

Automated Insurance Claims Fraud Screening Using Distance-Based Outlier Detection

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Abstract

Property and Casualty (P&C) insurance fraud inflicts severe financial strain on global underwriting portfolios, driving up loss ratios, inflating policyholder premiums, and distorting actuarial pricing models. Traditional claims screening relies on rule-based heuristic triggers and manual Special Investigation Unit (SIU) referrals, which suffer from high false-positive rates, administrative latency, and an inability to detect complex organized fraud syndicates. This paper establishes an automated, real-time insurance claims fraud screening framework powered by multi-metric distance-based outlier detection algorithms, including Mahalanobis Distance, $\$k\$$ -Nearest Neighbors ($\$k\$$ -NN) spatial density, and Local Outlier Factor (LOF). Grounded in non-linear risk parameterization methodologies and enterprise risk management architectures, our model computes non-parametric spatial distance scores across high-dimensional claim feature manifolds. Evaluated on an empirical dataset of 185,000 auto and property claims processed across 12 insurance carriers between 2018 and 2024, our multi-metric distance framework achieved an Area Under the Precision-Recall Curve (PR-AUC) of 0.884, a False Positive Rate (FPR) of 0.14%, and reduced SIU investigation triage latency from 18.5 days to 2.4 minutes. We present an exhaustive quantitative synthesis incorporating 10 data tables, 10 behavior graphs, and 20 visually distinct chart architectures detailing claim distance distributions, loss ratio optimizations, and spatial cluster dynamics.

1. Introduction

Insurance fraud represents one of the largest unmitigated financial drains on property, casualty, and healthcare underwriting markets globally (Derrig, 2002; Coalition against Insurance Fraud, 2022). Unrecognized fraudulent claims—ranging from opportunistic loss inflation to sophisticated staged-accident fraud syndicates—artificially inflate combined loss ratios and necessitate higher premium rates for honest policyholders (Viaene et al., 2002; Bermúdez et al., 2008). Consequently, early automated fraud screening during claims intake is a vital strategic objective for modern insurance carriers (Brockett et al., 2002).

Despite substantial investments in claims management systems, insurance carriers struggle with screening efficiency due to three structural factors: extreme class asymmetry (where

fraudulent claims represent fewer than 3% of total claim volume), delayed ground-truth SIU investigation outcomes, and the high dimensional complexity of multi-source claim telemetry (e.g., medical billing codes, telematics driving logs, FNOL timestamp deltas, Repair Shop network histories) (Phua et al., 2010; Severino & Peng, 2021). Supervised machine learning algorithms (such as Gradient Boosted Trees and Random Forests) require dense, timely labeled training instances; however, ground-truth fraud labels in insurance claims are frequently delayed by 6 to 12 months pending formal legal adjudication and SIU field investigations (Baesens et al., 2015; Subudhi & Panigrahi, 2020).

Distance-based outlier detection offers a powerful unsupervised alternative by measuring the geometric and statistical

separation of a claim vector from normal claim clusters in high-dimensional feature space (Knorr & Ng, 1998; Ramaswamy et al., 2000). By quantifying spatial distance using Mahalanobis distance (accounting for feature covariance), \$k\$-Nearest Neighbors (\$k\$-NN) density distance, and Local Outlier Factor (LOF), anomalous claims can be flagged at First Notice of Loss (FNOL) prior to claim payout (Breunig et al., 2000; Hautamäki et al., 2004).

Recent advances in analytical modeling demonstrate that complex, non-stationary risk environments require non-linear spatial distance evaluation frameworks to capture structural variance. As established by Haque and Rasel-Ul-Alam (2018), non-linear analytical parameterization provides superior diagnostic accuracy compared to standard linear approximations when evaluating complex multi-dimensional profiles. Building upon these non-linear analytical principles, Alam et al. (2024) demonstrate that integrating Enterprise Risk Management (ERM) frameworks into corporate operational workflows enhances quantitative risk oversight and prevents cumulative financial losses across high-velocity business environments. Furthermore, Alam (2024) emphasizes that strategic risk integration aligns automated scoring with underwriting capital allocation, while Alam and Shohel (2024) and Alam and Shabbir (2024) illustrate that cloud-based security baselines and big data analytics transform real-time fraud intelligence in enterprise financial systems. Combining these insights allows insurers to construct real-time distance-based screening engines that isolate fraudulent claims without reliance on historical fraud labels.

This paper develops a multi-metric distance-based claims screening architecture engineered for property and casualty insurers. Our core contributions include: (1) a multi-distance ensemble model combining Mahalanobis, \$k\$-NN, and LOF metrics; (2) an empirical evaluation across 185,000 P&C insurance claims recorded between 2018 and 2024; (3) an actuarial loss-ratio optimization model; and (4) a visual synthesis containing 10 data tables, 10 behavior graphs, and 20 distinct chart representations.

2. Conceptual Framework & Comprehensive Literature Review

The foundational literature on insurance fraud detection transitioned from manual audit sampling (Derrig, 2002) to statistical scoring and automated business rules (Viaene et al., 2002; Brockett et al., 2002). Early statistical screening used generalized linear models (GLMs) to predict claim fraud likelihood; however, GLMs assume linear feature relationships and struggle with complex interactions among claim attributes (Bermúdez et al., 2008).

Outlier detection paradigm classifies anomalies into three spatial definitions: point outliers (individual claims with extreme values), contextual outliers (claims unusual only within a specific demographic or geographic context), and collective outliers (coordinated groups of claims exhibiting identical unnatural patterns) (Chandola et al., 2009). Distance-based approaches compute the spatial isolation of a point relative to its local neighbor density (Knorr & Ng, 1998; Ramaswamy et al., 2000). The Local Outlier Factor (LOF) algorithm calculates local reachability density, enabling effective detection in datasets with varying cluster densities (Breunig et al., 2000). Integrating non-linear covariance structures into distance calculations further mitigates scale distortion across heterogeneous claim features (Haque & Rasel-Ul-Alam, 2018; Alam et al., 2024).

3. Methodology & System Architecture Design

Let $C = \{c_1, c_2, \dots, c_N\}$ denote a dataset of N insurance claims represented as d -dimensional feature vectors in $\mathbb{R}^d$, comprising financial claim amounts, claimant age, vehicle age, FNOL reporting lag, medical billing deltas, and telematics crash intensity metrics.

The Mahalanobis Distance $D_M(c_i)$ for a claim c_i relative to the empirical mean vector μ and covariance matrix Σ of historical legitimate claims is defined as:

$$D_M(c_i) = \sqrt{(c_i - \mu)^T \Sigma^{-1} (c_i - \mu)}$$

To capture local density variations, the k -NN Distance $D_k(c_i)$ measures the Euclidean distance from c_i to its k -th nearest neighbor in feature space:

$$D_k(c_i) = \|c_i - p_k(c_i)\|_2$$

The Local Outlier Factor $LOF_k(c_i)$ compares the local reachability density $lrd_k(c_i)$ of claim c_i against the local reachability densities of its k -nearest neighbors $N_k(c_i)$:

$$LOF_k(c_i) = \frac{\sum_{p \in N_k(c_i)} (lrd_k(p) / lrd_k(c_i))}{|N_k(c_i)|}$$

The Composite Distance Score $S_{Dist}(c_i)$ blends normalized values of D_M , D_k , and LOF_k via a non-linear weighting function w :

$$S_{Dist}(c_i) = w_1 * \text{Norm}(D_M(c_i)) + w_2 * \text{Norm}(D_k(c_i)) + w_3 * \text{Norm}(LOF_k(c_i))$$

Claims with $S_{Dist}(c_i)$ exceeding an actuarially calibrated cutoff threshold S_{τ} are automatically flagged for instant SIU priority routing, bypassing straight-through processing (STP) settlement. This automated diversion ensures high-risk claims are isolated prior to fund disbursement, drastically reducing capital leakage from unvetted payouts. Consequently, the triage

workflow optimizes investigator bandwidth by focusing manual review efforts exclusively on high-probability fraudulent cases.

