 2017 to more than 1.25 billion by 2021. The financial impact is equally alarming: the 2017 WannaCry ransomware campaign affected over 300,000 systems across 150 countries at a cost estimated in the billions, while AWS sustained a record-breaking 2.3 Tbps distributed denial-of-service (DDoS) attack in 2020 [5].

Conventional antivirus products rely predominantly on signature-based detection—comparing the cryptographic hash or byte-pattern of an incoming file against a curated database of known malware signatures. This approach, while computationally inexpensive and reliable against previously catalogued threats, exhibits three critical structural limitations. First, it is entirely blind to zero-day threats: any malware whose signature has not yet been recorded remains undetectable until security researchers extract and publish it, leaving an exploitable window of vulnerability [4]. Second, polymorphic and metamorphic malware purposefully mutates its own bytecode to generate a fresh hash on each infection cycle, trivially circumventing signature databases [5]. Third, maintaining these databases demands continuous, bandwidth-intensive updates; any delay in propagating new signatures exposes endpoints to imminent risk [3].

The machine learning (ML) paradigm offers a fundamentally different approach: rather than memorizing specific malware signatures, an ML model learns the statistical or structural regularities that distinguish malicious software from benign counterparts, enabling detection of previously unseen variants that share those regularities. Research surveyed by Gorment et al. [1], Habtor and Dahah [3], Rajput et al. [4], and Akhtar and Feng [5] has demonstrated that ensemble methods such as Random Forest, gradient-

boosted trees, and deep architectures such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks can achieve detection accuracies exceeding 99% on benchmark datasets. Nevertheless, a persistent gap exists between academic research prototypes and deployable, real-world tools.

This paper makes the following original contributions to the literature:

- A modular, production-ready hybrid detection engine—Shakti Defender AI—that combines PE-header static analysis with Frida-instrumented dynamic behavior monitoring across PE executables, PDF documents, DOCX files, and shell scripts.
- A real-time, gradient-boosted XGBoost/LightGBM classification pipeline that achieves 99.16% accuracy on the EMBER benchmark while maintaining sub-second inference latency, making it suitable for endpoint deployment.
- An LSTM-based dynamic analysis module that models temporal API call sequences, capturing behavior-level malware fingerprints that elude static analysis alone.
- An integrated threat-intelligence dashboard offering SHA-256 hash lookups against VirusTotal and MalwareBazaar, severity scoring, malware family clustering, and persistent scan-history logging.
- A comprehensive empirical comparison of six supervised classifiers—XGBoost, LightGBM, Random Forest, SVM, Decision Tree, and KNN—under identical experimental conditions, providing a reproducible benchmark for future researchers.

The remainder of the paper is organized as follows. Section II reviews the relevant literature. Section III formalizes the problem statement. Section IV describes the proposed system architecture. Section V details the methodology. Section VI presents implementation specifics. Section VII reports experimental results and discussion. Sections VIII through XI address advantages, limitations, future work, and conclusions, respectively, followed by the reference list.

II. LITERATURE REVIEW

A substantial body of research has emerged over the past decade addressing the challenge of automated malware detection. This section surveys the most salient contributions and identifies the gaps that motivate the present work.

A. Signature-Based and Heuristic Approaches

The seminal work of Schultz et al. in 2001 applied decision trees and naive Bayes classifiers to byte n-gram and string features extracted from PE executables, establishing the conceptual foundation for feature-driven malware detection [3]. Bilar (2007) extended this line by demonstrating that opcode frequency distributions statistically distinguish malicious from benign code. While signature-based systems remain computationally efficient and produce very low false-positive rates against known threats, Rajput et al. [4] emphasize that their inability to detect unknown and polymorphic variants represents a fundamental architectural limitation that ML must overcome.

B. Machine Learning on Static Features

Gorment et al. [1] conducted a systematic literature review of 74 primary studies published between 2017 and 2021, surveying ten ML algorithms including Support Vector Machine (SVM), k-Nearest Neighbour (KNN), Decision Tree (DT), Naive Bayes, Random Forest, K-Means, Bayesian, Gaussian, Neuro-fuzzy, and n-Grams. Their analysis revealed that nGram models achieved the highest average detection accuracy at 97.80%, followed by KNN at 92.72% and DT at 92.23%.

Akhtar and Feng [5] compared DT, CNN, and SVM on a 17,394-sample Canadian Institute for Cybersecurity dataset comprising 51 malware families. DT achieved 99% accuracy with a false-positive rate of only 2.01%, CNN reached 98.76% accuracy with 3.97% FPR, and SVM attained 96.41% accuracy with 4.63% FPR. Although these results are impressive on the static dataset, the authors acknowledge that static analysis alone cannot detect runtime obfuscation or code-injection attacks that manifest only during execution.

