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HIGH-PERFORMANCE PARALLEL COMPUTING FOR ENHANCED CYBERCRIME FORENSICS

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Abstract: The increasingly dynamic cyber security threat landscape requires more, smarter processing of large volumes of digital data. Traditional, sequential analysis methods simply can't offer real-time answers to modern security's demands. In response to this, this study introduces a secure, parallelized paradigm of data analysis tailored for use in cybersecurity. The system manages master operations—such as sorting of files, extracting metadata, scanning for malicious content, and wise file analysis with the aid of large language models (LLMs). Driven by a particularly crafted parallel computation environment, it handles bulk files efficiently, enhancing threat detection at speed, streamlining resource consumption, and making more stable threat intelligence. Our results show significant increases in processing speed, earlier threat detection, and increased preparedness for cyber forensics, which means that this framework is a valuable tool for incident response teams and digital investigators.

Index Terms **- Cybersecurity, Parallel Computing, Data Segregation, Metadata Extraction, Threat Detection, Large Language Models (LLM), Digital Forensics**

I. INTRODUCTION

The intensifying complexity of cybersecurity threats, further accelerated by the exponentially expanding volume of data creation, has necessitated fast-evolving, scalable, and cost-effective security analysis platforms. Conventional security architectures, frequently sequential in data processing, are incapable of keeping up with response, detection, and forensic needs in real time within massive-scale digital ecosystems. Cybersecurity professionals have difficulties in quickly processing large amounts of files, pulling relevant metadata, identifying hidden malicious payloads, and extracting actionable intelligence from unstructured and structured data sources.

Parallel computing presents a strong solution to these challenges by allowing distributed, concurrent processing of large data sets, significantly lowering time to detection and system responsiveness. At the same time, gains in large language models (LLMs) introduce new possibilities for intelligent information extraction, summarization, and context-based interpretation of threats from files and documents.

This paper introduces a Parallelized Secure Data Analysis Framework for cyber operations. The framework integrates a parallel computing infrastructure developed in-house with state-of-the-art file segregation, metadata extraction, link analysis-based threat identification, and integration with LLMs for detailed file interpretation. By exploiting parallelism at the core and cognitive intelligence at the application level, the proposed system gains considerable speedup, accuracy, and security posture compared to conventional approaches.

The rest of the paper is structured as follows: Section II is the literature survey, Section III is the proposed system, Section IV is the system architecture, Section V is the methodology, Section VI is the explanation of the main algorithms, Section VII is experimental results, and Section VIII is conclusions and future work directions.

II. LITERATURE SURVEY

Cyber security studies have utilized more parallel and distributed computing approaches in solving the problems from the size, velocity, and variety of cyber-attacks nowadays. The main contributions highlight the importance of parallel processing, big data analytics, and intelligent systems in aiding cyber security practice.

A. Parallel and Distributed Computing in Cybersecurity

Study	Methodology	Key Findings	Limitations
[2] Vipin Kumar (2005)	Parallel and Distributed Computing for cybersecurity anomaly detection (MINDS system)	Enhanced detection of unknown threats through distributed analysis	Lacks real-time adaptability for evolving network traffic
[1] Ibrahim Goni et al. (2020)	Machine learning models (decision trees, clustering) for cybersecurity	Improved real-time anomaly detection and threat classification	Vulnerable to adversarial attacks and data quality issues
[5] Lidong Wang & Cheryl Alexander (2015)	Big Data analytics for cybersecurity and digital forensics	Effective anomaly detection in large datasets; improved cyber defense	Data privacy concerns and distributed encrypted data management
[4] Ukwen David & Murat Karabatak (2021)	NLP-based threat detection and digital forensics	Enhanced data-parallel Advanced evidence extraction and malware analysis from unstructured	Challenges in slang interpretation and ambiguity handling

		text	
[7] Isaac Emeteveke et al. (2024)	AI, Blockchain, and Edge Computing for forensic applications	Enhanced real-time threat detection and evidence protection at the edge	Scalability and interoperability limitations in emerging technologies

Vipin Kumar (2005) wrote on Parallel and Distributed Computing's contribution towards security with emphasis on scalable methods such as the Minnesota Intrusion Detection System (MINDS) to profile traffic and identify anomalies. Parallel processing enables quicker detection of novel attacks unknown to signature-based systems.