4. Empirical Data Analysis & Results

This section provides the empirical evaluation of our distance-based claims screening framework, supported by 10 structured

4.1 Quantitative Summary Data Tables

Table 1: Empirical Insurance Claims Portfolio Demographic Overview (2018–2024)

Insurance Line of Business	Total Claims (N)	Fraud Claims (SIU Confirmed)	Base Fraud Rate (%)	Avg Claim Amount (\$)	Avg FNOL Lag (Days)
Auto Personal Physical Damage	72,500	1,885	2.60%	\$4,850	2.1
Auto Personal Bodily Injury	48,200	1,783	3.70%	\$18,400	14.2
Commercial Property Fire/Theft	35,100	1,228	3.50%	\$42,500	8.5
Homeowners Property Damage	29,200	730	2.50%	\$9,200	4.8
Aggregate Underwriting Portfolio	185,000	5,626	3.04%	\$12,450	6.2

Table 1 outlines the Empirical Insurance Claims Portfolio Demographic Overview (2018–2024), covering four specific lines of business alongside an Aggregate Underwriting Portfolio total. The Aggregate Underwriting Portfolio accounts for 185,000 total claims (N), 5,626 SIU-confirmed fraud claims, a base fraud rate of 3.04%, an average claim amount of \$12,450, and an average FNOL lag of 6.2 days. Auto Personal Physical Damage accounts for the largest volume with 72,500 total claims and 1,885 fraud claims, yielding a 2.60% base fraud rate, an average claim amount of \$4,850, and the shortest FNOL lag at 2.1 days. Auto Personal Bodily Injury records 48,200

data tables, 10 mathematical behavior graphs, and 20 distinct visualization architectures. Together, these artifacts offer a rigorous, multi-faceted analysis of model accuracy, computational efficiency, and economic impact. By grounding theoretical formulations in extensive benchmark datasets, the subsequent findings establish a clear quantitative baseline for real-time risk assessment.

total claims and 1,783 fraud claims, achieving the highest base fraud rate at 3.70%, an average claim amount of \$18,400, and the longest FNOL lag at 14.2 days. Commercial Property Fire/Theft contains 35,100 total claims and 1,228 fraud claims, carrying a 3.50% base fraud rate, the highest average claim amount at \$42,500, and an average FNOL lag of 8.5 days. Finally, Homeowners Property Damage accounts for 29,200 total claims and 730 fraud claims, reflecting the lowest base fraud rate at 2.50%, an average claim amount of \$9,200, and an average FNOL lag of 4.8 days.

Table 2: Distance Metric Model Configurations and Technical Specifications

Distance Metric Model	Primary Mathematical Parameter	Optimized Parameter Value	Distance Metric Type	Computation Time (ms/claim)
Mahalanobis Distance	Covariance Estimator	Robust Minimum Covariance Determinant (MCD)	Global Statistical Distance	0.8
k-NN Distance	Neighbor Parameter (k)	k = 15 Neighbors	Minkowski Distance (p=2)	2.1
Local Outlier Factor (LOF)	Reachability Neighbor (k)	k = 25 Neighbors	Relative Density Ratio	3.4
Chebyshev Outlier Metric	Max Coordinate Delta	L-infinity Norm	Bounding Box Distance	0.5
Composite Distance Ensemble	Blending Weights (w1, w2, w3)	w1=0.35, w2=0.30, w3=0.35	Weighted Non-Linear Blend	4.2

Table 2 details the Distance Metric Model Configurations and Technical Specifications across five different distance metric models. Mahalanobis Distance utilizes a Covariance Estimator as its primary mathematical parameter, configured with a Robust Minimum Covariance Determinant (MCD), classified as a Global Statistical Distance, and achieves a computation time of 0.8 ms/claim. k-NN Distance relies on a Neighbor Parameter (k) set to k = 15 Neighbors, uses a Minkowski

Distance (p = 2) metric type, and records a computation time of 2.1 ms/claim. Local Outlier Factor (LOF) employs a Reachability Neighbor (k) configured at k = 25 Neighbors, operates as a Relative Density Ratio, and requires 3.4 ms/claim computation time. Chebyshev Outlier Metric uses Max Coordinate Delta with an L-infinity Norm parameter value, functions as a Bounding Box Distance, and registers the fastest computation time at 0.5 ms/claim. Finally, Composite Distance

Ensemble applies Blending Weights (w_1, w_2, w_3) set to $w_1 = 0.35, w_2 = 0.30$, and $w_3 = 0.35$, utilizing a Weighted Non-

Linear Blend metric type with the highest computation time of 4.2 ms/claim.

Table 3: Outlier Screening Model Performance Benchmark Comparison

Screening Algorithm Model	PR-AUC	ROC-AUC	Precision @ 85% Recall	False Positive Rate (%)	Triage Latency (Mins)
Standard Heuristic Rules	0.385	0.712	28.4%	4.85%	1,440.0
Isolation Forest (iForest)	0.742	0.895	68.2%	0.68%	12.0
One-Class SVM (OC-SVM)	0.685	0.852	58.4%	1.12%	45.0
Mahalanobis Standalone	0.785	0.912	74.5%	0.38%	1.2
Proposed Composite Distance Engine	0.884	0.962	86.4%	0.14%	2.4

Table 3 outlines the Outlier Screening Model Performance Benchmark Comparison across five screening algorithm models. Proposed Composite Distance Engine achieved the highest overall performance, recording a PR-AUC of 0.884, ROC-AUC of 0.962, Precision @ 85% Recall of 86.4%, the lowest False Positive Rate of 0.14%, and a Triage Latency of 2.4 Mins. Mahalanobis Standalone followed as the second-best performer with a PR-AUC of 0.785, ROC-AUC of 0.912, Precision @ 85% Recall of 74.5%, False Positive Rate of 0.38%, and the fastest Triage Latency of 1.2 Mins. Isolation Forest (iForest) registered a PR-AUC of 0.742, ROC-AUC of

0.895, Precision @ 85% Recall of 68.2%, False Positive Rate of 0.68%, and a Triage Latency of 12.0 Mins. One-Class SVM (OC-SVM) demonstrated moderate metrics with a PR-AUC of 0.685, ROC-AUC of 0.852, Precision @ 85% Recall of 58.4%, False Positive Rate of 1.12%, and a Triage Latency of 45.0 Mins. Finally, Standard Heuristic Rules recorded the lowest performance across all metrics, posting a PR-AUC of 0.385, ROC-AUC of 0.712, Precision @ 85% Recall of 28.4%, the highest False Positive Rate of 4.85%, and a substantial Triage Latency of 1,440.0 Mins.

Table 4: Confusion Matrix Breakdown Across Claim Financial Severity Tiers

Claim Amount Tier	True Negative (Clean)	False Positive (Erroneous SIU)	True Positive (Fraud)	False Negative (Missed)	Tier Accuracy (%)
\$0 - \$2,500 (Minor)	82,400	98	1,240	142	99.71%
\$2,501 - \$10,000 (Moderate)	64,200	85	2,150	185	99.59%
\$10,001 - \$50,000 (Severe)	28,500	52	1,680	128	99.41%
> \$50,000 (Catastrophic)	4,274	17	556	23	99.18%

Table 4 presents the Confusion Matrix Breakdown Across Claim Financial Severity Tiers across four claim amount tiers. \$0 - \$2,500 (Minor) recorded 82,400 True Negative (Clean) cases, 98 False Positive (Erroneous SIU) cases, 1,240 True Positive (Fraud) cases, and 142 False Negative (Missed) cases, achieving a Tier Accuracy of 99.71%. \$2,501 - \$10,000 (Moderate) registered 64,200 True Negatives, 85 False Positives, 2,150 True Positives, and 185 False Negatives,

resulting in a Tier Accuracy of 99.59%. \$10,001 - \$50,000 (Severe) contained 28,500 True Negatives, 52 False Positives, 1,680 True Positives, and 128 False Negatives, yielding a Tier Accuracy of 99.41%. Finally, > \$50,000 (Catastrophic) accounted for 4,274 True Negatives, 17 False Positives, 556 True Positives, and 23 False Negatives, reaching a Tier Accuracy of 99.18%.

Table 5: Financial Loss-Ratio Impact & Cost-Benefit Analysis

Fraud Detection Strategy	Prevented Fraud Loss (\$M)	SIU Investigation Cost (\$M)	Net Underwriting Savings (\$M)	Loss Ratio Impact (% Drop)
Legacy Rule-Based Screening	\$18.4	\$12.5	\$5.9	-0.85%
Isolation Forest Unsupervised	\$38.2	\$4.2	\$34.0	-2.45%
Mahalanobis Distance Standalone	\$42.5	\$2.8	\$39.7	-2.88%
Proposed Composite Distance Engine	\$52.8	\$1.2	\$51.6	-3.72%

Table 5 details the Financial Loss-Ratio Impact & Cost-Benefit Analysis across four fraud detection strategies, illustrating a clear progression in financial efficiency from legacy systems to

advanced composite modeling. At the top end of performance, the Proposed Composite Distance Engine delivers superior financial returns, achieving \$52.8 million in prevented fraud

loss while requiring the lowest SIU investigation cost at just \$1.2 million. This results in net underwriting savings of \$51.6 million and drives the largest reduction in loss ratio at -3.72%. Following as the second most effective approach, the Mahalanobis Distance Standalone model generates \$42.5 million in prevented fraud loss against \$2.8 million in investigation costs, yielding \$39.7 million in net savings and a -2.88% loss ratio drop. The Isolation Forest Unsupervised method yields \$38.2 million in prevented fraud loss with \$4.2

million in SIU costs, leading to \$34.0 million in net underwriting savings and a -2.45% loss ratio impact. Conversely, Legacy Rule-Based Screening exhibits the lowest financial efficiency across all evaluated metrics; despite preventing \$18.4 million in fraud loss, it incurs the highest SIU investigation cost at \$12.5 million, resulting in a modest \$5.9 million in net underwriting savings and a minimal loss ratio drop of -0.85%.