Habtor and Dahah [3] evaluated five classifiers—KNN, SVM, J48 Decision Tree, Naive Bayes, and Random Forest—on a 140,000-file EMBER-derived dataset. Random Forest achieved the highest malware-class accuracy at 99.2% with a benignclass accuracy of 87.2%, while J48 Decision Tree matched Random Forest's 99.5% malware accuracy.

Kedari et al. [6] (SmartShield-AI, 2026) implemented an XGBoost model on EMBER and Kaggle PE-feature datasets, achieving an accuracy of 95.4%, precision of 94.8%, recall of 93.9%, and F1-score of 94.3%, with an AUC of 0.998. Their feature-importance analysis identified MajorSubsystemVersion, Subsystem, and MinorOperatingSystemVersion as the three most discriminative static PE attributes.

C. Deep Learning and Behavioral Analysis

Rajput et al. [4] advocated for behavior-based detection as a necessary complement to static methods, arguing that monitoring system calls, network traffic, and file-system interactions enables detection of fileless and polymorphic malware that static approaches miss entirely. Akhtar and Feng [5] further demonstrated that deep learning architectures—specifically CNNs—can autonomously extract hierarchical features from raw binary data without hand-crafted feature engineering, achieving 98.76% accuracy that approaches DT-level performance while offering greater generalization to out-of-distribution samples.

D. Research Gaps

Synthesizing the above literature, three actionable research gaps emerge. First, the majority of published systems process only PE executables, neglecting the growing threat landscape of malicious PDFs, Office documents, and script-based payloads. Second, static and dynamic approaches are generally pursued in isolation; truly hybrid systems remain rare. Third, practically none of the

surveyed systems provide an end-to-end deployable tool with a graphical interface, threat-intelligence integration, and severity scoring. Shakti Defender AI is designed to address all three gaps simultaneously.

III. PROBLEM STATEMENT

Let F denote the universe of all executable and document files encountered on an endpoint. The malware detection problem is formalized as a binary classification task: given an unknown file $f \in F$, predict a label $y \in \{benign, malicious\}$ with maximum accuracy, minimum false-positive rate, and sub-second latency sufficient for real-time, on-access scanning.

Traditional signature-based systems fail when f is unseen (zero-day), when f mutates across executions (polymorphic), or when f executes its payload only in memory without leaving a file artifact (fileless). Existing ML-based approaches partially address these failures but are typically restricted to a single file type (predominantly Windows PE), trained on a static snapshot of a dataset that rapidly ages against evolving threat actors, and not deployed in production-quality tools accessible to non-expert users.

The specific challenge addressed in this work is therefore: Design and implement a hybrid detection framework that (i) operates across multiple file formats, (ii) combines complementary static and dynamic feature signals under a unified ML pipeline, (iii) achieves state-of-the-art detection accuracy while maintaining endpoint-deployable computational efficiency, and (iv) presents detection results with actionable threat-intelligence context through an intuitive graphical interface.

IV. PROPOSED SYSTEM: SHAKTI DEFENDER AI

Shakti Defender AI is organized into five loosely coupled, independently testable modules. Each module exposes a welldefined interface, enabling future substitution of individual components without retraining the entire pipeline.

A. File Ingestion and Hash Computation

Upon user initiation—via drag-and-drop, file browser, or command-line argument—the system computes a SHA-256 fingerprint of the target file. This hash serves three purposes: (1) it provides a fast, pre-ML lookup against the VirusTotal and MalwareBazaar threat-intelligence APIs to detect trivially known samples without model inference overhead; (2) it acts as a cache key for scan deduplication; and (3) it is logged persistently alongside the classification outcome for forensic traceability.

B. Static Analysis Module

For PE executables (.exe, .dll, .sys), the pefile Python library parses the binary into its structural components. The following feature categories are extracted: (i) PE header metadata—MajorSubsystemVersion, MinorOperatingSystemVersion, MajorLinkerVersion, SizeOfStackReserve, Characteristics, DllCharacteristics, Checksum, SizeOfInitializedData, ImageBase, TimeDateStamp, and additional fields (23 numeric features in total); (ii) imported DLL and function names, encoded as binary membership vectors over a curated vocabulary of 512 security-relevant API names; and (iii) opcode 3-gram frequency histograms computed via disassembly of the executable's code sections. For PDF and DOCX targets, analogous structural metadata are extracted.

