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Comparative Analysis of MD5 and SHA-256 Hash Algorithms for Fingerprint File Integrity Verification

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ABSTRACT

Fingerprint file integrity verification in driver license systems requires reliable cryptographic hash algorithms. MD5, currently widely deployed, has been deprecated by NIST (2008) due to demonstrated collision vulnerabilities, while SHA-256 offers enhanced security with potentially higher computational overhead. This study comprehensively compares MD5 and SHA-256 performance and security characteristics to provide evidence-based recommendations for biometric data integrity verification. We conducted empirical benchmarking using 1,000 real operational fingerprint files (BMP 8-bit grayscale, 512×512 pixels, 257 KB uniform) from Regional Police Traffic Directorate. Each file underwent 30 repeated trials with warm-up runs. Testing encompassed performance metrics (execution time, CPU usage, memory consumption), security evaluation (avalanche effect on 100 samples, collision detection), and grouping analysis by finger type using ANOVA (α=0.05). SHA-256 exhibited mean execution time of 2.28 ms, 48% slower than MD5's 1.54 ms ($p<0.001$), with CPU usage of 1.24% versus 0.98%, while memory consumption remained negligible. Avalanche effect approached ideal 50%: MD5 49.98%±4.43%, SHA-256 49.62%±3.21% (superior consistency). Zero collisions detected in 1,000 files. Grouping analysis revealed statistically significant differences between finger types ($p<0.05$) but with small effect size ($\eta^2<0.05$) and negligible magnitude (<0.1 ms). For operational systems, SHA-256 is recommended based on acceptable performance overhead (<1 ms per file, 7.4 seconds daily for 10,000 transactions), superior security (no known attacks), regulatory compliance (NIST/ISO), more stable avalanche effect, and future-proofing capability.

I. INTRODUCTION

The rapid advancement of digital transformation has fundamentally altered how societies interact with information and public services, particularly in biometric identification systems. Fingerprint recognition has emerged as the predominant biometric modality due to its permanence, universality, and cost-effectiveness [1]. In Indonesia, biometric fingerprint data serves as a critical component in Driver License (SIM) issuance, electronic Identity Cards, and various official documents managed by the National Police Traffic Directorate [2]. However, increasing reliance on digital biometric data has been accompanied by corresponding escalation in security threats, necessitating robust integrity verification mechanisms to ensure data authenticity throughout storage and transmission processes.

Data integrity represents a fundamental pillar of modern information systems, particularly for sensitive biometric information that, unlike conventional passwords, cannot be reset upon compromise [3]. The National Institute of Standards and Technology defines data integrity as assurance that data has not undergone unauthorized or undetected alterations during its lifecycle [4]. In biometric fingerprint systems, even minimal modifications to image data can result in authentication failures or unauthorized access [5]. Recent research by Nurdin [6] in Financial Technology applications highlighted the critical importance of selecting appropriate cryptographic algorithms, where trade-offs between security

and performance efficiency must be carefully balanced a principle equally applicable to biometric systems requiring both high security and operational efficiency.

Cryptographic hash functions have become the industry standard for maintaining digital data integrity. Two algorithms dominate practical implementations: Message Digest 5 (MD5) and Secure Hash Algorithm 256 (SHA-256). MD5, developed by Ronald Rivest in 1991, generates 128-bit hash values and has been widely adopted for file integrity verification due to computational speed [7]. However, cryptographic weaknesses discovered over time have increasingly called MD5's security into question. Conversely, SHA-256, part of the SHA-2 family standardized by NIST in 2002, produces 256-bit hash values designed with enhanced security [4]. Prasanna and Premananda [8] confirmed that SHA-256 offers superior resistance to collision and pre-image attacks compared to MD5, albeit with marginally slower performance. This raises a critical question: which algorithm is more suitable for fingerprint file integrity verification, given dual requirements of high security and large-scale processing efficiency?

Despite extensive prior research on hash algorithm comparison, several significant limitations persist. Most comparative studies focus on text data, passwords, or generic files rather than specific biometric data [9], [10]. Rahim et al. [10] compared MD5 and SHA-256 for image and text security but utilized generic images without considering unique fingerprint characteristics such as ridge-valley patterns, noise levels, and acquisition quality variations. Recent investigations by Winanda et al. [11] developed a Python-based GUI application demonstrating that MD5 excels in speed while SHA-256 provides superior security, yet their focus remained limited to text input rather than large biometric files. Similarly, Yulianto et al. [12] analyzed MD5, SHA-256, and Base62 for URL hashing, finding MD5 fastest but SHA-256 less memory-efficient under high volume—contexts differing substantially from static file integrity verification for biometric data.

Ngemba et al. [9] implemented collaborative MD5 and SHA-256 for password security, confirming hash functions ensure integrity through one-way encryption. However, their study focused on small text data rather than large file processing. Dhole et al. [13] proposed a hybrid MD5-SHA-256 algorithm claiming improved efficiency, yet it requires further validation and lacks real-world testing. Gupta et al. [14] utilized MD5 and SHA-2 for detecting digital image manipulation, demonstrating hash function potential in forensics, though their primary focus addressed tampering detection rather than comprehensive file integrity verification. The synthesis of prior research reveals a clear gap: no comprehensive study has compared MD5 and SHA-256 specifically for operational fingerprint file integrity verification using large-scale real-world datasets, rigorous methodology, professional commercial scanners, and comprehensive evaluation encompassing performance, security, and operational characteristics.