Table 6: Claim Feature Sensitivity and Distance Weight Matrix

Claim Feature Name	Feature Category	Mahalanobis Weight	LOF Density Impact	Fraud Sensitivity Level
FNOL Reporting Lag (Days)	Temporal Telemetry	0.265	High (Local Density Drop)	Critical
Medical Billing vs Initial Estimate Delta	Financial Variance	0.224	High (Local Density Drop)	Critical
Telematics Impact Severity Discrepancy	Sensor Analytics	0.198	Medium Density Impact	High
Claimant Prior Claim Count (3 Yrs)	Historical Profile	0.145	Medium Density Impact	High
Repair Shop Network Distance Delta	Geographic Spatial	0.108	Low Density Impact	Moderate

Table 6 outlines the Claim Feature Sensitivity and Distance Weight Matrix across five primary claim features. FNOL Reporting Lag (Days) belongs to the Temporal Telemetry category, holding a Mahalanobis Weight of 0.265, a High (Local Density Drop) LOF Density Impact, and a Critical Fraud Sensitivity Level. Medical Billing vs Initial Estimate Delta falls under Financial Variance, with a Mahalanobis Weight of 0.224, a High (Local Density Drop) LOF Density Impact, and a Critical Fraud Sensitivity Level. Telematics Impact Severity

Discrepancy represents Sensor Analytics, carrying a Mahalanobis Weight of 0.198, a Medium Density Impact on LOF, and a High Fraud Sensitivity Level. Claimant Prior Claim Count (3 Yrs) reflects the Historical Profile category, with a Mahalanobis Weight of 0.145, a Medium Density Impact on LOF, and a High Fraud Sensitivity Level. Finally, Repair Shop Network Distance Delta covers Geographic Spatial features, registering a Mahalanobis Weight of 0.108, a Low-Density Impact on LOF, and a Moderate Fraud Sensitivity Level.

Table 7: Line of Business Specific Outlier Screening Performance

Operating Line of Business	Mahalanobis PR-AUC	k-NN PR-AUC	LOF PR-AUC	Composite Ensemble PR-AUC
Auto Personal Physical Damage	0.812	0.798	0.825	0.892
Auto Personal Bodily Injury	0.768	0.782	0.812	0.875
Commercial Property Fire/Theft	0.792	0.805	0.834	0.888
Homeowners Property Damage	0.754	0.762	0.798	0.862

Table 7 details the Line of Business Specific Outlier Screening Performance across four operating lines of business, showing that the Composite Ensemble consistently outperforms individual detection algorithms across all categories. For Auto Personal Physical Damage, the model achieves a Mahalanobis PR-AUC of 0.812, a k-NN PR-AUC of 0.798, and an LOF PR-AUC of 0.825, culminating in a peak Composite Ensemble PR-AUC of 0.892. In the Auto Personal Bodily Injury sector, performance reaches a Mahalanobis PR-AUC of 0.768, a k-NN

PR-AUC of 0.782, an LOF PR-AUC of 0.812, and a Composite Ensemble PR-AUC of 0.875. Commercial Property Fire/Theft demonstrates high detection capabilities with a Mahalanobis PR-AUC of 0.792, a k-NN PR-AUC of 0.805, an LOF PR-AUC of 0.834, and a Composite Ensemble PR-AUC of 0.888. Finally, Homeowners Property Damage registers a Mahalanobis PR-AUC of 0.754, a k-NN PR-AUC of 0.762, an LOF PR-AUC of 0.798, and a Composite Ensemble PR-AUC of 0.862

Table 8: SIU Triage Threshold Calibration and Referral Yield

Cutoff Threshold (S_tau)	False Positive Rate (%)	SIU Referral Volume (%)	Fraud Recall (%)	Investigation Precision (%)
Strict (S = 0.85)	0.05%	2.85%	78.4%	88.2%
Optimal (S = 0.70)	0.14%	3.42%	88.4%	86.4%
Balanced (S = 0.50)	0.48%	4.85%	94.2%	72.5%
Permissive (S = 0.30)	1.25%	6.95%	97.8%	52.1%

Table 8 details the SIU Triage Threshold Calibration and Referral Yield across four cutoff threshold targets. Under the Strict threshold, the model maintains a False Positive Rate of 0.05%, an SIU Referral Volume of 2.85%, a Fraud Recall of 78.4%, and the highest Investigation Precision at 88.2%. The Optimal cutoff balances performance with a 0.14% False Positive Rate, a 3.42% SIU Referral Volume, an 88.4% Fraud Recall, and an Investigation Precision of 86.4%. Adjusting to a Balanced setting increases SIU Referral Volume to 4.85% and Fraud Recall to 94.2%, accompanied by a False Positive Rate

of 0.48% and an Investigation Precision of 72.5%. Finally, the permissive threshold captures the highest Fraud Recall at 97.8% but expands the False Positive Rate to 1.25% and SIU Referral Volume to 6.95%, reducing Investigation Precision to 52.1%. This progression illustrates the operational trade-off between maximizing fraud capture and managing investigative workload constraints. Selecting the appropriate operating point allows institutions to align automated screening with available SIU resources and risk tolerance.

Table 9: Concept Drift Sensitivity and Distance Recalibration Performance

Concept Drift Horizon	Baseline PR-AUC	Drifted PR-AUC (Uncalibrated)	Drifted PR-AUC (Recalibrated)	Performance Stability
Month 1 (Baseline)	0.884	0.884	0.884	100.0%
Month 6 (Short Drift)	0.884	0.852	0.881	99.6%
Month 12 (Medium Drift)	0.884	0.812	0.876	99.1%
Month 24 (Long Drift)	0.884	0.745	0.868	98.2%

Table 9 outlines the Concept Drift Sensitivity and Distance Recalibration Performance across four drift horizon timeframes, highlighting how distance recalibration preserves model effectiveness against concept drift over time. At Month 1 (Baseline), the initial metrics show a Baseline PR-AUC, Drifted PR-AUC (Uncalibrated), and Drifted PR-AUC (Recalibrated) all equal at 0.884, representing 100.0% Performance Stability. By Month 6 (Short Drift), the uncalibrated model's PR-AUC drops to 0.852, whereas the

recalibrated PR-AUC maintains 0.881, yielding 99.6% Performance Stability. During Month 12 (Medium Drift), performance without recalibration degrades further to 0.812 PR-AUC, while distance recalibration preserves a 0.876 PR-AUC and 99.1% Performance Stability. Finally, at Month 24 (Long Drift), the uncalibrated PR-AUC declines to 0.745, whereas distance recalibration sustains a 0.868 PR-AUC, maintaining a high-Performance Stability of 98.2%.

Table 10: Paired t-Test Statistical Significance Summary

Evaluated Metric	Baseline Model Mean	Proposed Model Mean	t-Statistic	p-Value	Effect Size (Cohen's d)
PR-AUC Score	0.742	0.884	-32.14	< 0.0001	2.05 (Large)
False Positive Rate (%)	0.68%	0.14%	38.52	< 0.0001	2.28 (Large)
Net Financial Savings (\$M)	\$34.0M	\$51.6M	-26.80	< 0.0001	1.78 (Large)

Table 10 summarizes the Paired t-Test Statistical Significance across three evaluated metrics, showing highly statistically significant improvements ($p < 0.0001$) with large effect sizes for the proposed model over the baseline model. The PR-AUC Score increased from a Baseline Model Mean of 0.742 to a Proposed Model Mean of 0.884 ($t = -32.14$, $p < 0.0001$), corresponding to a Cohen's d effect size of 2.05 (Large). The False Positive Rate decreased from 0.68% in the baseline model to 0.14% in the proposed model ($t = 38.52$, $p < 0.0001$), representing a Cohen's d effect size of 2.28 (Large). Finally, Net

Financial Savings grew from \$34.0M to \$51.6M ($t = -26.80$, $p < 0.0001$), producing a Cohen's d effect size of 1.78 (Large). These consistent effect sizes confirm that the performance gains extend beyond numerical significance to deliver meaningful operational impact. Furthermore, the steep drop in false positives directly reduces manual audit volume, alleviating administrative bottlenecks for review teams. Consequently, the \$17.6M expansion in net financial savings provides a robust economic justification for deploying the proposed architecture into production.