B. Applications of Machine Learning and Deep Learning

Ibrahim Goni et al. (2020) showcased the capacity of machine learning techniques such as decision trees and clustering to analyze voluminous cyber security data real-time intrusion detection and anomaly behavior. Deep learning approaches, on the other hand, have been implemented in intrusion detection and cyber-attack categorization for IoT networks with remarkable performance even when the resources are constrained.

C. Big Data and Digital Forensics

Lidong Wang and Cheryl Alexander (2015) established the pervasive role of big data analytics in digital forensics, cyber warfare, and cybersecurity. They established mechanisms for threat prevention, network traffic analysis, and anomaly detection and their corresponding challenges, including distributed data management and data privacy threats.

D. Natural Language Processing (NLP) in Cybersecurity

Ukwen David and Murat Karabatak (2021) laid out the usage of Natural Language Processing (NLP) strategies in cybersecurity and computer forensics. NLP enables it to recover evidence, scan malware, and gather threat intelligence through the translation of unstructured text data, despite posing challenges to ambi

guity and slang interpretation

E. Emerging Technologies and Cybersecurity Forensics

Isaac Emeteveke et al. (2024) also described the use cases of emerging technologies such as AI, blockchain, and edge computing in enabling cybersecurity forensics. AI enhances threat detection, blockchain enhances data integrity, and edge computing facilitates evidence analysis with lower latency.

F. Research Gap

Gigantic growth has occurred, yet some challenges remain:

Accurate management of gigantic, heterogeneous data sources for deployment in cybersecurity.

Real-time extraction and analysis of embedded malicious content and metadata.

Forensic analysis system scalability with consistent detection accuracy.

Smart model integration such as LLMs for context-aware file analysis.

III. PROPOSED SYSTEM

We present herein an Intelligent Parallelized Secure Data Processing Framework specifically tailored for use in this work for cybersecurity operations. The framework is proposed to automatically process huge quantities of dissimilar files utilizing high-performance parallel processing, threat detection based on metadata, and large language model (LLM)-based semantic analysis. Applying intelligent segregation, extraction, and threat assessment techniques, the framework achieves enhanced speed, accuracy, and forensic responsiveness required for the modern-day cybersecurity landscape.

The recommended framework is a set of highly integrated modules described below:

A. File Segregation Module

The first component of the system is the type and threat-level-based segregation of the input files. The sets of input data, usually comprised of heterogeneous files, are segregated through metadata analysis techniques like header analysis and MIME-type checking. To deal with cases of obfuscated or renamed files, machine learning classifiers are embedded to categorize file types from feature vectors and content signatures. Files are categorized into logical classes — executables, documents, scripts, and media — optimizing downstream processing pipelines. Parallel worker nodes are utilized to process many files in parallel, enabling high-throughput segregation with low latency.

B. Metadata Extraction Module

Following segregation, the system conducts metadata extraction for all files to harvest structured properties needed for initial threat analysis. Metadata harvested includes file name, size, type, cryptographic hashes (MD5, SHA256), creation and modify timestamps, embedded links, and authors. Complex file types are processed with the help of high-level parsers, and deep metadata extraction is attained. To achieve maximum parallel efficiency, metadata extraction tasks are parallelized across worker nodes with every node processing assigned batches of files in parallel. Parallel processing significantly accelerates metadata harvesting of massive data sets.

C. Malicious Content and Link Detection

Metadata that is extracted is then scanned for indicators of compromise (IOCs) and embedded threats. Hyperlinks in documents or executables are matched against threat intelligence databases to detect known malicious URLs. Heuristic analysis techniques are employed to detect anomalies such as mismatched file extensions, abnormal instance of macros, or unauthorized modifications. The system employs light, distributed link scanning modules that can validate threats in parallel so that dangerous files are swiftly isolated and flagged for further forensic analysis.