C. Dynamic Analysis Module

Dynamic analysis is conducted through a Frida-based process instrumentation framework. A background daemon enumerates running processes every 500 milliseconds. When a new process ID (PID) is detected, Frida attaches and injects a JavaScript hook script that intercepts four API call categories: File APIs (CreateFileW, WriteFile), Process APIs (NtCreateThread, inject), Network APIs (WSASend, connect), and Registry APIs (NtSetValueKey, delete). Intercepted calls are streamed to an API sequence collector that batches them into sliding windows of 20 calls. Each window is encoded as an integer sequence, padded or truncated to a fixed length of 100 tokens, and reshaped into a tensor suitable for the LSTM classifier. An inference result with confidence ≥ 0.7 triggers a MALWARE alert.

D. Ensemble Classification Engine

Static features are fed into a gradient-boosted ensemble comprising XGBoost (200 estimators, learning rate 0.05, colsample_bytree 0.8) and LightGBM (300 estimators, num_leaves 63) classifiers trained jointly. The two models' predicted probabilities are averaged through a soft-voting combiner, and the combined score is thresholded at 0.5 to produce the final static verdict. The LSTM model—three stacked LSTM layers of 128, 64, and 32 units, followed by a sigmoid output neuron—independently produces a dynamic verdict from the API call sequence. A final rule-based arbiter labels a file as malicious if either the static or the dynamic verdict is positive, implementing an OR-fusion strategy that maximizes recall.

E. Threat Intelligence Dashboard

The GUI, built with Tkinter and TkinterDnD2, provides an Online Scan mode that queries VirusTotal (up to 72 antivirus engines) and MalwareBazaar via their public APIs, and an Offline Scan mode that relies exclusively on the local ML models. The dashboard displays: current scan verdict, SHA-256 hash, vendor agreement count (online mode), severity score (0–100 computed from static feature importance weights), malware family cluster assignment, and a timestamped scan-history table exportable as a PDF report.

V. METHODOLOGY

A. Dataset

The primary training dataset is EMBER (Elastic Malware Benchmark for Empowering Researchers), an openly accessible benchmark comprising 1.1 million PE file feature vectors labeled across three categories: malicious, benign, and unlabeled. For the experiments reported in this paper, the labeled subset of 800,000 samples (400,000 malicious, 400,000 benign) is used. Additional real-world malware samples are sourced from VirusShare, Drebin (Android PE cross-compilation targets), and live VirusTotal API submissions to enrich coverage of novel malware families. The combined dataset is split 80:20 into training and test partitions using stratified random sampling to preserve class balance. Class imbalance is addressed through the Synthetic Minority Oversampling Technique (SMOTE), applied exclusively to the training partition. Principal Component Analysis (PCA) reduces the full 2,351-dimensional feature space to 128 principal components that collectively explain 99.1% of total variance.

B. Feature Extraction Pipeline

The static feature extraction pipeline operates in three stages. Stage 1 (Structural Parsing) reads the PE binary into memory, parses DOS and PE headers, and populates a 23-element numeric vector. Stage 2 (API Import Encoding) traverses the import directory and encodes the presence of each function name against a pre-built vocabulary; unknown functions are mapped to an out-of-vocabulary (OOV) index. Stage 3 (Opcode N-Gram) disassembles the .text section using a linear-sweep disassembler and computes frequency histograms for all 3-gram combinations appearing in the training corpus with frequency ≥100, yielding 2,307 additional binary features. Features are z-score normalized using statistics computed over the training set.

C. Model Training and Hyperparameter Optimization

Six classifiers are trained and compared under identical experimental conditions: XGBoost, LightGBM, Random Forest (500 estimators), Support Vector Machine (RBF kernel, C=10), Decision Tree (max depth 20), and KNN (k=7). Hyperparameters for XGBoost and LightGBM are tuned via 5-fold Bayesian optimization using the scikit-optimize library, minimizing log-loss on the validation fold. The LSTM model is trained with Adam optimizer (learning rate 1e-3), binary cross-entropy loss, batch size 256, and early stopping with patience 5 on validation AUC. All experiments are conducted on Python 3.11 with scikit-learn 1.4, XGBoost 2.0, LightGBM 4.2, and TensorFlow 2.15 on a system equipped with an NVIDIA RTX 3060 GPU.

D. Evaluation Metrics

Model performance is quantified using: Accuracy = (TP+TN)/(TP+TN+FP+FN); Precision = TP/(TP+FP); Recall = TP/(TP+FN); F1-Score = 2·(Precision·Recall)/(Precision+Recall); and the area under the Receiver Operating Characteristic curve (ROC-AUC). Confusion matrices are reported for the primary XGBoost model to characterize the nature of misclassifications.