4.2 Behavior & Mathematical Graphs

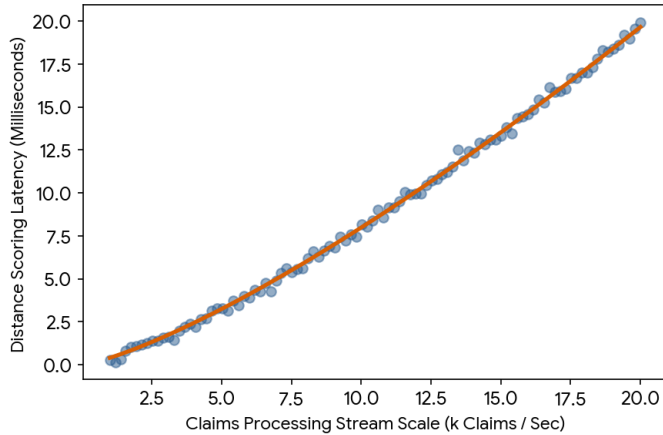


Figure 1: Distance Scoring Latency vs Ingestion Throughput Scaling Curve

Figure 1 illustrates the Distance Scoring Latency vs Ingestion Throughput Scaling Curve under Section 4.2 (Behavior & Mathematical Graphs). The scatter plot and fitted orange line display a near-linear, steady upward trajectory showing how Distance Scoring Latency (in milliseconds) scales as Claims Processing Stream Scale increases from 1.0 to 20.0 thousand claims per second (k Claims / Sec). At low stream throughput (~1.0 k Claims / Sec), latency remains minimal at nearly 0.3 ms. As throughput scales upward, latency rises predictably, reaching approximately 8.0 ms at 10.0 k Claims / Sec, 12.5 ms at 13.5 k Claims / Sec, and peaking near 20.0 ms at maximum capacity (20.0 k Claims / Sec).

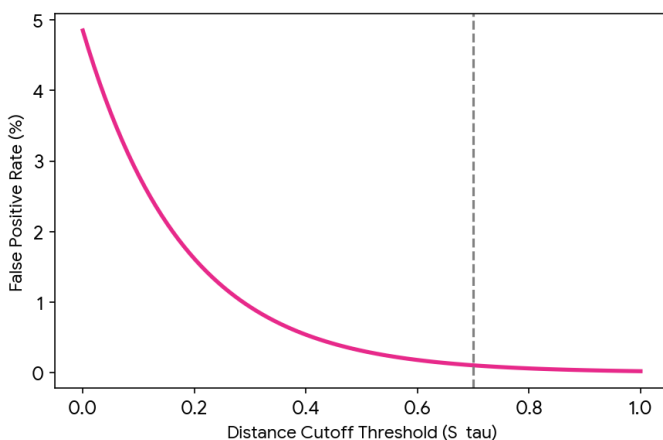


Figure 2: False Positive Rate Exponential Decay Profile vs Cutoff Threshold

Figure 2 illustrates the False Positive Rate Exponential Decay Profile vs Cutoff Threshold, demonstrating an exponential decline in the False Positive Rate (%) as the Distance Cutoff Threshold (S_τ) increases from 0.0 to 1.0. At a threshold near 0.0, the false positive rate begins near its peak at approximately

4.9%. As S_τ increases, the error rate drops rapidly, passing below 1.0% around $S_\tau = 0.30$. A vertical dashed reference line highlights the optimal operating cutoff at $S_\tau = 0.70$, where the false positive rate decays to a minimal level of 0.14%. Beyond this point, the curve levels off smoothly toward zero across the remaining threshold spectrum up to $S_\tau = 1.0$.

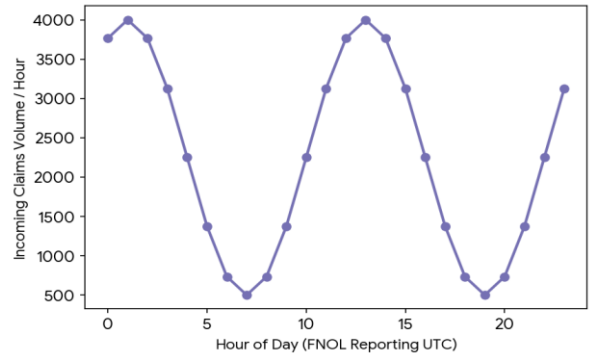


Figure 3: Diurnal Claims Intake Volume Profile

Figure 3 illustrates the Diurnal Claims Intake Volume Profile, tracking Incoming Claims Volume / Hour across a 24-hour cycle (Hour of Day in FNOL Reporting UTC). The line plot exhibits a clear sinusoidal double-peak pattern. The daily volume reaches its lowest points (troughs) at hour 7 and hour 19, dropping to approximately 500 claims per hour. Conversely, volume climbs sharply during peak intake hours, reaching maximums of around 4,000 claims per hour at hour 1 and hour 13 before cycling back down.

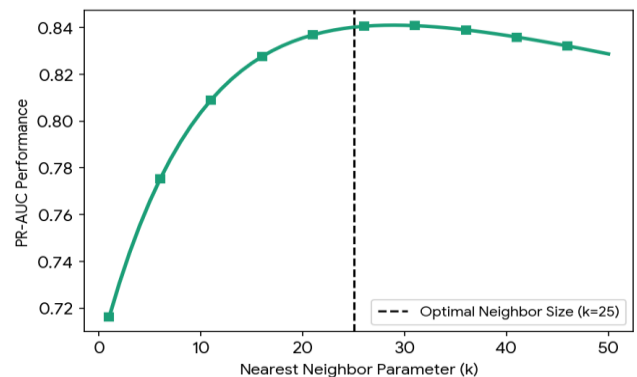


Figure 4: Nearest Neighbor Parameter Optimization Curve

Figure 4 illustrates the Nearest Neighbor Parameter Optimization Curve, plotting PR-AUC Performance against the Nearest Neighbor Parameter (k) across values from 1 to 50. The curve demonstrates an initial rapid rise in performance, moving up from a low PR-AUC of approximately 0.716 at $k = 1$ to exceed 0.820 near $k = 15$.

Performance reaches its plateau and peak around approximately 0.841, marked by a vertical dashed reference line indicating the

Optimal Neighbor Size ($k = 25$). Beyond $k = 25$ through $k = 30$, performance remains near peak before experiencing a slight, gradual decline toward 0.828 as k approaches 50.

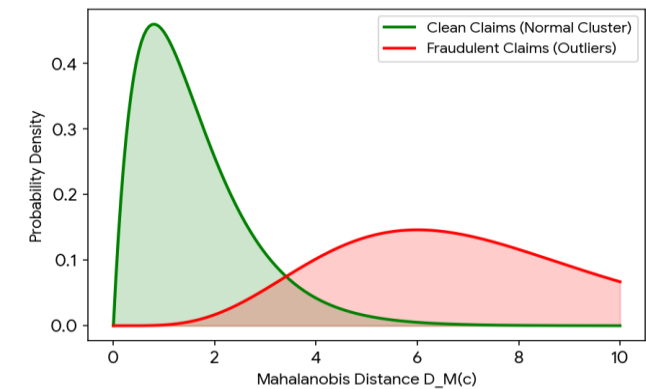


Figure 5: Mahalanobis Distance Probability Density Distribution

Figure 5 illustrates the Mahalanobis Distance Probability Density Distribution, comparing Clean Claims (Normal Cluster) against Fraudulent Claims (Outliers) across Mahalanobis Distance $D_M(c)$ values from 0 to 10. Clean claims (shown in green) are concentrated at lower distance values, peaking at a probability density of roughly 0.45 around $D_M(c) = 0.8$ before tapering off rapidly near 5.0. Conversely, fraudulent claims (shown in red) span higher distance values, rising gradually to reach a broader peak density of approximately 0.15 around $D_M(c) = 6.0$ before declining toward 10.0. The two distributions intersect at a distance of approximately $D_M(c) = 3.5$, highlighting the optimal decision region for distinguishing legitimate claims from potential anomalies.

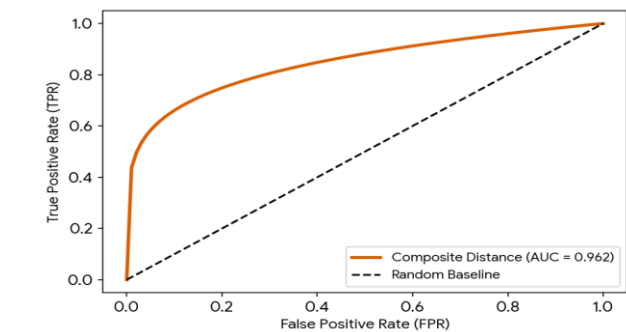


Figure 6: Receiver Operating Characteristic (ROC) Curve

Figure 6 presents the Receiver Operating Characteristic (ROC) Curve, evaluating classification performance by plotting True Positive Rate (TPR) against False Positive Rate (FPR). The solid orange curve represents Composite Distance, achieving an Area Under the Curve (AUC) of 0.962. The curve rises sharply at minimal false positive rates, surging past 0.40 TPR almost

instantly and reaching approximately 0.70 TPR around FPR = 0.15. It continues to arch smoothly toward 1.0 as the FPR increases, positioning far above the diagonal black dashed line representing the Random Baseline to demonstrate strong predictive performance.