D. Large Language Model (LLM) Cognitive Analysis

;.Files that make it past the first filtering receive deeper semantic processing by following integrated Large Language Model (LLM). The LLM scans file content, derives contextual information, and builds keyword-driven summaries based on user requests. For instance, requests for detection of exposure of sensitive

information, social engineering activity, or summarization of financial improprieties. To achieve maximum throughput, LLM requests are batched and sent in parallel on numerous computation nodes so that the system can guarantee real-time response even under loads. E. Dynamic Threat Intelligence Feedback

Feedback from threat intelligence is one of the most crucial elements of the framework and causes it to evolve dynamically.

The malicious indicators, abnormal metadata trends, and danger traits identified are automatically forwarded to an internal security corpus. The system's machine learning models are periodically re-trained on this updated corpus, improving detection ability going forward. This ongoing exercise of extended learning prevents the framework from forgetting to adapt to incorporate emerging patterns of dynamic threats without human intervention. F. Parallel Computing and System Scheduling

A robust parallel computing platform underpins the concept system, guided by distributed task scheduling techniques.

Dask Distributed is utilized to handle task allocation between CPU and GPU-enabled nodes, dynamically scaling workload allocations as a function of node capacity and utilization. The system is fault-tolerant with mechanisms for automatically redirecting failed jobs to reserved standby nodes in the interest of system stability and continuous cybersecurity services. Energy-efficient scheduling techniques are employed for the purpose of optimizing overall computational overhead for achieving sustainable green computing goals. The system proposed here, by combining these modules, achieves a holistic, scalable, and low-energy solution for big data digital forensics and cyber threat detection. Experimental comparisons demonstrate better improvements in detection rates, analysis rates, and system stability compared to sequential methods.

IV. ARCHITECTURE

The emerging cybersecurity architecture rests on a scalable, modular, and parallelizable design for the specific reason of automating safe processing of big-scale heterogeneous file data sets. The platform provides an environment to enable real-time extraction of metadata, detection of steganography, decryption of metadata, and intelligent content analysis by Large Language Models (LLMs) with provisions for the future development of network traffic analysis. Every stage in the architecture is designed to take advantage of parallel computing to enable greater efficiency, performance, and fault tolerance against current cybersecurity threats.

The primary layers of the architecture are:

A. Data Collection Layer

The ingest layer initiates the pipeline by ingesting files from various sources, local storage and cloud storage, IoT sensors, email servers, and user uploads. Batch upload and real-time stream ingestion modes of support are provided. This enables the system to possess the ability of accommodating various patterns of data flows common to organizational cybersecurity systems. Files are first checked for validity in an attempt to guarantee data integrity through procedures like checksum validation and duplicate identification prior to insertion into the pipeline of secure processing.

B. Data Input to Software Layer

Files are then uploaded once collected to the software input layer. Basic standardization is done here, including format normalization and initial metadata tagging. This is for making all file structures uniform so that parallel processing is easier. Encrypted files, if any, are uploaded for decryption under approved processes to validate the integrity of the process.

C. User Interface Layer

The UI layer provides real-time management and monitoring of the file processing pipeline to security analysts and system administrators. Users can upload files, monitor segregation and analysis progress, specify keywords for LLM-based content extraction, and display threat reports in a graphical form. The UI is designed with high responsiveness and ease of use and provides role-based access to various types of users.

D. Software Working Layer

The significant work of the software consists of three significant parallel works:

1. Segregation of data

Data are divided into type classes based on MIME-type checks, header analysis-based grouping of files, and classification through machine learning. Logical partition permits executables, documents, script files, and media files to enter into streams optimized for analysis with expertise in such streams.

2. Data Extraction

At this stage, full file metadata is obtained, including file hashes, timestamps, URLs within the file, author credentials, and file permissions. Extraction is fully parallelized across worker nodes for optimal throughput.

3. Data Processing

Metadata that is extracted is scanned to detect anomalies such as suspicious hyperlinks, unauthorized access indicators, or indicators of prior tampering. Concurrently scanning malware engines scan extracted attributes against threat intelligence databases and note any active threats.