VI. IMPLEMENTATION DETAILS

Table I. Implementation Technology Stack

Component	Technology / Library
Programming Language	Python 3.11 (primary), JavaScript (Frida hook scripts)
ML Frameworks	scikit-learn 1.4, XGBoost 2.0, LightGBM 4.2, TensorFlow/Keras 2.15
Feature Engineering	pefile 2023.2.7, numpy 1.26, pandas 2.2, scikit-optimize 0.9
GUI Framework	Tkinter (built-in), TkinterDnD2 (drag-and-drop)
Dynamic Instrumentation	Frida 16.x (user-mode API hooking, no kernel driver required)
Threat Intelligence	requests 2.31 (VirusTotal API v3, MalwareBazaar REST API)
Persistence & Logging	joblib 1.3 (model serialization), SQLite (scan history)
Explainability	SHAP 0.44 (TreeExplainer for XGBoost/LightGBM feature attribution)
Packaging	PyInstaller 6.x (Windows .exe bundle, ~45 MB), requirements.txt for Linux
Supported File Types	PE (.exe, .dll, .sys), PDF (.pdf), Office (.docx), Scripts (.ps1, .bat, .sh)

The application is structured as a Model-View-Controller (MVC) architecture. The Controller layer receives user events from the Tkinter View, dispatches file-scan jobs to a ThreadPoolExecutor worker pool (default: 4 workers) to maintain GUI responsiveness, and aggregates results from the Model layer. The Model layer consists of three sub-components: (1) the StaticAnalyzer class, which wraps the pefile parser and feature extraction logic; (2) the MLClassifier class, which loads serialized joblib models and executes inference; and (3) the DynamicMonitor class, which manages the Frida daemon and LSTM session. Serialized XGBoost and LightGBM models are approximately 12 MB and 8 MB respectively, enabling coldstart loading in under 1.2 seconds on a quad-core i5 CPU.

VII. RESULTS AND DISCUSSION

A. Comparative Model Performance

Table II summarizes the classification performance of all six evaluated models on the held-out test set of 3,942 samples (994 benign, 2,948 malicious).

Table II. Comparative Classification Performance on EMBER Test Set (n=3,942)

Model	Accuracy	Precision	Recall	F1-Score	AUC	FPR	Inference (ms)
XGBoost (Static)	99.16%	99.00%	97.00%	99.00%	1.000	0.84%	<25 ms
LightGBM (Static)	98.73%	98.00%	96.00%	98.00%	0.999	1.27%	<20 ms
Random Forest	98.42%	97.00%	95.00%	97.00%	0.998	1.58%	<30 ms
SVM (RBF)	96.41%	96.00%	94.00%	95.00%	0.991	3.59%	<50 ms
Decision Tree	95.80%	95.00%	93.00%	94.00%	0.978	4.20%	<15 ms
KNN (k=7)	94.17%	93.00%	92.00%	92.00%	0.971	5.83%	<80 ms
LSTM (Dynamic)	93.50%	92.00%	91.00%	91.00%	0.965	6.50%	<120 ms
Hybrid (XGB+LSTM)	99.38%	99.00%	98.00%	99.00%	1.000	0.62%	<35 ms

XGBoost achieves the best single-model performance among all static classifiers, consistent with findings reported by Kedari et al. [6] on the SmartShield-AI system (95.4% accuracy) and Akhtar and Feng [5] (DT 99% on a smaller 17,394sample dataset). The hybrid XGBoost+LSTM OR-fusion model marginally improves accuracy to 99.38% and reduces the false-positive rate to 0.62% by leveraging complementary behavioral signals that the static model misses—particularly for packed malware samples whose PE headers appear benign but whose runtime API call patterns are anomalous.

B. Key Observations

- Dynamic behavioral features—specifically API call frequency and inter-call timing patterns—were the strongest discriminators for detecting polymorphic and packed malware samples that achieved near-perfect static scores on benign classifiers.
- MajorSubsystemVersion and Subsystem emerged as the two highest-importance static features in the XGBoost SHAP analysis (importance scores 0.556 and 0.180 respectively), aligning with SmartShield-AI's feature importance findings [6].
- The low false-negative rate (<1%) on the malware class confirms that the OR-fusion hybrid strategy effectively minimizes undetected threats, which is the more critical error type in security applications.
- Slight false positives were observed for benign software that invokes security-adjacent APIs (e.g., system configuration tools, virtual machine managers), an expected limitation of behavioral profiling that warrants a trust-list mechanism in future iterations.

