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AN INTEGRATED RANDOM FOREST-BASED FRAMEWORK FOR INSURANCE CLAIM AMOUNT REGRESSION AND FRAUD RISK CLASSIFICATION IN IMBALANCED DATASETS

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ABSTRACT

The insurance industry confronts two analytically critical and financially consequential challenges: accurate prediction of claim settlement amounts and timely detection of fraudulent claims. Conventional approaches — rule-based heuristics, logistic regression scorecards, and manual adjuster assessments — are demonstrably inadequate for capturing the nonlinear, high-dimensional interactions that characterise modern insurance claim data. This paper presents ClaimSmart AI, a comprehensive, modular, end-to-end machine learning pipeline that addresses both challenges within a unified analytical framework. The system operates on a synthetically generated dataset of 15,000 insurance claim records encompassing 19 attributes spanning policyholder demographics, policy characteristics, vehicle parameters, claim specifics, and behavioural indicators. A dual-model architecture employs a Random Forest Regressor (150 estimators) for claim amount prediction and a Random Forest Classifier (150 estimators, balanced class weights) for binary fraud risk detection, both trained on a stratified 80/20 holdout split with StandardScaler feature normalisation and LabelEncoder categorical transformation. The regression model achieves a Mean Absolute Error below INR 15,000 and an R-squared coefficient of determination exceeding 0.70, while the classification model delivers accuracy above 0.80, fraud-class recall exceeding 0.74, and F1-Score above 0.76, surpassing logistic regression and rule-based baselines on equivalent evaluation protocols. Prediction outputs are enriched with four derived business metrics — predicted claim amount, claim variance, fraud risk probability, and a three-tier fraud risk category — and persisted to a MySQL relational database for direct consumption by Power BI and enterprise analytics platforms. Eight publication-quality visualisation charts provide comprehensive analytical coverage from fraud distribution and regional heatmaps to actual-versus-predicted scatter analysis. A mysqldump-format SQL export module ensures enterprise portability and regulatory archival compliance. The complete pipeline executes through a single orchestration script, establishing ClaimSmart AI as both a rigorous academic contribution and a practical template for production insurance analytics deployment.

KEYWORDS *Random Forest; Insurance Fraud Detection; Claim Amount Regression; Imbalanced Classification; Business Intelligence Integration*

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1. INTRODUCTION

The global insurance industry manages trillions of dollars in premium income annually, functioning simultaneously as a personal financial safety net, a corporate risk transfer mechanism, and one of the largest classes of institutional investor worldwide. Within this structurally complex ecosystem, two analytically distinct but operationally interrelated challenges represent the most consequential computational problems facing contemporary insurance data science: the accurate regression estimation of individual claim settlement amounts and the binary classification of claims as fraudulent or legitimate prior to adjudication.

Insurance fraud — encompassing staged vehicle accidents, inflated repair estimates, fictitious property theft claims, arson for financial gain, and medical billing manipulation — is estimated to account for between five and fifteen percent of total insurance claims costs globally, representing hundreds of billions of dollars in direct annual losses **[2]**. The financial impact extends beyond direct monetary losses to include elevated premium costs borne by legitimate policyholders, increased investigative overhead, and erosion of the systemic trust that underpins the mutual risk-pooling function of insurance. Simultaneously, inaccurate claim amount estimation introduces financial misalignment between premium pricing and reserve adequacy, creating capital shortfalls under loss-event scenarios and reducing investment efficiency when reserves are systematically over-provisioned.

Existing approaches to these challenges — rule-based early warning systems, logistic regression scoring models, and commercial InsurTech platforms — suffer from well-documented limitations including inability to capture nonlinear feature interactions, static decision boundaries that cannot adapt to evolving fraud schemes, binary flag outputs that preclude risk stratification, and proprietary architectures that resist independent validation and customisation **[4]**. The academic literature has extensively demonstrated the superiority of ensemble machine learning methods, particularly Random Forest classifiers and regressors, for insurance analytics tasks, but the majority of published studies present isolated model evaluations without addressing the full production deployment pipeline from data engineering through business intelligence integration **[1]**.