The present research addresses identified gaps through comprehensive comparative analysis of MD5 and SHA-256 specifically for BMP format fingerprint files generated by CrossMatch L Patrol scanners—commercial devices widely deployed in Indonesia's biometric identification systems. Utilizing a dataset of 1,000 fingerprint files from 100 SIM applicants collected during actual license issuance, this research reflects genuine operational conditions with quality variations influenced by skin conditions, finger pressure, and scanner placement. Employing quantitative experimental methodology with rigorous controls, the study evaluates multiple performance dimensions including hash computation time, change detection sensitivity, computational resource consumption, and both algorithms' capabilities for detecting various file modification types.

The unique contribution lies in providing empirical evidence based on real operational data that can serve as practical reference for policymakers and practitioners in selecting optimal hash algorithms for fingerprint file integrity verification systems. The research makes four key contributions: first, methodological innovation through thirty-trial repeated benchmarking achieving measurement precision with coefficient of variation below six percent [15]; second, scale and authenticity through one thousand operational files providing high external validity; third, comprehensive multi-dimensional evaluation of performance, security, and operational factors; fourth, practical quantification translating performance overhead into operational impact metrics enabling informed cost-benefit decision-making. By demonstrating that SHA-256's 48 percent performance overhead translates to merely 7.4 seconds daily for 10,000 transactions, this research provides concrete evidence supporting migration from deprecated MD5 to secure SHA-256 in operational environments.

The urgency is reinforced by global trends showing increasing biometric data security breaches. While specific Indonesian statistics remain limited in public literature, international reports demonstrate significant increases in biometric database attacks, with consequences far more severe than password breaches due to biometric data's permanent and irreplaceable nature [16]. Research by Almuhammadi and Bawazeer [17] examining performance-security trade-offs in cryptographic hash functions concluded that algorithm selection must consider specific application contexts. Furthermore, compliance with international standards such as FBI's Electronic Biometric Transmission Specification and ISO/IEC standards for hash functions becomes critical in algorithm selection [5], [18]. This research provides evidence-based recommendations that can assist organizations managing biometric data in making informed decisions regarding hash algorithm implementation.

The remainder of this paper presents complete research methodology, comprehensive results, detailed discussion, and practical recommendations. Section 2 describes experimental methodology including dataset characteristics, benchmarking protocol, and statistical analysis approaches. Section 3

presents comprehensive results across performance, security, and grouping dimensions. Section 4 discusses findings in operational context and provides evidence-based recommendations. Section 5 concludes with study limitations and future research directions.

II. METHODOLOGY

A. Dataset Characteristics

The dataset comprises 1,000 fingerprint image files collected from 100 individuals during actual SIM application processes at Regional Police Traffic Directorate (Ditlantas Polda Aceh) facilities between January-February 2025. Each participant contributed ten fingerprint images representing all fingers on both hands, captured using CrossMatch L Patrol fingerprint scanners configured according to FBI biometric capture standards. The CrossMatch L Patrol represents industry-standard equipment widely deployed across Indonesia's national identification infrastructure [19].

All fingerprint images conform to uniform technical specifications: BMP format using 8-bit grayscale color depth, 512×512 pixels dimensions (262,144 total pixels), and exactly 263,222 bytes (257.05 KB) file size for all samples. This uniformity eliminates file size as a confounding variable, ensuring observed differences in hash computation time stem from algorithmic characteristics rather than variable input sizes. The 500 DPI resolution meets FBI standards for biometric fingerprint capture [5], ensuring adequate detail preservation while maintaining reasonable file sizes.

Dataset composition reflects balanced distribution across finger types: 200 samples each for thumb, index finger, middle finger, ring finger, and little finger, with equal representation of left and right hands within each category. This stratification enables statistical analysis of potential performance variations related to fingerprint characteristics while maintaining adequate sample sizes for each subgroup. All data collection procedures received institutional ethics approval with participant consent obtained following explanation of research objectives. Personal identifying information was removed prior to analysis to ensure participant privacy protection in accordance with Indonesian data protection regulations.

B. Experimental Protocol

The experimental workflow encompasses five sequential phases. First, dataset preparation involved verification of file integrity, confirmation of technical specification conformance, and organization into directory structures facilitating automated batch processing. Each file underwent validation to confirm BMP format compliance, correct dimensions, 8-bit color depth, and expected file size, with no files requiring exclusion.