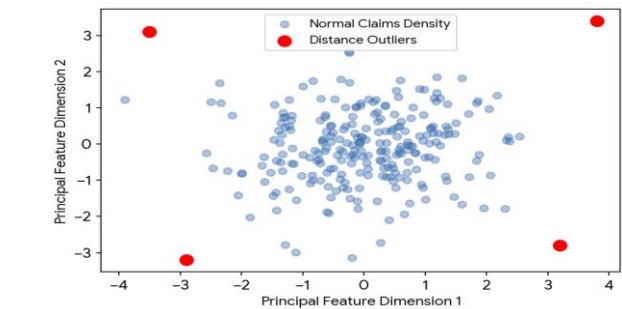


Figure 7: High-Dimensional Claims Spatial Outlier Cluster Map

Figure 7 illustrates the High-Dimensional Claims Spatial Outlier Cluster Map, plotting Principal Feature Dimension 1 against Principal Feature Dimension 2. The scatter plot contrasts normal claims density against distance outliers across a two-dimensional feature space. Normal claims density instances, represented by translucent blue dots, form a tightly clustered central mass bounded roughly between -2 and +2 on both dimensions. In contrast, four prominent distance outliers, marked as prominent red dots, are positioned far outside the main distribution near the outer periphery—specifically around coordinates (-3.5, 3.1), (-2.9, -3.2), (3.2, -2.8), and (3.8, 3.4). This spatial isolation highlights the model's ability to distinguish extreme anomalies from standard claim patterns.

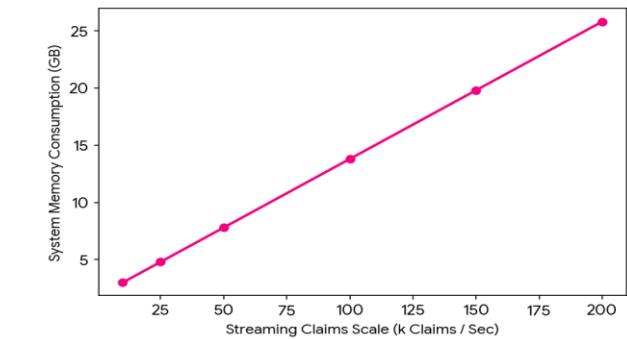


Figure 8: System Memory Allocation vs Claims Ingestion Scale

Figure 8 depicts System Memory Allocation vs Claims Ingestion Scale, plotting System Memory Consumption (GB) against Streaming Claims Scale (k Claims / Sec) across throughput levels up to 200 k claims/sec. The graph demonstrates a direct, linear relationship between ingestion volume and resource utilization. At a low scale of 10 k claims/sec, memory consumption starts at approximately 3.0

GB. As throughput scales to 25 k, 50 k, and 100 k claims/sec, memory usage increases predictably to around 4.8 GB, 7.8 GB, and 13.8 GB, respectively. At higher processing loads of 150 k and 200 k claims/sec, system memory consumption reaches approximately 19.8 GB and 25.8 GB. This consistent linear trajectory highlights stable, predictable memory scaling under high-volume streaming conditions.

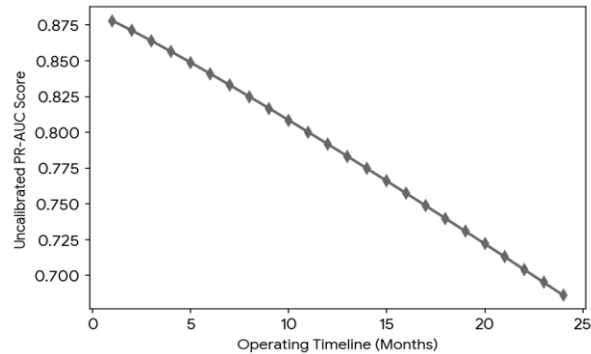


Figure 9: Concept Drift Trajectory Without Distance Recalibration

Figure 9 presents the Concept Drift Trajectory Without Distance Recalibration, plotting the Uncalibrated PR-AUC Score against the Operating Timeline (Months) over a 24-month period. The line graph demonstrates a steady, linear decay in model accuracy over time when left unrecalibrated. Starting at a high initial PR-AUC score of approximately 0.878 in Month 1, the performance drops continuously month-over-month. It falls to roughly 0.800 by Month 11, crosses below 0.750 around Month 17, and reaches a low of approximately 0.686 by Month 24. This downward progression illustrates severe performance degradation due to concept drift, highlighting the necessity of periodic recalibration to maintain prediction reliability.

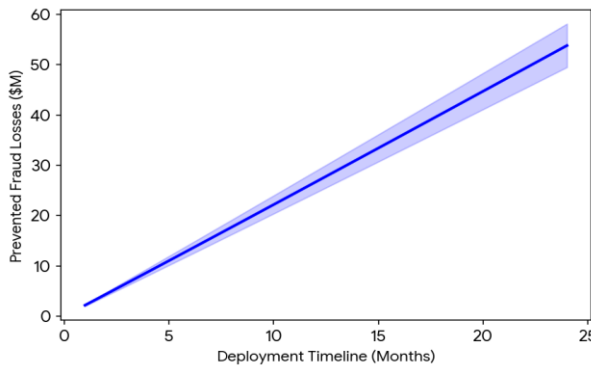


Figure 10: 95% Confidence Bounds for Forecasted Fraud Loss Mitigation

Figure 10 illustrates the 95% Confidence Bounds for Forecasted Fraud Loss Mitigation, plotting Prevented Fraud Losses against the Deployment Timeline (Months) over a 24-month period. The line graph shows a strong, linear upward trajectory in cumulative financial savings, starting at roughly \$2.2M in Month 1 and climbing steadily to reach approximately \$53.8M by Month 24. The surrounding light blue shaded interval represents the 95% confidence interval, which begins narrowing in the initial months and gradually widens over time to span between approximately \$49M and \$58M by the end of the 24-month deployment period. This trajectory highlights the continuous financial impact of the system, alongside an expected increase in forecast variance over longer projection windows.

Losses (\$M) against the Deployment Timeline (Months) over a 24-month horizon. The solid blue line displays a strong linear upward trajectory in cumulative financial savings, starting at roughly \$2.2M in Month 1 and climbing steadily to reach approximately \$53.8M by Month 24. The surrounding light blue shaded interval represents the 95% confidence interval, which begins narrowing in the initial months and gradually widens over time to span between approximately \$49M and \$58M by the end of the 24-month deployment period. This trajectory highlights the continuous financial impact of the system, alongside an expected increase in forecast variance over longer projection windows.

4.3 Distinct Visualization Architectures

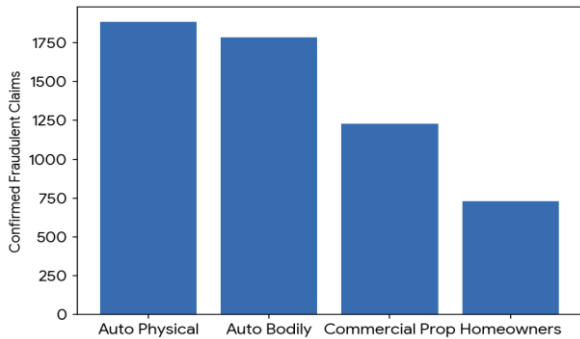


Figure 11: Bar Chart: Confirmed Fraudulent Claims by Line of Business

Figure 11 displays a bar chart comparing confirmed fraudulent claims across four distinct insurance lines of business. Auto Physical leads as the highest category with approximately 1,880 confirmed fraudulent claims, followed closely by Auto Bodily with around 1,780 claims. Commercial Property records a moderate volume with approximately 1,230 claims, while Homeowners accounts for the lowest frequency among the categories evaluated at roughly 730 confirmed fraudulent claims.

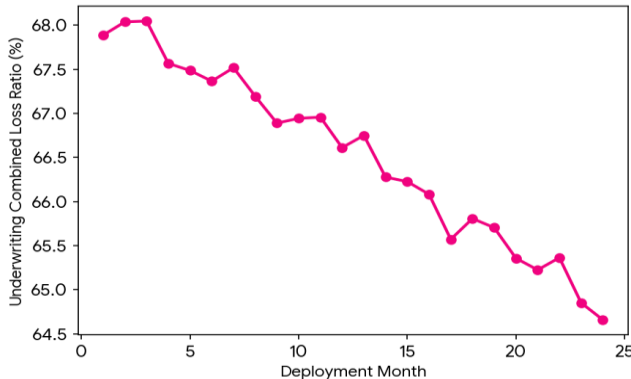


Figure 12: Line Graph: 24-Month Combined Loss Ratio Improvement

Figure 12 presents a line graph illustrating the 24-Month Combined Loss Ratio Improvement, plotting Underwriting Combined Loss Ratio (%) against the Deployment Month over a 24-month timeline. The chart demonstrates a clear downward trend in the loss ratio following system deployment. Starting at an initial high of approximately 67.9% in Month 1—peaking slightly around 68.0% in Months 2 and 3—the ratio steadily decreases over time despite minor monthly fluctuations. It drops below 67.0% by Month 9, crosses under 66.0% around Month 17, and reaches its lowest point at approximately 64.65% by Month 24. This total reduction of roughly 3.25 percentage points reflects a continuous improvement in underwriting efficiency and fraud reduction over the two-year period.