The present paper addresses this gap through the design and implementation of ClaimSmart AI: a five-stage, end-to-end machine learning pipeline that integrates synthetic data generation, dual-model ensemble learning, relational database persistence, Power BI-style analytical visualisation, and enterprise SQL export within a reproducible, orchestrated pipeline architecture. The system's dual-model design — a Random Forest Regressor for claim amount estimation and a Random Forest Classifier with balanced class weights for fraud detection — provides a principled algorithmic response to the distinct statistical natures of the two target variables: continuous claim amounts requiring regression, and imbalanced binary fraud labels requiring classification with minority-class-aware loss functions.

1.1 Contribution of the Paper

The principal contributions of this paper are as follows. **(i) Unified dual-model pipeline:** A single end-to-end architecture simultaneously addresses claim amount regression and fraud risk classification, sharing a common feature engineering foundation and pipeline infrastructure, reducing system complexity relative to maintaining independent analytical workflows for each task. **(**ii) Domain-aware synthetic data generation: A simulation engine incorporating empirically motivated distributional assumptions and causal feature relationships produces a 15,000-record dataset that exhibits realistic statistical properties — including appropriate class imbalance and feature correlations — while remaining free of privacy and regulatory constraints that limit access to real insurance data. (iii) Imbalance-corrected classification: The application of inverse-frequency class weighting to the Random Forest Classifier directly addresses the inherent class imbalance of insurance fraud datasets without requiring physical resampling, preserving the statistical properties of the training data while improving minority-class recall. (iv) Enterprise integration architecture: MySQL persistence, Power BI connectivity, and mysqldump SQL export bridge the gap between machine learning model outputs and

enterprise business intelligence infrastructure, enabling consumption of prediction results by non-technical stakeholders through familiar analytical tools. (v) Comprehensive analytical visualisation: Eight publication-quality charts provide a complete analytical overview spanning fraud distribution, claim amount patterns, prediction accuracy assessment, risk stratification, and regional-product heatmaps, constituting a ready-to-deploy business intelligence dashboard for insurance analytics operations.

2. LITERATURE SURVEY

The academic literature on insurance analytics and fraud detection spans multiple decades and methodological generations, evolving from purely statistical approaches through rule-based automation to modern ensemble machine learning. A critical synthesis of the most relevant existing research establishes the intellectual foundations of the proposed system and delineates the specific gaps that ClaimSmart AI is designed to address.

Breiman's seminal 2001 paper introducing the Random Forest algorithm **[1]** remains the foundational reference for ensemble-based prediction, establishing the theoretical guarantees of ensemble error reduction through decorrelated trees and demonstrating empirical performance exceeding that of individual decision trees and competing algorithms across diverse classification and regression tasks. The algorithm's robustness to outliers, implicit feature selection through variable importance rankings, and natural handling of mixed-type features have made it the dominant choice for insurance analytics applications.

Bolton and Hand's comprehensive review of statistical fraud detection **[2]** provides essential theoretical grounding for the fraud detection component of ClaimSmart AI. Their analysis systematically categorises fraud detection approaches into supervised classification, unsupervised anomaly detection, and social network analysis, identifying class imbalance as the most persistent technical challenge across all supervised learning approaches. Their review confirms that evaluation metrics beyond accuracy — specifically Precision, Recall, and F1-Score on the minority fraud class — are essential for assessing the practical utility of fraud detection systems.

Artis, Ayuso, and Guillen **[3]** investigated automobile insurance fraud detection using discrete choice models, demonstrating the significant predictive value of reporting delay, police report absence, and claims history — factors that are explicitly encoded as fraud risk indicators in the ClaimSmart AI data generation engine and feature set. However, their logistic regression framework assumes linear separability and cannot capture the interaction effects that ensemble methods exploit. Specifically, the combination of high repair estimates, absence of witnesses, and prior claims history creates a fraud risk signal that is stronger than the sum of its individual components — a nonlinear interaction that Random Forest naturally captures through split-based feature combinations.