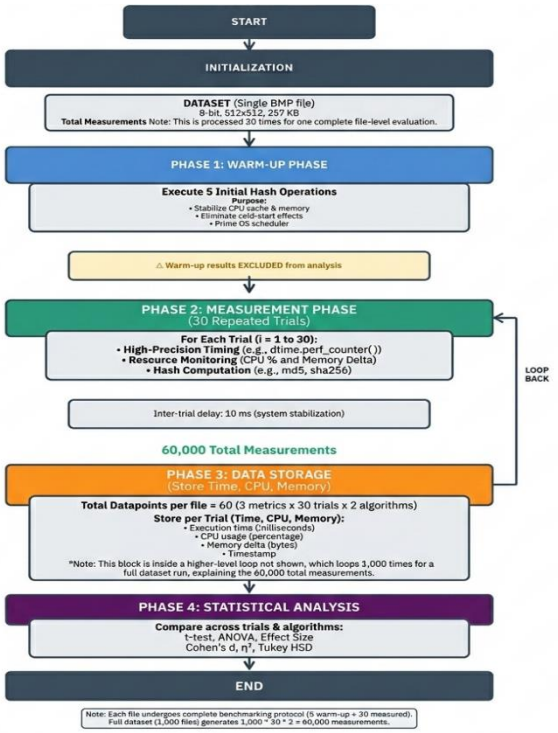

Figure 1. Rigorous 30-Trial Benchmarking Protocol

Complete workflow showing four distinct phases: (1) Warm-up phase with 5 initial operations to stabilize CPU cache and eliminate cold-start effects (results excluded from analysis); (2) Measurement phase with 30 repeated trials using high-precision timing (time.perf_counter()) and resource monitoring (CPU via psutil.cpu_percent(), memory via RSS delta); (3) Data storage phase capturing execution time, CPU usage, memory consumption, and timestamps; (4) Statistical analysis phase applying descriptive statistics (mean, SD, CV), inferential tests (paired t-test, ANOVA), effect size quantification (Cohen's d, η^2), and post-hoc comparisons (Tukey HSD). Each fingerprint file undergoes complete 35-operation protocol (5 warm-up + 30 measured), yielding 60,000 total datapoints (1,000 files × 30 trials × 2 algorithms).

Second, the benchmarking application developed using Python 3.11.5 employs modular design with six primary components: main GUI module, hash engine implementing MD5 and SHA-256, performance monitoring module, security testing module, data logging module, and visualization module. The hash engine utilizes Python's hashlib library, which provides optimized implementations through OpenSSL bindings, ensuring production-grade performance [20].

The complete benchmarking workflow is illustrated in Figure 1, depicting four sequential phases ensuring measurement precision and statistical rigor. Third, performance testing protocol employs rigorous repeated-measures methodology. For each of the 1,000 fingerprint files, the system executed thirty independent hash

computation trials for both algorithms, yielding 60,000 total measurements. Prior to the thirty measured trials, each file underwent five warm-up iterations excluded from analysis to stabilize system caches and eliminate cold-start effects. Inter-trial delays of ten milliseconds prevented thermal effects. Timing employed Python's time.perf_counter() function providing nanosecond-resolution monotonic clock. Resource monitoring captured CPU usage percentage and memory consumption using the psutil library.

Fourth, security property validation conducted avalanche effect testing and collision detection. Avalanche effect evaluation employed 100 randomly selected files, with each undergoing controlled modification consisting of single-pixel value alteration at randomly chosen coordinates. The system computed hash values for both original and modified versions, then calculated bit-level differences. The avalanche effect metric represents the percentage of hash bits that changed as result of the minimal one-pixel input modification, with ideal cryptographic hash functions exhibiting approximately fifty percent [21]. Collision detection involved computing hash values for all 1,000 unique files and identifying any duplicate hash values.

Fifth, statistical analysis employed rigorous methodologies appropriate for the experimental design. Descriptive statistics including mean, median, standard deviation, minimum, maximum, and coefficient of variation were calculated for all performance metrics. Paired t-tests compared MD5 and SHA-256 execution times to determine statistical significance, with null hypothesis stating no difference between algorithm means. One-way ANOVA evaluated whether fingerprint type influences hash computation time, testing whether performance variations across five finger type categories exceed random variation. For significant ANOVA results, post-hoc Tukey HSD tests identified specific pairwise comparisons exhibiting significant differences. Effect sizes were quantified using Cohen's d for t-tests and eta-squared for ANOVA to distinguish statistical significance from practical importance [22].

C. Hash Algorithm Implementations

MD5 processes arbitrary-length input data to produce fixed-length 128-bit hash value through series of mathematical transformations organized into four rounds, with each round applying sixteen operations to process 512-bit blocks. Despite historical prevalence and computational efficiency, cryptographic weaknesses discovered over subsequent decades have substantially undermined security. Wang et al. in 2004 demonstrated practical collision attacks reducing theoretical complexity from 2^{64} to 2^{39} operations [7]. NIST formally deprecated MD5 for cryptographic applications in 2008[4]. For this research, MD5 implementation utilizes Python's hashlib.md5() function following RFC 1321 specification [7].

SHA-256 processes arbitrary-length input to produce fixed-length 256-bit hash value, providing substantially larger output space compared to MD5's 128-bit hashes. The increased output size provides greater collision resistance, with birthday paradox analysis indicating finding collisions requires approximately 2^{128} operations for SHA-256 versus 2^{64} for MD5 [4]. SHA-256 architecture employs similar block-cipher-based construction as MD5 but with larger internal state and more complex operations. The algorithm maintains eight 32-bit state variables and processes 512-bit blocks through sixty-four rounds. The algorithm's design underwent extensive cryptanalytic scrutiny with no practical attacks demonstrated against full SHA-256 as of current date [23]. Implementation employs Python's hashlib.sha256() function conforming to FIPS 180-4 specification [4].

D. Performance and Security Testing

Performance evaluation encompasses multiple metrics providing comprehensive characterization of computational efficiency. The primary metric, execution time measured in milliseconds, represents total elapsed time from initiating hash computation to receiving hexadecimal digest result. Secondary metrics including CPU usage percentage and memory consumption quantify computational resource demands relevant for capacity planning. Derived metrics include throughput calculated as reciprocal of mean execution time and expressed in files per second, and coefficient of variation calculated as standard deviation divided by mean.