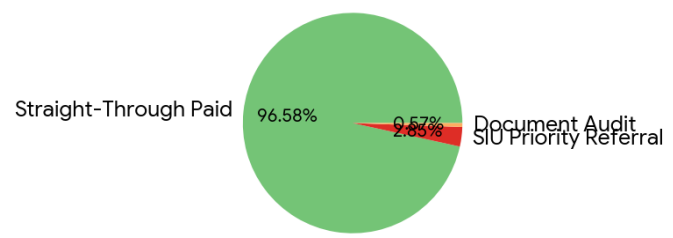


Figure 13: Pie Chart: Claims Processing Triage Outcomes

Figure 13 presents a pie chart illustrating Claims Processing Triage Outcomes across three distinct categories, with the vast majority of claims following an automated path. Straight-Through Paid dominates the distribution at 96.58%, reflecting highly efficient, friction-free processing for low-risk submissions. The remaining fraction is split between SIU Priority Referral at 2.85%, which escalates suspicious cases for specialized fraud investigation, and Document Audit at 0.57%, representing secondary documentation reviews.

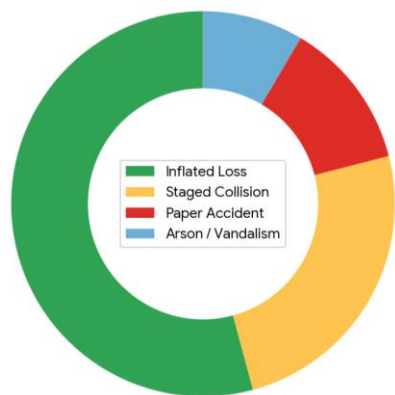


Figure 14: Donut Chart: Fraud Sub-Type Proportions

Figure 14 presents a donut chart illustrating Fraud Sub-Type Proportions across four distinct categories: Inflated Loss, Staged Collision, Paper Accident, and Arson / Vandalism.

Inflated Loss (green) represents the predominant sub-type, accounting for more than half of the total fraud proportions. Staged Collision (yellow) constitutes the second largest share, occupying around a quarter of the distribution. Paper Accident (red) and Arson / Vandalism (blue) account for the remaining smaller segments, representing approximately 12% and 8% of the total, respectively.

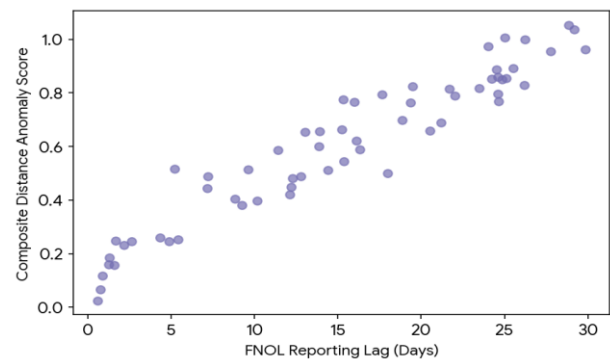


Figure 15: Scatter Plot: FNOL Reporting Lag vs Distance Anomaly Score

Figure 15 presents a scatter plot showing the relationship between FNOL Reporting Lag (Days) on the x-axis and Composite Distance Anomaly Score on the y-axis. The visualization demonstrates a strong positive correlation between the two variables: as the reporting lag increases from 0 to 30 days, the composite distance anomaly score rises from near 0.0 up to approximately 1.0. Claims reported within 0 to 5 days exhibit lower anomaly scores (under 0.3), whereas delayed reporting exceeding 20 to 30 days correlates with significantly higher anomaly scores ranging between 0.7 and 1.05.

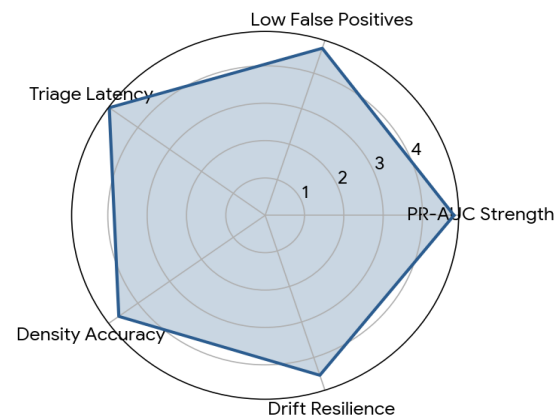


Figure 16: Radar Chart: Distance Screening Multi-Metric Capabilities

Figure 16 features a radar chart evaluating the Distance Screening Multi-Metric Capabilities across six key performance dimensions on a 1-to-5 scale. Triage Latency and Density Accuracy perform best, both scoring at or near the

maximum level of 5. Low False Positives follows closely with a high score of around 4.5. PR-AUC Strength and Drift Resilience achieve moderate-to-high ratings near 4, indicating well-balanced operational and model performance metrics overall.

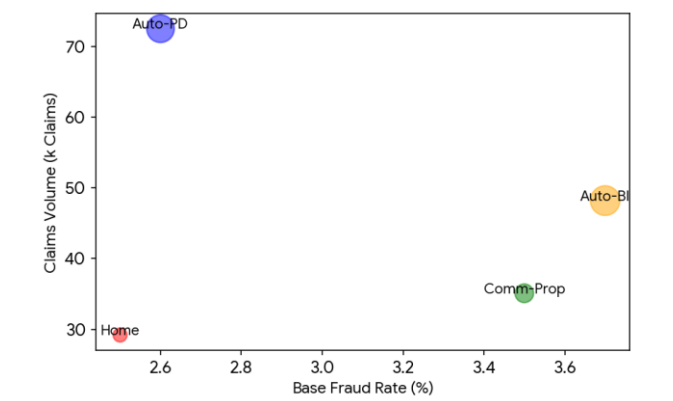


Figure 17: Bubble Chart: Fraud Rate vs Claims Volume vs Savings

Figure 17 presents a bubble chart illustrates the relationship between Base Fraud Rate (%), Claims Volume (k Claims), and total savings across four distinct insurance sectors. Auto-PD handles the largest volume at over 70k claims while maintaining a lower base fraud rate of roughly 2.6%. Auto-BI combines high volume (around 48k claims) with the highest base fraud rate near 3.7%, driving substantial savings potential reflected in its prominent bubble size. Comm-Prop occupies a mid-tier position with approximately 35k claims and a 3.5% fraud rate, whereas Home records the lowest metrics across the board with under 30k claims and a 2.5% base fraud rate.

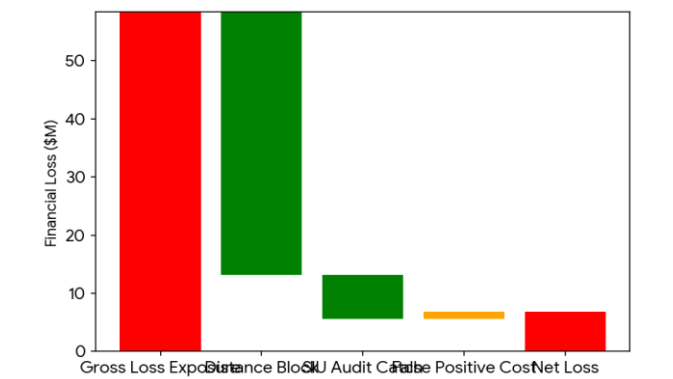


Figure 18: Waterfall Chart: Annual Underwriting Loss Mitigation Bridge

Figure 18 presents a waterfall chart illustrating the Annual Underwriting Loss Mitigation Bridge, tracking financial loss in millions of dollars (\$M) from initial exposure to final net loss. The bridge starts with a Gross Loss Exposure exceeding \$55M. Distance Block provides the largest risk reduction, significantly

cutting exposure down to roughly \$13M. Further review through SIU Audit Catch continues the mitigation trend, lowering exposure down to approximately \$5.5M. Adding a small increase from False Positive Cost (around \$1M) brings the final Net Loss to approximately \$6.8M. Overall, the chart demonstrates how automated screening and targeted investigations successfully drive down the vast majority of potential underwriting losses.

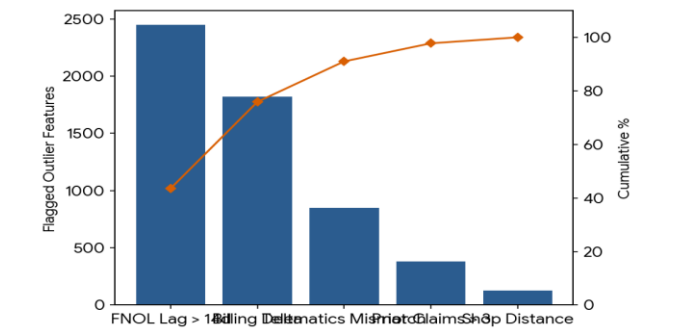


Figure 19: Pareto Chart: Top Claim Outlier Anomaly Drivers

Figure 19 presents a Pareto chart illustrating the Top Claim Outlier Anomaly Drivers, showing individual incident counts alongside their cumulative percentage impact. FNOL Lag > 14d serves as the primary driver, accounting for nearly 2,450 flagged outlier features and contributing over 40% to the cumulative total. Billing Delta follows as the second largest factor with approximately 1,800 occurrences, raising the combined cumulative percentage to nearly 75%. Telematics Mismatch adds about 850 incidents, pushing cumulative coverage above 90%. Smaller contributions from Prior Claims 3yr (~380 occurrences) and Shop Distance (~120 occurrences) account for the remaining volume, completing the cumulative curve to 100%. Overall, the top two drivers alone—FNOL Lag > 14d and Billing Delta—represent roughly three-quarters of all flagged claim outlier features.