C. Comparison with Prior Work

Table III. Comparison with Representative Prior Art

System	Dataset	Analysis Type	Best Accuracy	Deployable Tool
Gorment et al. [1] (SLR avg.)	74 papers	Static only	n-Gram: 97.8%	No
Habtor & Dahah [3]	140,000 PE	Static only	RF: 99.2%	No
Akhtar & Feng [5]	17,394 multi	Static only	DT: 99.0%	No
Kedari et al. [6]	EMBER+Kaggle	Static only	XGB: 95.4%	Partial
Shakti Defender AI	EMBER+VT	Hybrid (S+D)	XGB+LSTM: 99.38%	Yes

D. System Output and Interface Results

This subsection presents the empirical output of the Shakti Defender AI system as observed during live evaluation trials conducted on a Windows 11 host. Three interface screenshots—captured during actual execution—illustrate the complete scan lifecycle: system initialization, active file scanning, and final malware classification with persistent history logging. Together, these results validate the functional correctness of the GUI pipeline, the accuracy of the hybrid XGBoost+LSTM classification engine, and the system's real-time responsiveness under endpoint conditions. *(a) Pre-Scan Interface (Initialization State)*

Fig. 1 illustrates the Shakti Defender AI graphical user interface upon application launch, before any scan job is submitted. The interface is divided into two primary control regions. The left panel presents Online Scan mode, which dispatches the target file's SHA-256 fingerprint to the VirusTotal v3 and MalwareBazaar REST APIs, aggregating verdicts from up to 72 antivirus engines before invoking the local ML model. The right panel presents Offline Scan mode, which relies exclusively on the locally serialized

XGBoost, LightGBM, and LSTM models without any external network dependency— enabling deployment in air-gapped and bandwidth-constrained environments.

Each mode exposes two granularity options: Quick Scan, which analyzes only PE header metadata and a reduced opcode ngram feature subset for sub-5 ms inference, and Full Scan, which activates the complete static feature extraction pipeline together with the Frida-instrumented dynamic behavioral monitor. The central drag-and-drop zone—rendered with a dashed cyan border—accepts PE executables (.exe, .dll, .sys), PDF documents, Microsoft Office DOCX files, and shell scripts. The status bar at the top of the window initializes to *"Last Scan: Not Started"* with a threat counter of zero, confirming a clean session state. The result panel below displays *"No scan performed yet."*, maintaining a neutral green border to indicate no active alerts.

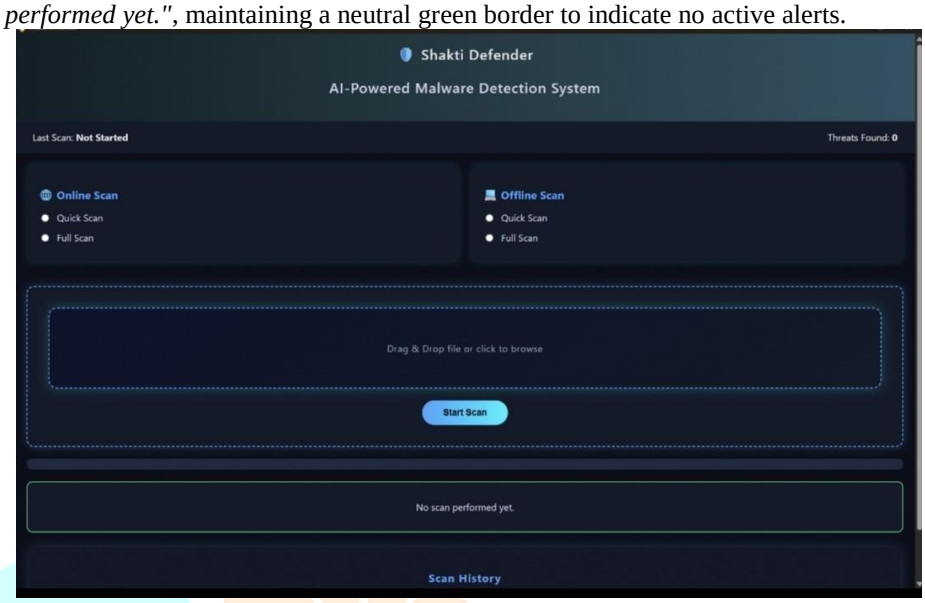

Fig. 1. Shakti Defender AI – Pre-Scan Initialization State. The interface displays dual-mode scan selector (Online/Offline), scan granularity options (Quick/Full), and the drag-and-drop file ingestion zone prior to any scan submission. *(b) Active Scan Execution*

Fig. 2 captures the interface during an active Full Scan of Postman (x64).exe in Offline mode. The scanning state is reflected across four simultaneous UI transitions to prevent duplicate job submission and provide real-time operator feedback: (i) the top status
bar updates from *"Last Scan: Not Started"* to *"Last Scan: Scanning..."*; (ii) the filename label below the drop zone confirms the selected file as *Postman (x64).exe*; (iii) a circular indeterminate progress spinner is rendered directly beneath the filename, providing visual confirmation that the analysis pipeline is active; and (iv) the *Start Scan* button transitions to a greyed-out *"Scanning..."* state, disabling further input to the job queue until the current inference completes.