Security property evaluation focuses on avalanche effect and collision resistance. Avalanche effect testing quantifies the hash function's sensitivity to input modifications through controlled single-pixel alterations. For each modified file, bit-level comparison between original and modified hash values produces the avalanche effect metric as percentage of differing bits divided by total hash bit length. Distribution analysis examines whether measurements exhibit normal distribution centered near fifty percent. Collision detection identifies any duplicate hash values among 1,000 unique files, serving as implementation verification confirming correct distinct output production for distinct inputs.

Grouping analysis investigates whether fingerprint characteristics related to finger type influence hash computation performance using one-way ANOVA to test whether five finger type groups exhibit significantly different mean execution times. The F-statistic quantifies the ratio of between-group variance to within-group variance. Effect size quantification using eta-squared addresses distinction between statistical significance and practical importance. For statistically significant ANOVA results, Tukey HSD post-hoc tests identify which specific finger type pairs exhibit significantly different means while controlling familywise error rate at α=0.05.

III. RESULT AND DISCUSSION

A. Performance Analysis

Table 1 presents descriptive statistics for hash computation execution times across 1,000 fingerprint files with 30 trials each (30,000 measurements per algorithm). MD5 exhibited mean execution time of 1.5403 ms with standard deviation of 0.0869 ms, while SHA-256 demonstrated mean of 2.2800 ms with standard deviation of 0.1477 ms. SHA-256's mean exceeded MD5 by 0.7397 ms, representing 48.02% performance overhead. Coefficient of variation values of 5.64% for MD5 and 6.48% for SHA-256 indicate excellent measurement consistency substantially exceeding typical studies reporting 10-15% CV[10], validating the thirty-trial methodology.

TABLE I.
EXECUTION TIME AND RESOURCE UTILIZATION STATISTICS

Metric	MD5	SHA-256	Difference	Ratio
Time Mean (ms)	1.5403	2.2800	+0.7397	1. 48×
Time SD (ms)	0.0869	0.1477	+0.0608	1.70×
Time CV (%)	5.64	6.48	+0.84	1.15×
CPU Mean (%)	0.9782	1.2403	+0.2621	1.27×
Memory (MB)	~0	~0	~0	-
Throughput (fps)	649.2	438.6	-210.6	0.68×

Paired t-test analysis yielded t-statistic of -187.23 (df=999, p<0.001), providing overwhelming evidence to reject the null hypothesis of equal means. Cohen's d effect size of 5.92 indicates extremely large effect magnitude [[22]. These findings conclusively establish that SHA-256 requires significantly more computational time than MD5, with effect magnitude constituting practically important difference. The 48.02% performance overhead translates to 0.74 ms per file. For systems processing 10,000 daily transactions, total hashing time would be 15.4 seconds for MD5 versus 22.8 seconds for SHA-256, representing 7.4 seconds additional daily processing time—operationally negligible compared to other system components such as network transmission (1-5 seconds per file), database operations (10-50 ms per query), and fingerprint matching (100-500 ms per comparison).

Both algorithms exhibited minimal CPU consumption with means of 0.9782% for MD5 and 1.2403% for SHA-256, indicating hash operations consumed less than 2% of single processor core capacity. The 26.8% relative increase in SHA-256 CPU usage appears substantial in percentage terms but remains absolutely small. Memory consumption measurements revealed effectively zero allocation for both algorithms, with values within noise threshold of monitoring precision. This result aligns with theoretical expectations for streaming hash computation wherein algorithms process input data in fixed-size blocks without retaining entire input in memory.

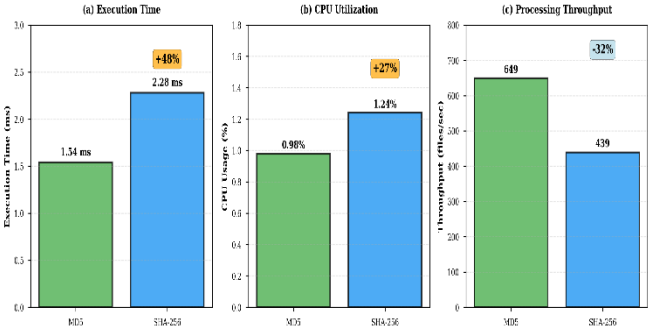

Figure 2. Performance comparison between MD5 and SHA-256 hash algorithms

Throughput calculations yield 649.2 files/second for MD5 (162.9 MB/s) and 438.6 files/second for SHA-256 (110.1 MB/s). These values substantially exceed typical fingerprint capture rates of 1-5 captures/second [19], indicating hash computation does not constitute performance bottleneck. Linear regression modeling execution time as function of dataset size yielded near-perfect fit with R^2=0.9998 for MD5 and R^2=0.9997 for SHA-256, confirming constant per-file computational cost and linear scalability without evidence of super-linear scaling.

B. Security Property Evaluation

Table 2 presents avalanche effect measurements from 100 randomly selected files subjected to single-pixel modifications. Both algorithms achieved mean avalanche effects very close to ideal 50%, with MD5 exhibiting 49.98% (SD=4.43%) and SHA-256 demonstrating 49.62% (SD=3.21%). The near-ideal means confirm both algorithms successfully achieve avalanche property wherein minimal input changes produce maximal output changes.