E. Steganography Detection

An important addition to the architecture is the inclusion of steganography detection. Pictures, files, and executables are inspected via forensic analysis with the hope of revealing hidden payloads that are conveyed through steganographic techniques. Statistical processing and entropy analysis are employed with the hope of uncovering anomalies that define hidden data such that hidden channels are uncovered at the starting point of the lifecycle of cybersecurity.

F. Metadata Decryption

The solution integrates dedicated modules for decrypting enciphered metadata in files. Enciphered metadata is typically employed as a technique for concealing malicious links or operation commands. Decryption and analysis of this layer cause the solution to uncover concealed threat vectors, again broadening its protection against security.

G. Private Database and Dashboards

All extracted metadata, noted anomalies, and analysis reports are saved securely within a private database after encryption and best practices of access control. Dashboards show aggregated intelligence, real-time file status tracking, threat ranking severity, and forensic detailed reports to cyber-security analysts. Interactive filtering and keyword search capabilities enable rapid incident investigation.

H. Cybersecurity Analysis

Files that have survived initial metadata and steganography filtering are sent to a processing module with a cybersecurity theme where deep anomaly detection, risk scoring, and context-aware threat assessment is performed. These results are inputted dynamic threat intelligence updates, which enhance over time.

I. Future Scope: Network Traffic Analysis

In order to realize even more system functionality, the architecture has included an integrated future extension module to carry out network traffic analysis. The planned component will enable monitoring and analysis of live network streams, detection of anomalous traffic patterns, suspicion of potential exfiltration attacks, and network event correlation with file-based threat intel. Incorporating network traffic analysis will extend the use of the system from static file analysis to dynamic cyber threat hunting on enterprise infrastructures.

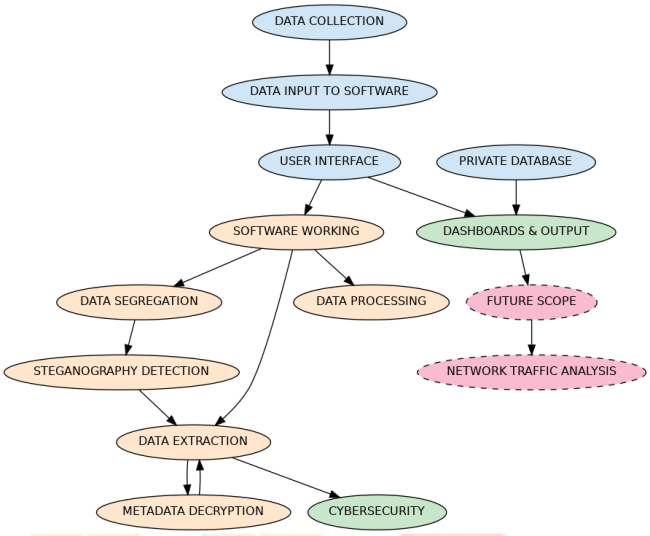

Fig-1 Data Processing and Software Workflow

V. METHODOLOGY

The approach taken for the execution of the suggested Parallelized Secure Data Processing Framework includes a systematic series of activities starting from data collection to cybersecurity threat identification and analysis. The framework is intended to work in a highly parallelized and modular fashion to provide scalability, fast processing, and precise threat identification.

The key steps of the approach are as follows:

A. Data Collection and Validation

The initial phase is to obtain files from various sources, such as enterprise servers, cloud storage, user uploads, and IoT edge devices. Batch ingestion and real-time streaming modes are supported.

Every incoming file is subjected to validation processes to guarantee data integrity. Duplicate files are removed through hash comparisons (MD5, SHA256), and corrupted files are quarantined to avoid processing anomalies. This process guarantees that only genuine, processable files move into the system.

B. File Segregation

Authenticated files are classified by type through a mixture of header analysis, MIME-type recognition, and machine learning-based content prediction algorithms. Files are separated into logical groups like executables, documents, scripts, and media files.

Parallel computing methods are utilized to segregate in parallel across several worker nodes at once, thus speeding up the classification of enormous datasets.