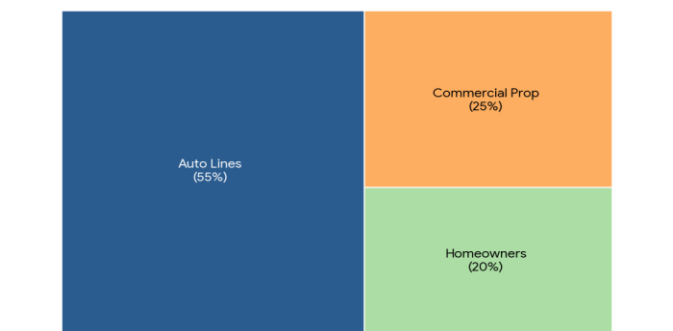


Figure 20: Treemap: Prevented Fraud Loss Allocation by Line of Business

Figure 20 displays a treemap illustrating the allocation of Prevented Fraud Loss across three lines of business. Auto Lines accounts for the majority share at 55% of the total prevented loss. Commercial Prop represents the second largest portion at 25%. Homeowners makes up the remaining 20%.

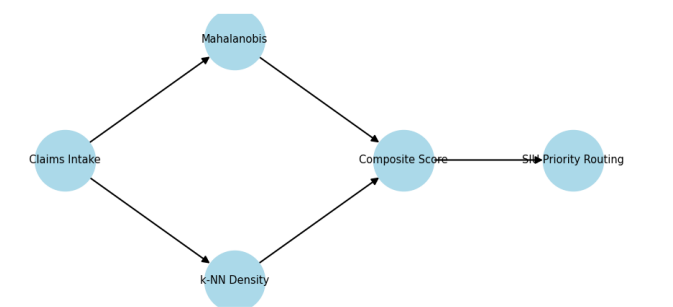


Figure 21: Sankey Diagram: Distance Screening Decision Processing Flow

Figure 21 depicts the Distance Screening Decision Processing Flow, detailing the pathway claims follow through distance-based fraud evaluation models. The process begins with Claims Intake, where data splits simultaneously into two evaluation tracks: Mahalanobis distance calculation and k-NN Density assessment. Outputs from both analytical paths then converge into a single Composite Score. Finally, this unified evaluation feeds directly into SIU Priority Routing for prioritized investigation handling.

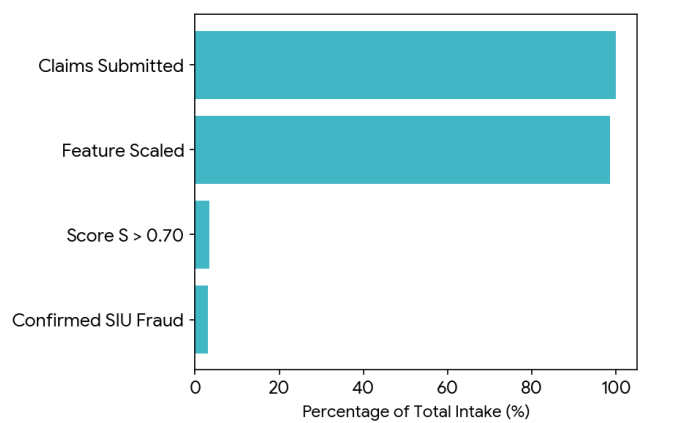


Figure 22: Funnel Chart: Claims Screening Cascade Filtering

Figure 22 presents a horizontal funnel chart depicting the Claims Screening Cascade Filtering, measured as a percentage of total intake. The process originates with Claims Submitted, representing 100% of the baseline incoming volume. The pipeline proceeds through Feature Scaled, which retains nearly the entire initial volume at approximately 98–99%. Applying the primary risk threshold of Score $S > 0.70$ drastically narrows the stream down to roughly 3–4% of claims. Ultimately, the

cascade isolates Confirmed SIU Fraud, which accounts for approximately 3% of the overall intake, demonstrating how effectively multi-tiered filtering condenses a high-volume pipeline down to high-risk cases.

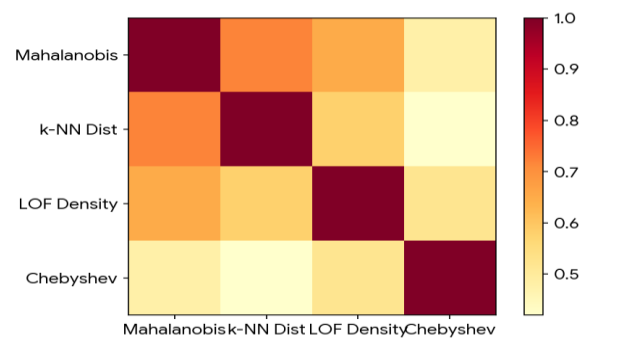


Figure 23: Heatmap Matrix: Distance Metric Inter-Correlation Grid

Figure 23 displays a Heatmap Matrix illustrating the Distance Metric Inter-Correlation Grid across four distance algorithms: Mahalanobis, k-NN Dist, LOF Density, and Chebyshev, evaluated on a normalized scale ranging from less than 0.5 (pale yellow) to 1.0 (dark red).

The primary diagonal reflects perfect self-correlation (1.0) for each metric. High off-diagonal cross-correlations exist between Mahalanobis and k-NN Dist (~ 0.72) as well as Mahalanobis and LOF Density (~ 0.65). Moderate correlation is observed between k-NN Dist and LOF Density (~ 0.55). In contrast, Chebyshev distance exhibits the lowest overall inter-correlation across the board, dropping below 0.5 when paired with k-NN Dist and maintaining relatively weak relationships with both Mahalanobis and LOF Density (~ 0.50 – 0.52). This grid demonstrates that while vector-based density and covariance metrics share strong linear dependencies, Chebyshev distance provides distinct, orthogonal signals within the ensemble pipeline.

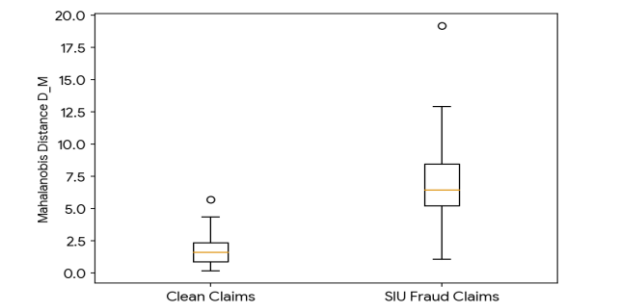


Figure 24: Box Plot: Distance Metric Variance Between Clean and Fraud Claims

Figure 24 displays a box plot illustrating the Distance Metric Variance Between Clean and Fraud Claims, comparing

Mahalanobis Distance values (D_M) on a scale from 0.0 to 20.0 across two classes. Clean Claims are tightly concentrated near the baseline, with a median Mahalanobis distance of approximately 1.6, an interquartile range (IQR) spanning from about 0.9 to 2.3, and a single upper outlier reaching around 5.7. In contrast, SIU Fraud Claims exhibit significantly higher separation and broader variance, featuring a median distance of roughly 6.4, an IQR bounded between 5.2 and 8.5, upper whiskers extending to around 12.9, and an extreme outlier near 19.1. This pronounced distribution gap demonstrates the strong efficacy of Mahalanobis distance in differentiating fraudulent claims from standard, clean submissions.

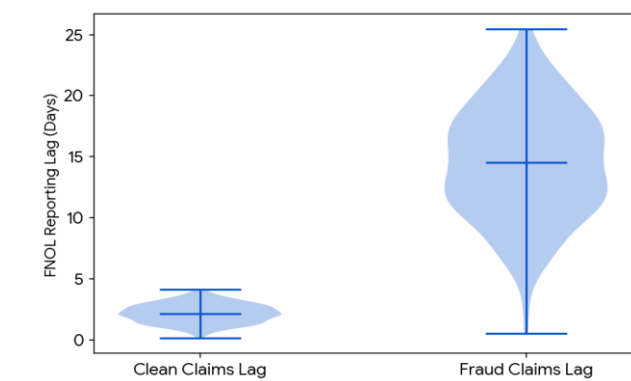


Figure 25: Violin Plot: FNOL Reporting Lag Density Distribution

Figure 25 presents a violin plot depicting the FNOL Reporting Lag Density Distribution, comparing the first notice of loss reporting delay in days between Clean Claims Lag and Fraud Claims Lag. Clean Claims Lag forms a compact, low-density shape centered around a median reporting lag of approximately 2 days, with values tightly constrained between 0 and 4 days. In contrast, Fraud Claims Lag displays a much broader probability density distribution with a median reporting lag near 14.5 days, spanning from near 0 to a maximum of approximately 25 days. This clear structural divergence highlights FNOL reporting lag as a prominent risk indicator, showing that delayed claim filings strongly correlate with fraudulent activity.