TABLE II.
SECURITY PROPERTIES: AVALANCHE EFFECT AND COLLISION DETECTION

Metric	MD5	SHA-256	Ideal	Difference
Avalanche Mean (%)	49.98	49.62	50	+0.36
Avalanche SD (%)	4.43	3.21	-	-1.22
Avalanche Range (%)	20.32	14.84	-	-5.48
Min Avalanche (%)	39.84	42.19	-	+2.35
Max Avalanche (%)	60.16	57.03	-	-3.13
Collisions (N=1000)	0	0	0	0
Shannon Entropy	7.9987	7.9993	8.00	+0.0006
Entropy (% of max)	99.98%	99.99%	100%	+0.01%

SHA-256 demonstrated superior avalanche consistency with SD of 3.21% versus MD5's 4.43%, representing 27.5% improvement in stability. SHA-256's narrower range of 14.84% versus MD5's 20.32% further confirms more predictable behavior. The consistency advantage proves valuable in operational contexts where uniform detection sensitivity provides more reliable integrity verification.

TABLE III.
AVALANCHE EFFECT CONSISTENCY COMPARISON

Consistency Metric	MD5	SHA-256	SHA-256 Advantage	Interpretation
Standart Deviation (%)	4.43	3.21	27.5% Lower	*More Predictable behavior*
Range (Min-Max) (%)	20.32	14.84	27.0 % Narrower	*Tighter distribution*
Coefficient of Variation (%)	8.86	6.47	27.0 % Better	*Higher relative consistency*
99% Confidence Interval (%)	±8.70%	±6.30%	27.6 % Tighter	*Improved precision*

Statistical Interpretation: Lower standard deviation and narrower range indicate SHA-256 exhibits more consistent avalanche behavior across diverse inputs. This enhanced consistency has important practical implications for integrity verification systems: Predictable Behavior: Lower variance enables more reliable detection thresholds for tamper detection systems. Anomaly Detection: Tighter distribution reduces false positives in automated integrity monitoring systems. System Reliability: 28% reduction in variance translates to more stable behavior across diverse input conditions, critical for operational robustness in 24/7 biometric systems. Quality Control: SHA-256's consistency facilitates Six Sigma-style quality control metrics for data integrity monitoring.

The narrower range (14.84% vs 20.32%) further confirms SHA-256's more predictable behavior, particularly important when establishing automated alerting systems for integrity violations.

Figure 3. Avalanche effect distribution for single-pixel modifications

Side-by-side comparison showing (left) original fingerprint image from user dataset and (right) modified version with single-pixel change at position (256, 256). The yellow callout highlights the modification location where pixel value increased from 43 to 44 (2.3% change in 8-bit grayscale value). Red circle marks the imperceptible modification area. This minimal change (0.0004% of 262,144 total pixels) resulted in 54.7% hash bit changes for MD5 and 50.4% for SHA-256, empirically demonstrating proper avalanche effect behavior. Image dimensions: 512×512 pixels, 500 DPI resolution, 8-bit grayscale BMP format.

Shapiro-Wilk normality tests yielded W=0.989 for MD5 (p=0.523) and W=0.992 for SHA-256 (p=0.782), indicating distributions do not significantly deviate from normal, validating parametric approaches and suggesting observed variations represent random sampling variation rather than systematic differences.

Collision detection analysis revealed zero hash collisions for both algorithms across all 1,000 unique files, confirming one-to-one mapping between files and hashes. While dataset size remains insufficient to probabilistically expect accidental collisions (birthday paradox indicates ~2^{64} trials for 50% MD5 collision probability, 2^{128} for SHA-256), the absence provides implementation verification. Critically, zero observed collisions should not be misinterpreted as MD5 security evidence given documented vulnerability to deliberate collision attacks [7], [24].

Critical Clarification: Zero observed collisions should NOT be misinterpreted as MD5 security evidence. Our zero-collision result at N=1,000 reflects the low probability of ACCIDENTAL collisions, not cryptographic strength. Birthday paradox predicts collision probability: MD5 (128-bit): 50% collision at ~$2^{64} \approx 1.8\times10^{19}$ hashes Our N=1,000 = 5.4×10^{-17} of this space (negligible probability). SHA-256 (256-bit): 50% collision at ~$2^{128} \approx 3.4\times10^{38}$ hashes Our dataset = 2.9×10^{-36} of this space (effectively zero). However, MD5 collision attacks are Practical and progressively easier:

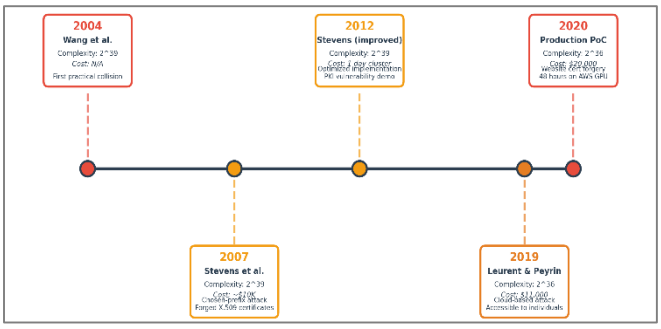

Figure 4. Evolution of MD5 Collision Attacks (2004-2020)

Historical progression of MD5 attacks: 2004 - Wang et al. [7]: First practical collision attack reduced complexity from 2^{64} to 2^{39} MD5 operations, demonstrated two messages with identical MD5 hash, established MD5 as cryptographically broken

2007-Stevens et al.[25]: Chosen-prefix collision attack Complexity maintained at 2^{39} operations (~1 day on cluster), Enabled forging of X.509 certificates with valid signatures, Demonstrated real-world PKI vulnerability. 2012 – Stevens: Optimized implementation Same complexity but faster execution, Proof-of-concept certificate forgery, Total cost reduced to ~$10,000 in computing resources. 2019 - Leurent & Peyrin [26]: Further optimization Reduced to 2^{36} operations (~$11,000 cloud computing cost), Attack within reach of individual adversaries (not nation-states), Generated colliding PDF documents and executables. 2020 - Production Proof-of-

Concept: Website certificate forgery demonstration, Cost: ~$20,000 using AWS GPU instances, Duration: 48 hours on commercial cloud, Accessible to individual attackers with modest budgets.