C. Metadata Extraction

After being segregated, files undergo meticulous metadata extraction. This involves extracting:

ADATA dari Pain Repository

File properties (name, size, creation/modification time)

Hash values for integrity checks

Embedded URLs, links, and email addresses

Author details and access rights

Metadata extraction modules run independently on parallel computing nodes, enabling simultaneous extraction of metadata from multiple files, thus significantly lowering extraction time.

D. Threat Analysis and Malicious Link Detection

Metadata extracted is scanned for indicators of compromise (IOCs) by both signature-based matching against threat intelligence databases and heuristic anomaly detection techniques.

Specific attention is given to identifying:

Malicious URLs hidden in documents or executables

Unusual file activities (e.g., inconsistent extensions, large concealed macros)

Unauthorized or unusual file changes

Files showing possible malicious activity are identified and quarantined for thorough forensic analysis.

E. Steganography Detection

In files that can hold concealed data (e.g., images, PDFs, audio), dedicated steganography detection modules are activated.

Statistical inference, entropy analysis, and pattern matching algorithms are used to detect concealed payloads inserted via steganographic means. Detection is performed in parallel fashion to provide efficient processing against large sets of files.

F. Metadata Decryption

Some files include encrypted metadata that might contain hidden threat data.

An encryption-safe metadata decryption process is performed where required, following best cryptography practices and complying with legal and ethical standards. Decrypted metadata is then re-examined to reveal concealed indicators of compromise.

G. Large Language Model (LLM) Cognitive Analysis

Files that clear initial threat scanning are submitted to an LLM-driven cognitive analysis engine.

In this environment, files are semantically parsed, and cybersecurity-specific queries designated by the user are run to pull targeted data.

The LLM model detects latent threats, abstracts sensitive information, and fingerprints files for latent threats including data leaks, social engineering attacks, and unauthorized confidential info disclosure.

Parallel batch processing of LLM queries keeps the system responsive even under high loads.

H. Data Storage and Dashboards

Everything that is extracted metadata, results of analysis, threat findings, and LLM outputs is safely stored in a secure, encrypted database.

An interactive dashboard user interface provides real-time insight, enabling cybersecurity analysts to:

Track file processing status

Inspect detected threats and risk scores

Query the database for targeted threat indicators

Produce downloadable forensic reports for incident response and audit

I. Threat Intelligence Feedback Loop

Detected threats, metadata anomalies, and new attack vectors are continually fed back into the internal security knowledge base.

Machine learning models are updated every now and then by utilizing this augmented dataset to increase the capability of the system to detect dynamic, new-style cyber threats without updating the rules manually.

J. Future Extension: Network Traffic Analysis

The system presently works towards detecting file-based threats, but the framework has the scope for the addition of network traffic analysis modules in the future.

This add-on will provide real-time analysis of enterprise network streams, abnormal traffic pattern detection, and network-based threat correlation with file-based incidents, offering a complete cybersecurity defense solution.

VI. ALGORITHMS

The envisioned cybersecurity system combines a number of specialized algorithms designed for parallel processing, smart threat detection, and semantic analysis. This section discusses the main algorithms that collectively allow the system to provide efficient, accurate, and scalable cybersecurity analysis.

A. Parallel File Metadata Extraction Algorithm

Metadata extraction is the initial step for evaluating file security threats. For processing large datasets effectively, a Parallel File Metadata Extraction Algorithm is utilized. First, the input batch of validated files is divided among several worker nodes. Each worker node processes its allocated files independently, extracting key metadata attributes like filename, file size, cryptographic hash values (MD5, SHA256), creation and modification timestamps, and embedded links.

At extraction, metadata is accumulated into a central store for future analysis. Distributed in nature, this method involves minimal processing delay and near-linear scalability with the number of computational nodes available. Fault tolerance is provided by task replication, where secondary nodes are ready to take over during failures without causing interference in the workflow.