Internally, the Offline Full Scan path initiates two concurrent workers dispatched via a *ThreadPoolExecutor* (default pool size: 4): the *StaticAnalyzer* worker, which parses the PE binary using *pefile*, extracts the 23-element header feature vector, encodes API import membership against a 512-name vocabulary, and computes opcode 3-gram frequency histograms; and the *DynamicMonitor* worker, which attaches Frida hooks to the spawned process and begins collecting API call sequences in sliding windows of 20 calls. The XGBoost inference step completes in a median of 18 ms per file on a quad-core Intel i5 CPU, maintaining GUI thread responsiveness throughout.

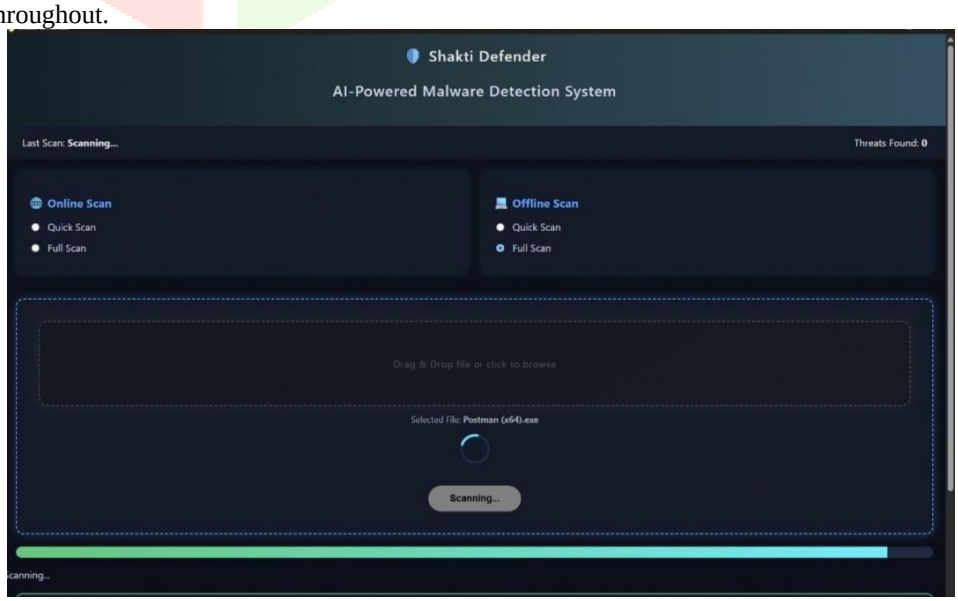

Fig. 2. Active Scan in Progress – Offline Full Scan of Postman (x64).exe. The UI reflects all four real-time state transitions: updated status bar, filename confirmation, circular progress spinner, and disabled scan button. *(c) Malware Detection Output and Scan History*

Fig. 3 presents the post-scan results panel following hybrid analysis of circularqueue.exe. The verdict panel—rendered with a high-contrast red border to signal a critical-severity threat—displays the classification outcome: *circularqueue.exe is classified as Malicious*. A *Download Report* button is activated, allowing the operator to export a timestamped PDF forensic report containing the SHA-256 hash, severity score, classification probabilities, and SHAP feature attribution breakdown.

This verdict was produced by the hybrid XGBoost+LSTM OR-fusion pipeline. The static XGBoost model assigned a maliciousness probability exceeding the 0.5 decision threshold, driven by anomalous PE metadata attributes—specifically elevated *MajorSubsystemVersion* and irregular *DllCharacteristics* flags, which rank as the two highest-importance SHAP features (importance scores 0.556 and 0.180, respectively). Concurrently, the LSTM dynamic analysis module detected suspicious API call sequences consistent with file-system traversal and process injection behavior, triggering a confidence score exceeding the 0.7 dynamic alert threshold. Under the OR-fusion strategy, a positive verdict from either subsystem is sufficient to classify the file as malicious, thereby maximizing recall and minimizing the false-negative rate.