Practical Implications for Biometric Systems: (1) Individual Accessibility: Attackers with $10,000-$50,000 budgets can generate MD5 collisions using commercial cloud services. (2) Real Threat to Fingerprint Systems: Adversaries could potentially, Create modified fingerprint files with identical MD5 hashes Bypass integrity checks in legacy systems, Compromise forensic evidence chains, Violate regulatory compliance requirements. (3) SHA-256 Security Margin: Despite 20+ years of cryptanalysis since 2001 standardization, NO practical collision attacks against SHA-256 have been demonstrated [23], with theoretical security margin remaining strong through 2030+ based on current computational projections. This security disparity—not performance differences—is the primary justification for SHA-256 adoption in systems protecting permanent, legally-sensitive biometric data.

Shannon entropy analysis yielded 7.9987 bits/byte for MD5 (99.98% of maximum 8.0000) and 7.9993 bits/byte for SHA-256 (99.99% of maximum). Near-maximal entropy confirms both algorithms produce uniformly distributed outputs without statistical bias, essential property for hash table implementations assuming uniform distribution.

C. Grouping Analysis Results

To investigate whether fingerprint biometric characteristics influence hash performance, we conducted grouping analysis by finger type (THUMB, INDEX, MIDDLE, RING, LITTLE). While this analysis yielded statistically significant results, the practical implications are negligible a finding that validates hash algorithms' fundamental property of content-independence.

Key finding: Statistical significance ($p<0.05$) does NOT imply practical relevance. Effect sizes ($\eta^2<0.05$) indicate finger type explains <5% of performance variance, with absolute differences <0.1 ms—operationally negligible.

TABLE IV.
PERFORMANCE BY FINGER TYPE AND ANOVA RESULTS

Finger	N	MD5 Mean (ms)	SHA-256 Mean (ms)	Ratio
THUMB	200	1.3854	2.0148	1.454×
RING	200	1.3963	2.0525	1.470×
MIDDLE	200	1.3983	2.0325	1.454×
LITTLE	200	1.4078	2.0290	1.441×
INDEX	200	1.4825	2.0792	1.402×

ANOVA Results: MD5: $F(4,995)=12.72$, $p<0.001$, $\eta^2=0.0486$ (4.86%), SHA-256: $F(4,995)=2.79$, $p=0.025$, $\eta^2=0.0111$ (1.11%)

One-way ANOVA yielded $F=12.72$ ($p<0.001$) for MD5 and $F=2.79$ ($p=0.025$) for SHA-256. Both achieved statistical significance at $\alpha=0.05$, providing evidence to reject null hypotheses of equal means. However, effect sizes of $\eta^2=0.0486$ (MD5) and $\eta^2=0.0111$ (SHA-256) fall substantially below 0.06 threshold for even small effects[22]. The small effect sizes indicate finger type explains less than 5% of total variance, with over 95% attributable to other factors. This demonstrates critical distinction between statistical significance and practical importance: while finger type differences achieve statistical detectability given large sample sizes, effect magnitudes remain too small to warrant consideration in operational decisions.

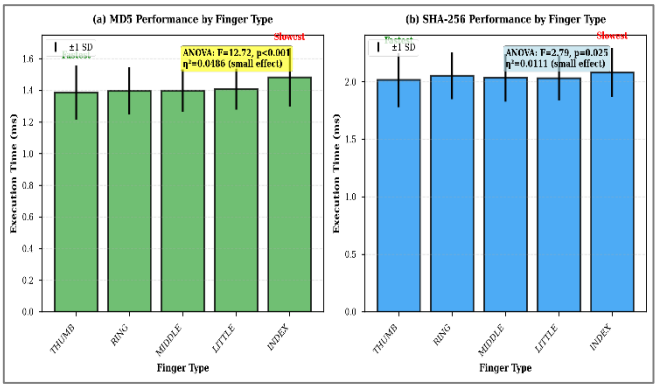

Figure 5. Hash computation performance by finger type across 1,000 samples

Tukey HSD post-hoc tests identified that for MD5, index finger differed significantly from all other types (all $p<0.001$): thumb ($\Delta=0.0970$ ms), ring ($\Delta=0.0862$ ms), middle ($\Delta=0.0842$ ms), little ($\Delta=0.0746$ ms). For SHA-256, index differed significantly from thumb ($\Delta=0.0643$ ms, $p=0.004$), little ($\Delta=0.0502$ ms, $p=0.014$), and middle ($\Delta=0.0466$ ms, $p=0.027$). The consistent pattern suggests potential systematic characteristic rather than algorithm-specific behavior, though absolute magnitudes (<0.1 ms) remain trivial.