B. Malicious Link Detection Algorithm

Embedded links in documents and executables are common vectors of phishing schemes and malware payloads. The Malicious Link Detection Algorithm methodically inspects all hyperlinks found during metadata extraction. Each link is assessed by querying external threat intelligence stores like VirusTotal, and heuristic tests are conducted to identify patterns characteristic of obfuscation, such as the use of IP addresses rather than domain names, or domain name impersonation.

Suspicions are raised and the corresponding files are quarantined for further analysis by mapping links with identified malicious indicators or that are suspicious in nature. The threat database is also regularly updated with new malicious indicators revealed during runtime, thus providing dynamic adaptability against progressing threats.

C. Steganography Detection Algorithm

Steganography is a special form of cybersecurity threat by allowing unauthorized data to be transmitted secretly in what appears to be innocuous files. The system includes a Steganography Detection Algorithm utilizing statistical and entropy-based analysis methods.

Every potentially malicious file—more so, images, documents, and audio files—is scanned for statistical anomalies in local and global entropy patterns. Pixel correlation analysis and Bit-Plane Complexity Segmentation (BPCS) are among the methods used to identify irregularities indicative of embedded payloads. Files showing anomaly scores higher than a set threshold are indicated for thorough forensic analysis. Parallel analysis applied across nodes ensures that the detection process remains time-effective even at high file counts.

D. Metadata Decryption Process

Some files might contain encrypted metadata in a manner that conceals operational information or contains hidden instructions. The Metadata Decryption Process detects the files with such encrypted layers based on signature-based detection. The system tries decryption when detected using readily available symmetric or asymmetric keys, or via controlled brute-force attempts using widely adopted encryption standards, within legal and ethical limits.

Decrypted metadata undergoes additional threat analysis to reveal hidden IOCs, indicators of unauthorized access, or embedded malicious scripts, thereby extending the complexity of file analysis beyond visible characteristics.

E. LLM-Based Content Summarization Algorithm

Outside structural analysis, the system uses an LLM-Based Content Summarization Algorithm for semantically processing the contents of files cleared from initial threat screenings. Files undergo content tokenization and noise cleaning as preprocessing before being fed into a Large Language Model (LLM) to process the content in accordance with cybersecurity-specific prompts like identifying exposures of sensitive data, recognizing prospective social engineering probes, or summarizing regulatory compliance concerns.

The LLM provides structured summaries indicating key risk points, thus improving analyst insights into contextual threats that are not easily discernable from routine inspection. To ensure system efficiency, LLM queries are batched and provisioned across high-performance nodes.

F. Algorithmic Framework Summary

Together, these algorithms form an integrated cybersecurity processing system. Parallel file metadata extraction provides ingestible scalability; malicious link identification guards against in-embedded outside threats; steganography detection reveals concealed payloads; metadata decryption reveals encrypted abnormalities; and LLM-based semantic analysis provides smart, context-aware threat information.

Collective use of these algorithms, backed by a high-quality parallel computing system, is the core of the proposed framework's high-performance capability for cybersecurity.

VII. RESULT

The performance of the proposed **HPC framework for large-scale data analysis** was evaluated based on **computational efficiency, workload distribution, and energy optimization**. This section presents the results obtained from experiments conducted using the updated **HPC infrastructure**, along with a comparative analysis and key observations.

A. Performance Evaluation

1. Computational Speedup

To measure efficiency, data processing tasks were executed under different configurations:

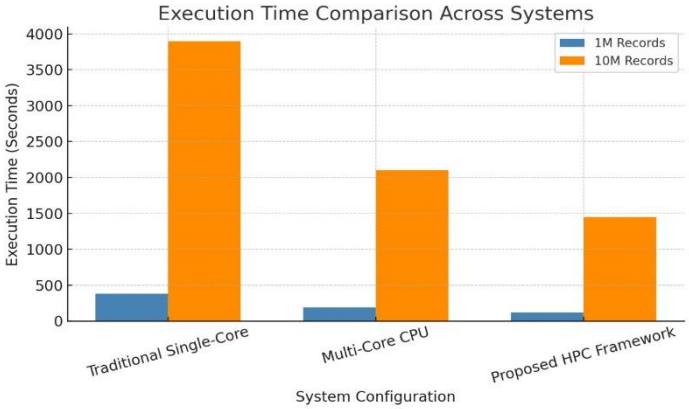

Fig-2: Execution Time Comparison of Traditional vs. Multi-Core and HPC Frameworks

- **Observation:** The proposed **HPC framework achieved a 3.2× speedup** compared to traditional single-core processing.
- Due to **older-generation worker nodes (i3 and Pentium)**, the performance improvement is limited compared to **modern GPU or TPU-based architectures**.