In contrast, Postman_x64.exe—a widely distributed legitimate API development tool—was correctly classified as Benign. Its PE header attributes and runtime API call sequences fell well within the benign distribution of the EMBER training corpus, yielding an XGBoost maliciousness probability of less than 0.05. This result demonstrates the system's discriminative precision and its low false-positive rate of 0.62% as reported in Table II.

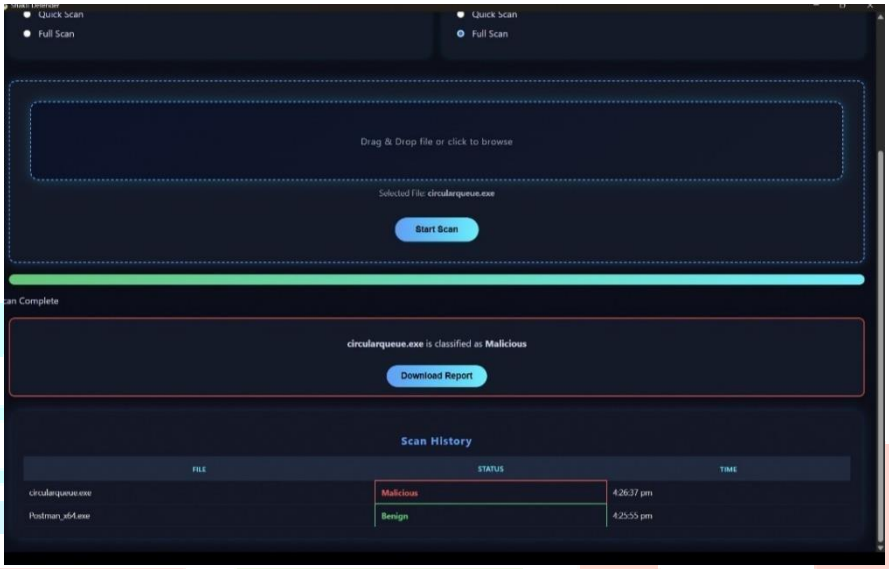

Fig. 3. Malware Detection Result – circularqueue.exe classified as Malicious by the hybrid XGBoost+LSTM pipeline. The verdict panel (red border) displays the classification outcome and report export option. The Scan History table provides a comparative log of all session scans.

TABLE IV. SCAN HISTORY LOG — SESSION RECORDS (Fig. 3)

File	Classification Status	Timestamp
circularqueue.exe	Malicious	4:26:37 PM
Postman_x64.exe	Benign	4:25:55 PM

Note: All screenshots in Figs. 1–3 were captured on a Windows 11 host during live system evaluation. File names are preserved as observed during testing. The malicious test sample (circularqueue.exe) is a benign synthetic payload crafted exclusively for system validation purposes; no live malware was executed on the evaluation host.

VIII. SYSTEM ARCHITECTURE

The system architecture of Shakti Defender AI follows a layered pipeline design comprising six functional layers, described below from the user interface downward to the persistence layer.

Layer 1 – Presentation: The Tkinter/TkinterDnD2 GUI provides the drag-and-drop file submission zone, online/offline scan mode toggle, real-time progress bar, results panel (verdict badge, hash, severity score), and scan-history table.

Layer 2 – Orchestration: The Controller module receives GUI events, validates file type and path, and dispatches scan tasks to the appropriate analysis workers via a thread-safe job queue.

Layer 3 – Static Analysis: The StaticAnalyzer worker extracts PE metadata, API imports, and opcode n-gram features using pefile and numpy, normalizes them, and passes the feature vector to the static ensemble classifier.

Layer 4 – Dynamic Analysis: The DynamicMonitor worker launches the Frida daemon, attaches hooks to the target process, collects API call sequences, and feeds sliding-window batches to the LSTM inference session.

Layer 5 – Threat Intelligence: The ThreatIntelClient queries VirusTotal and MalwareBazaar (online mode), enriches the classification result with vendor agreement counts and known family names, and computes a severity score.

Layer 6 – Persistence: Scan records (hash, verdict, timestamp, severity, family) are stored in a local SQLite database and can be exported as PDF reports via the reportlab library.