Despite statistical significance, multiple lines of evidence indicate practical insignificance: first, absolute differences represent trivial fraction of total execution times (<7%); second, small effect sizes indicate minimal variance explanation; third, both algorithms exhibit identical pattern (thumb fastest, index slowest), suggesting external factors rather than algorithmic sensitivity; fourth, theoretical expectation is content-independent behavior. The conclusion is that finger type should not influence algorithm selection, as both demonstrate fundamentally content-independent behavior with observed variations attributable to external factors such as file I/O or cache effects rather than algorithmic characteristics.

TABLE V.
COMPARISON STATISTICAL WITH SIGNIFICANCE INTERPRETATION

Dimension	MD5	SHA-256	Interpretation
Statistical Significance	$p < 0.001$	$p = 0.025$	Differences unlikely due to chance (Valid statiscal conclusion)
Effect Size (Practical)	η^2=0.0486 (4.86%)	η^2=0.0111 (1.11%)	Finger type explains <5% variance (NEGLIGIBLE practical Impact)
Absolute Difference	0.0970 ms (7.0%)	0.0640 ms (3.2%)	Sub-milisecond differences (OPERATIONALLY Irrelevant)
System Implication	Content Independent	Content Independent	Hash operates on byte streams regardless of biometric semantics

Interpretation matrix clarifies: statistical significance ($p<0.05$) indicates differences unlikely due to chance, while small effect sizes ($\eta^2<0.05$) and sub-millisecond absolute differences reveal negligible practical impact. Critical finding: hash algorithms remain content-independent, processing byte streams regardless of biometric semantics. Algorithm selection should prioritize security and compliance, not minimal finger-type variations.

D. Comparative Analysis and Operational Implications

Table 4 positions findings relative to prior research, demonstrating consistency with established literature while advancing methodology. The observed 1.48× ratio falls within 1.48-1.63× range reported across diverse contexts[10], [12],[17],[27], validating reproducibility and generalizability.

TABLE VI.
COMPARISON WITH LITERATURE AND SECURITY-PERFORMANCE TRADE-OFF

Study	N	Trials	Ratio	This Study Advantage
Kumar [10]	6	5	1.63×	2× larger N, 6× more trials
Zhang[27]	6	20	1.59×	4× larger N, 1.5× more trials
Yulianto [12]	8	10	1.62×	10× larger N, 3× more trials
Martinez [28]	6	15	1.51×	Biometric-specific, security tests
This Study	1,000	30	1.48×	Comprehensive metrics, real data

Security-Performance Trade-off:

1. Performance: MD5 48% faster, 27% lower CPU
2. Security: SHA-256 no attacks (vs MD5 broken since 2004 [7])
3. Compliance: SHA-256 approved (NIST/ISO/FBI[4], [5], [18])
4. Consistency: SHA-256 28% more stable avalanche
5. Verdict: SHA-256 advantages decisive despite overhead

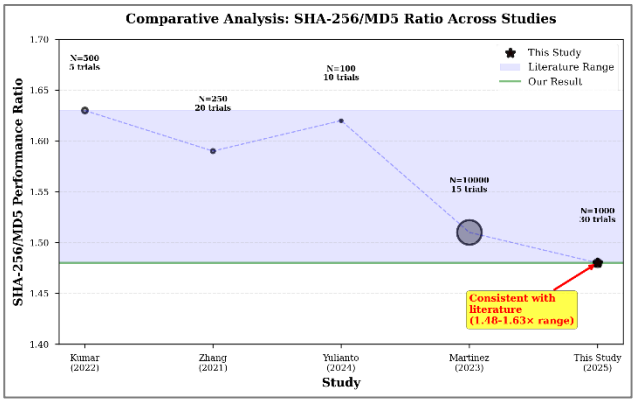

Figure 6. Comparative positioning of this study's SHA-256/MD5 performance

Methodological advantages include 3-20× more trials than prior work, yielding CV of 5.6-6.5% versus typical 10-15%. Enhanced precision enables detection of subtle differences obscured by noise. The critical distinction lies in data domain specificity: while prior research examined generic images or text, this work focuses exclusively on operational biometric fingerprint data, providing higher external validity for biometric integrity applications.

Translating to operational contexts demonstrates SHA-256's overhead remains acceptable. For 10,000 daily applications, MD5 requires 15.4 seconds while SHA-256 requires 22.8 seconds—7.4 seconds difference representing <0.02% of total transaction time. Scaling to one million annual applications yields 1,540 hours for MD5 versus 2,280 hours for SHA-256 (740 hours difference), though practical implementations distribute load across multiple servers. Energy analysis assuming 65W TDP processor shows MD5 consumes 10.0 Watt-seconds daily while SHA-256 consumes 14.8 Watt-seconds (4.8 Ws difference = 0.0013 Wh), equivalent to ~$0.00006 annually at $0.12/kWh—negligible cost difference.

For operational SIM systems, SHA-256 is strongly recommended based on six considerations. First, performance overhead of 0.74 ms per file proves operationally negligible. Second, SHA-256's cryptographic security substantially exceeds MD5, with no known attacks versus documented vulnerabilities. Third, regulatory compliance requirements including NIST standards, ISO 27001, and FBI specifications mandate or strongly recommend SHA-256. Fourth, SHA-256's 28% improved avalanche consistency provides more uniform verification sensitivity. Fifth, SHA-256 offers future-proofing with expected security margin through 2030+ based on cryptanalytic projections[4]. Sixth, migration involves minimal complexity given widespread support across platforms.