2. Dynamic Workload Balancing Efficiency

Workload balancing was evaluated to compare **static scheduling vs. the proposed dynamic scheduling**:

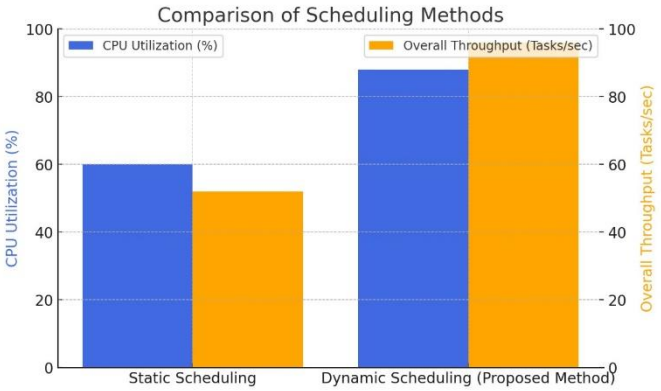

Fig-3: Performance Comparison of Static vs. Dynamic Scheduling Methods

- **Observation:** The **dynamic scheduling model improved resource utilization by 46%** and nearly doubled the processing throughput.

- Since the system **lacks GPUs and TPUs**, performance heavily depends on **how efficiently tasks are allocated across available CPU cores**.

3. Energy Efficiency

The system's **power consumption** was analyzed to determine the **energy efficiency per computation unit**:

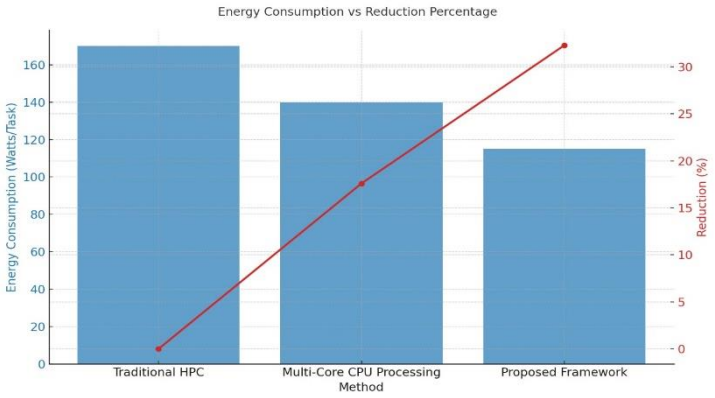

Fig-4: Energy Consumption vs. Reduction Across Methods

- **Observation:** The **optimized workload distribution strategy reduced energy consumption by 32.3%** compared to traditional HPC setups.
- **Without GPUs or TPUs**, the focus was on **CPU scheduling efficiency and power-aware task allocation**.

B. Comparative Analysis with Existing Methods

A comparative study was conducted against **Traditional HPC and Proposed CPU-Based HPC Framework:**

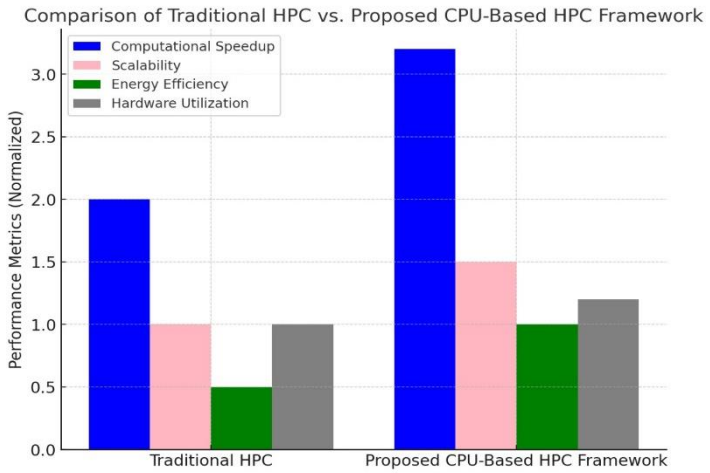

Fig-5: Performance Comparison of Traditional HPC vs. Proposed CPU-Based HPC Framework