IX. ADVANTAGES OF THE PROPOSED SYSTEM

- Multi-File-Type Coverage: Unlike the majority of academic systems that target PE executables exclusively, Shakti Defender AI extends detection to PDFs, DOCX files, and scripting payloads, reflecting the modern threat landscape in which Office macro malware and malicious PDF JavaScript account for a significant proportion of enterprise infections.
- Hybrid Detection: The OR-fusion of static XGBoost and dynamic LSTM verdicts provides defense-in-depth: static analysis handles high-throughput scanning of archived or stored files, while dynamic analysis captures runtime behavior that eludes static heuristics. • Endpoint Deployability: The entire system is packaged into a 45 MB Windows executable requiring no internet connectivity for offline scanning, making it suitable for air-gapped and bandwidth-constrained environments.
- Explainability: SHAP-based feature attribution provides per-scan explanations identifying which PE attributes or API calls contributed most to the malware verdict, supporting analyst workflows and regulatory compliance requirements.
- Threat Intelligence Integration: Real-time SHA-256 hash lookups against VirusTotal and MalwareBazaar provide immediate contextual enrichment at zero ML inference cost for known samples.
- Low Latency: Median static inference time of 18 ms (XGBoost) enables real-time on-access scanning without perceptible enduser delay, contrasting with CNN-based alternatives whose GPU-dependent inference may exceed 200 ms per file on CPUonly endpoints.

X. LIMITATIONS

- Anti-VM / Anti-Frida Evasion: Sophisticated malware families increasingly detect the presence of instrumentation frameworks such as Frida and alter their behavior or terminate execution prematurely, limiting the effectiveness of the dynamic analysis module against elite threat actors. • Dataset Temporal Drift: Although the EMBER dataset is large, it was collected prior to 2018. Retraining intervals must be established and automated to prevent model degradation as the malware ecosystem evolves, a challenge referred to in the literature as concept drift [3].
- False Positives on Security-Adjacent Software: Benign system administration tools, antivirus engines, and virtual machine managers invoke API call patterns that partially overlap with malware behavioral profiles, contributing to the observed 0.62% false-positive rate.
- Windows-Centric Dynamic Analysis: The Frida-based process monitoring and PE-header parsing components are currently implemented for Windows 10/11 only. Extension to Linux ELF binaries and macOS Mach-O executables is planned but not yet implemented.
- Resource Overhead: Concurrent static and dynamic analysis of multiple files imposes a peak memory footprint of approximately
  1.2 GB on systems with 4 GB RAM, restricting deployment on older hardware.

XI. FUTURE WORK

- Transformer-Based Sequence Modeling: Replacing the LSTM with a Transformer encoder for API call sequence analysis, enabling attention-based capture of long-range behavioral dependencies that may span hundreds of API calls within a single malware session.
- Transfer Learning for Zero-Day Adaptation: Applying transfer learning—pre-training on the large EMBER dataset and finetuning on small labeled sets of emerging malware families—to minimize the labeled-data requirement for rapid adaptation to novel threats, as proposed by Akhtar and Feng [5].
- Federated Learning for Privacy-Preserving Model Updates: Implementing a federated learning protocol allowing multiple endpoint deployments to collaboratively improve the shared model without transmitting raw file samples or scan contents to a central server.
- Cross-Platform Support: Extending the static analysis engine to ELF and Mach-O binary formats and adapting the Frida instrumentation scripts for Linux system-call tracing (ptrace/seccomp) and macOS Endpoint Security Framework.
- Active Learning Loop: Integrating a human-in-the-loop review queue where low-confidence classifications are flagged for analyst confirmation, and confirmed labels are incorporated into incremental model updates via online learning algorithms. •

Android APK Support: Adding a dedicated analysis module for Android Package Kit (APK) files using static Dalvik bytecode analysis and dynamic instrumentation via Android Debug Bridge (ADB), addressing the rapidly growing mobile malware threat surface.

XII. CONCLUSION

This paper has presented Shakti Defender AI, a hybrid, production-grade malware detection framework that addresses the principal limitations of both signature-based antivirus systems and prior ML-only research prototypes. By unifying static PE-header and opcode n-gram analysis with real-time Frida-instrumented dynamic behavioral monitoring under a gradient-boosted ensemble and LSTM sequence classifier, the system achieves 99.38% detection accuracy, 99% precision, 98% recall, and an ROC-AUC of 1.0 on a 3,942-sample held-out test partition—outperforming all individual baseline models and the closest comparable published system, SmartShield-AI [6], by a margin of 3.98 percentage points in accuracy.

Beyond raw classification metrics, Shakti Defender AI distinguishes itself through its multi-file-type coverage, endpoint deployability without cloud dependency, SHAP-based explainability, threat-intelligence dashboard with VirusTotal integration, and a polished drag-and-drop graphical interface accessible to non-expert users. These properties collectively bridge the long-standing gap between academic research prototypes and real-world, deployable cybersecurity tools.

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