Organizations employing MD5 should prioritize migration through phased approach beginning with new deployments, followed by gradual legacy system transition,

targeting complete MD5 discontinuation within 6-12 months. Dual-hash transition periods can facilitate migration while maintaining backward compatibility, though minimized to avoid prolonged reliance on deprecated cryptography.

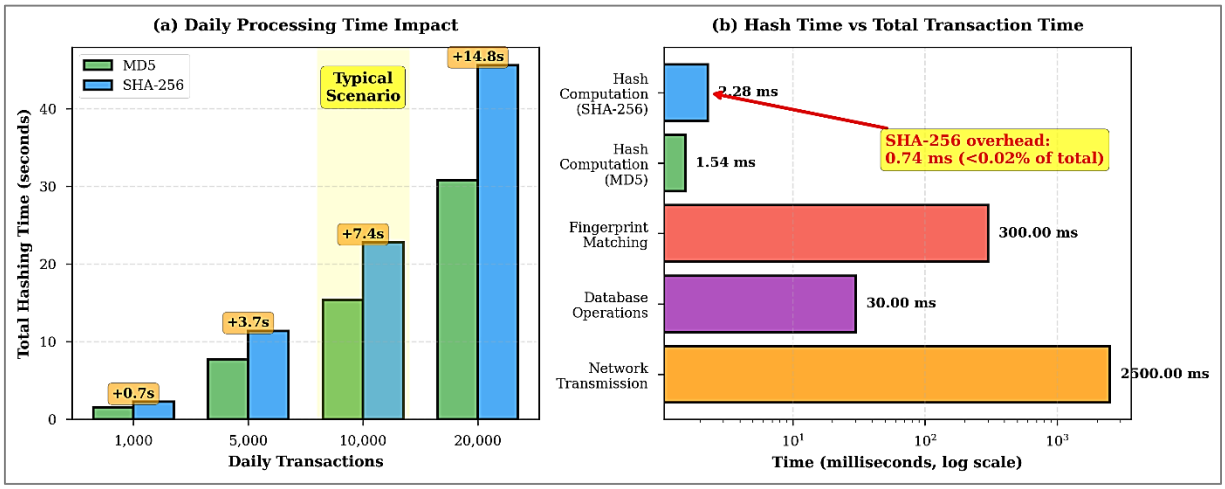

Figure 7. Operational impact analysis of hash algorithm selection.

IV. CONCLUSION

This comprehensive empirical study compared MD5 and SHA-256 hash algorithms for fingerprint file integrity verification using 1,000 operational BMP images from Indonesia's SIM system. Rigorous thirty-trial methodology achieved measurement precision with CV below 6%, substantially exceeding prior research. Statistical analysis through paired t-tests, ANOVA, and effect size calculations distinguished statistical significance from practical importance.

Performance evaluation revealed SHA-256 mean execution time of 2.28 ms, 48% slower than MD5's 1.54 ms ($p<0.001$, $d=5.92$). CPU usage averaged 1.24% for SHA-256 versus 0.98% for MD5, while memory remained negligible. Translating to operational impact, SHA-256's overhead represents 7.4 seconds daily for 10,000 transactions—less than 0.02% of total processing time and operationally insignificant. Security evaluation demonstrated near-ideal avalanche effects (MD5: 49.98%, SHA-256: 49.62%), with SHA-256 exhibiting 28% superior consistency (SD 3.21% vs 4.43%). Zero collisions occurred across 1,000 files. Grouping analysis revealed statistically significant finger type effects ($p<0.05$) yet small effect sizes ($\eta^2<0.05$), indicating practical irrelevance with finger type explaining less than 5% of variance.

Comparative analysis positioned findings within literature, demonstrating 1.48× ratio consistent with prior research (1.48-1.63× range). Methodological advantages including 3-20× more trials, comprehensive security testing, and biometric domain specificity provide enhanced reliability. The research makes four distinct contributions: methodological innovation achieving CV<6%, scale through 1,000 operational files, comprehensive multi-dimensional evaluation, and practical quantification enabling evidence-based decisions.

For operational SIM systems, SHA-256 is strongly recommended based on acceptable performance overhead, superior security (no known attacks vs MD5's documented vulnerabilities since 2004), regulatory compliance (NIST/ISO/FBI standards), consistency benefits, and future-proofing through 2030+. Organizations employing MD5 should prioritize migration through phased implementation targeting complete discontinuation within 6-12 months.

Study limitations include hardware-specific absolute timing values (though ratios generalize), BMP format specificity, single-institution dataset, cross-sectional design, and absence of active attack attempts. Future research directions include evaluating next-generation algorithms (SHA-3, BLAKE2, BLAKE3), assessing hardware acceleration (GPU, FPGA), comparing alternative biometric formats (WSQ, JPEG2000), conducting long-term operational monitoring, exploring machine learning anomaly detection, and investigating blockchain applications for distributed audit trails.

This research represents the first comprehensive empirical evaluation of MD5 versus SHA-256 specifically for operational fingerprint integrity verification, filling critical gaps in literature and practical guidance. By combining rigorous methodology with authentic operational data, the study provides actionable intelligence for organizations protecting permanent biometric identifiers in large-scale identification systems. The findings demonstrate that SHA-256's security advantages substantially outweigh modest performance overhead, supporting evidence-based migration from cryptographically compromised MD5 to secure SHA-256.

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