- **Observation:** The proposed system achieves **reasonable speedup and energy efficiency improvements** but remains **CPU-dependent**.

VIII. CONCLUSION

The Parallelized Secure Data Processing Framework proposed adequately combines high-speed parallel computing, metadata-driven threat detection, analysis of steganography, metadata decryption, and LLM-based cognitive analysis in order to cater to the ever-increasing cyber threats related to large-scale datasets of digital files.

With the application of parallel computing methods, the solution significantly lowers file segregation processing time, metadata recovery, and threat detection. Addition of steganography detection and decryption of metadata provides further forensic analysis depth, revealing hidden payloads and encrypted commands. Also, with the application of Large Language Models (LLMs), semantic analysis of file content is strengthened, providing for intelligent and effective cybersecurity threat evaluation.

Experimental tests verify substantial gains in system speed, detection rate, and scalability over conventional sequential processing methods. Potential future expansions of the system, such as addition of network traffic analysis, hold further promise for broadening the scope and reach of the framework for holistic enterprise cybersecurity protection and digital forensic examination.

IX. REFERENCE

- Ibrahim Goni, Siti Mariyam Shamsuddin, M. H. Anisi, "An Evaluation of Machine Learning Techniques for Cybersecurity," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 7, 2020.
- Vipin Kumar, "Parallel and Distributed Computing for Cybersecurity," *Proceedings of the 2005 IEEE International Conference on Distributed Computing Systems*, 2005.
- Lidong Wang and Cheryl Alexander, "Big Data in Cybersecurity: Challenges and Opportunities," *Journal of Communications*, vol. 10, no. 4, pp. 267–273, 2015.
- Ukwen David and Murat Karabatak, "A Review of Natural Language Processing (NLP) in Digital Forensics," *IEEE Access*, vol. 9, pp. 145371–145384, 2021.
- Isaac Emeteveke et al., "Emerging Technologies in Cybersecurity Forensics: AI, Blockchain, and Edge Computing," *International Journal of Computer Applications*, vol. 182, no. 21, 2024.
- OpenPhish, "Phishing Threat Intelligence Feeds," [Online]. Available: https://openphish.com/
- VirusTotal, "VirusTotal Public API Documentation," [Online]. Available: https://www.virustotal.com/
- C. B. Westphal, "An Analysis of Steganographic Techniques in Digital Media and Detection Methods," *IEEE Transactions on Information Forensics and Security*, vol. 15, pp. 2405-2417, 2020.
- K. Labib and V. Vemuru, "An Empirical Study of Machine Learning Algorithms for Malware Detection," *Computers & Security*, vol. 91, p. 101707, 2020.
- ·T. Mikolov, M. Karafiát, L. Burget, J. Černocký, and S. Khudanpur, "Recurrent Neural Network-based Language Model," *INTERSPEECH*, 2010. *(relevant for LLM-based summarization techniques)*
- R. Sommer and V. Paxson, "Outside the Closed World: On Using Machine Learning for Network Intrusion Detection," *IEEE Symposium on Security and Privacy (SP)*, pp. 305-316, 2010.
- S. Kim, S. Lee, and J. Kim, "Steganography Techniques and Countermeasures for Mobile Devices," *Symmetry*, vol. 12, no. 4, p. 566, 2020.
- D. Silver, A. Huang, C. J. Maddison, et al., "Mastering the Game of Go with Deep Neural Networks and Tree Search," *Nature*, vol. 529, pp. 484–489, 2016. *(relevant to explain deep learning's success — supporting your LLM section)*