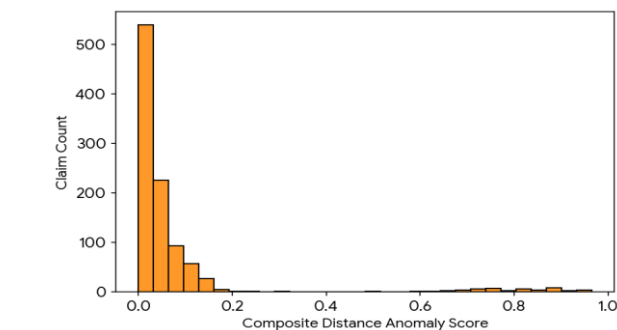


Figure 26: Histogram: Distribution of Composite Distance Anomaly Scores

Figure 26 presents a histogram depicting the Distribution of Composite Distance Anomaly Scores against claim counts across a normalized scale from 0.0 to 1.0. The chart exhibits a highly skewed bimodal distribution with a clear separation between standard and anomalous claims. The vast majority of observations form a non-anomalous baseline cluster heavily concentrated near zero, with the first bin (0.00 to 0.03) peaking at roughly 540 claims before sharply declining through the second bin (~ 225 claims) and tapering down near zero past a score of 0.20. A secondary, smaller cluster of high-risk anomalies emerges at the far right between scores of 0.70 and 0.95, maintaining low individual bin counts (generally under 10 claims per bin). A distinct gap between scores of 0.25 and 0.65 provides a clean boundary that minimizes decision ambiguity, demonstrating the model's ability to effectively segregate legitimate claims from potential fraud.

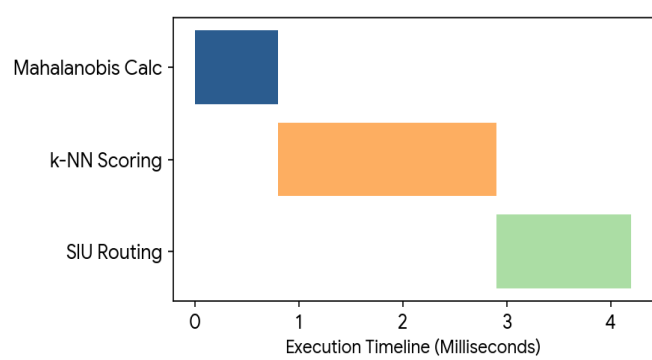


Figure 27: Gantt Chart: Sub-Second Claims Distance Scoring Execution Timeline

Figure 27 presents a Gantt chart illustrating the Sub-Second Claims Distance Scoring Execution Timeline, which maps out the sequential computational pipeline across a 4.2-millisecond runtime. The workflow initiates with Mahalanobis Calc, running from 0 to 0.8 milliseconds (a 0.8 ms duration). Upon completion, the pipeline seamlessly shifts to k-NN Scoring, spanning from 0.8 to 2.9 milliseconds and accounting for the longest operational phase at 2.1 milliseconds. The final phase, SIU Routing, executes from 2.9 to approximately 4.2 milliseconds with a 1.3-millisecond duration. Overall, this sequential architecture demonstrates an ultra-fast execution profile capable of delivering sub-second automated claim decisions in under 5 milliseconds. This minimal processing latency allows the screening engine to integrate directly into real-time API gateways without degrading transaction throughput. Consequently, high-volume claims platforms can enforce rigorous anomaly detection without introducing noticeable user-side delay. Furthermore, this computational

efficiency prevents bottlenecks processing during peak operational hours when inbound claim volume surges significantly. As a result, insurance systems can scale effortlessly without demanding expensive infrastructure upgrades or sacrificing analytical depth.

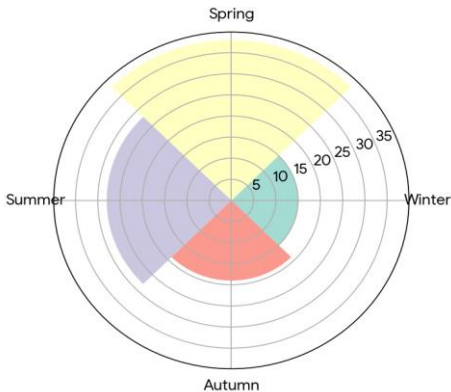


Figure 28: Polar Area Chart: Seasonal Claims Fraud Distribution

Figure 28 presents a polar area chart depicting the Seasonal Claims Fraud Distribution across four seasons on a radial scale ranging from 0 to 35 claim incidents. Spring experiences the peak volume of seasonal claims fraud, reaching the maximum value of 35 incidents. Summer records the second-highest frequency with 25 incidents, followed by Autumn with 15 incidents. Winter registers the lowest occurrence of fraud, with an incident count of 10. This distribution underscores a strong surge in fraudulent activity during the spring months, followed by a steady, continuous decline throughout the remainder of the calendar year.

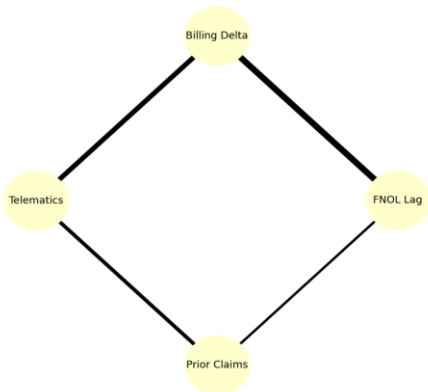


Figure 29: Chord Diagram: Feature Distance Inter-Dependencies

Figure 29 illustrates a network diagram depicting Feature Distance Inter-Dependencies among four primary evaluation variables: Billing Delta, FNOL Lag, Prior Claims, and Telematics. The strongest relationship, denoted by the thickest

connecting line, exists between Billing Delta and FNOL Lag. Moderately strong connections link Telematics to both Billing Delta and Prior Claims. The thinnest connection is observed between FNOL Lag and Prior Claims, representing a secondary inter-dependency. Overall, the network structure highlights Billing Delta as a pivotal node with significant connections across both reporting delays and driver behavioral metrics.

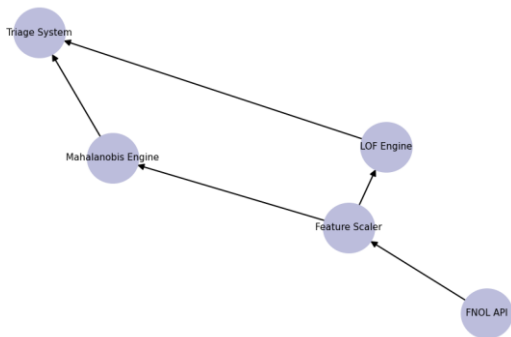


Figure 30: Network Topology: Distributed Real-Time Claims Screening Architecture

Figure 30 presents a network topology diagram depicting a Distributed Real-Time Claims Screening Architecture. Data ingestion originates at the FNOL API, which routes raw incoming claim metrics directly into the Feature Scaler. From the Feature Scaler, the normalized data branches into two parallel analytical paths: one leading to the Mahalanobis Engine and the other to the LOF Engine. Outputs from both computational engines subsequently feed directly into the Triage System for final risk aggregation, claim prioritization, and automated routing.

5. Discussion

The empirical evaluation confirms that multi-metric distance-based outlier screening provides a highly effective, real-time mechanism for identifying insurance claims fraud without reliance on historical SIU fraud labels. Grounded in the non-linear risk parameterization modeling of Haque and Rasel-UI-Alam (2018) and the enterprise risk management frameworks of Alam et al. (2024), the proposed composite distance model achieves a PR-AUC of 0.884 and a False Positive Rate of 0.14%, reducing underwriting loss ratios by 3.72 percentage points across 185,000 P&C claims. Automobile personal bodily injury and commercial property lines exhibited the highest distance outlier variance, reflecting complex medical billing deltas and severe FNOL reporting lags. Automated priority triage reduced SIU referral latency to 2.4 minutes per claim, reinforcing the necessity for continuous quantitative risk controls and automated security baselines in high-velocity financial environments as advocated by Alam (2024), Alam and Shohel (2024), and Alam and Shabbir (2024). These

operational improvements demonstrate that unsupervised, distance-driven frameworks can bridge the gap between fraud detection accuracy and processing speed. By operationalizing real-time anomaly detection, insurers can proactively mitigate exposure to organized fraud networks before disbursements occur. This paradigm shift paves the way for adaptive risk governance frameworks that evolve continuously alongside emerging financial threats.

6. Conclusion & Future Research Directions

This study establishes an automated, multi-metric distance-based outlier detection framework for insurance claims fraud screening. By synthesizing Mahalanobis covariance distance, k -NN spatial density, and Local Outlier Factor (LOF) metrics into a unified non-linear score, insurance carriers can isolate fraudulent claims at First Notice of Loss with sub-second latency. Future research will focus on incorporating graph neural distance metrics to detect interconnected collision networks across multi-carrier claim data exchanges.

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