Phua et al.'s comprehensive survey of data mining approaches to fraud detection across multiple domains **[4]** provides the most complete landscape assessment of the field. Their survey identifies Random Forest and gradient boosting as the algorithms achieving consistently superior discrimination performance, confirms that class imbalance handling is critical for practical utility, and notes that the integration of prediction outputs with enterprise systems is a universal deployment challenge that is rarely addressed in academic contributions. ClaimSmart AI directly addresses this identified gap through its MySQL persistence and SQL export architecture.

Chawla et al.'s introduction of the Synthetic Minority Over-sampling Technique (SMOTE) **[5]** established resampling as a mainstream approach to the class imbalance challenge in fraud detection. While SMOTE achieves recall improvements over purely threshold-based approaches, it introduces synthetic records into the training set that may not reflect genuine fraud patterns, and its computational overhead is significant for large datasets. The ClaimSmart AI classifier addresses class imbalance through the mathematically equivalent but computationally more efficient class_weight='balanced'

mechanism in scikit-learn's RandomForestClassifier, achieving comparable minority-class performance without physical dataset augmentation.

Pedregosa et al.'s documentation of scikit-learn **[6]** establishes the computational framework within which all machine learning operations in ClaimSmart AI are implemented. The consistent fit/transform/predict API design of scikit-learn estimators enables the modular construction of the feature engineering and modelling pipeline, and the library's comprehensive metrics module provides the evaluation infrastructure for both regression and classification performance assessment.

Lundberg and Lee's introduction of SHAP (SHapley Additive exPlanations) values **[7]** represents the most important recent development in machine learning interpretability with direct relevance to insurance analytics. SHAP values provide mathematically rigorous, individually attributable explanations of model predictions, addressing the regulatory and operational requirement for explainable insurance decisions. The absence of SHAP-based individual prediction explanation is identified as the principal limitation of the current ClaimSmart AI implementation and the highest-priority direction for future enhancement.

Table 1: Comparative Analysis of Related Work and Proposed System

Reference	Algorithm	Domain	Key Metric	Limitation Addressed by Proposed Work
Breiman [1]	Random Forest	General ML	AUC ~0.86	No CLV or DB integration
Bolton & Hand [2]	Statistical scoring	Insurance fraud	F1 ~0.62	Linear model; no ensemble
Artis et al. [3]	Logistic regression	Auto insurance	Accuracy ~0.72	No claim amount regression
Phua et al. [4]	Survey (SVM, NN, DT)	Multi-domain	Varies	No unified pipeline
Chawla et al. [5]	SMOTE + classifier	Imbalanced data	Recall improvement	Resampling only; no end-to-end system
Proposed System	RF Regressor + Classifier	Insurance (auto)	R^2>0.70, F1>0.76	Dual-model + MySQL + 8 visuals + SQL export

The critical analysis of existing literature reveals three consistent gaps that ClaimSmart AI addresses: the absence of unified dual-model architectures treating claim amount prediction and fraud detection as complementary tasks within a single pipeline; the lack of enterprise integration infrastructure (database persistence and BI connectivity) in academic machine learning contributions; and the scarcity of end-to-end reproducible systems with complete implementation documentation. The proposed system synthesises the algorithmic strengths identified across the reviewed literature — Random Forest ensemble methods, inverse-frequency class weighting, and standardised feature preprocessing — with an operational deployment architecture that transforms research outputs into actionable business intelligence.

3. PROPOSED WORK

The proposed ClaimSmart AI architecture leverages a layered pipeline design that partitions the analytical workflow into five functionally independent yet sequentially dependent modules, each producing a well-defined output artefact that serves as the input contract for subsequent stages. This architectural decision promotes modularity, testability, and independent maintainability of each pipeline component.

3.1 System Architecture

The five-layer architecture of ClaimSmart AI is formally described as follows:

Table 2: ClaimSmart AI System Architecture — Five-Layer Pipeline

Layer	Module	Primary Function	Output Artefact
1	Data Generation (1_data_generator.py)	Synthetic dataset creation via parameterised simulation engine; encodes domain-knowledge relationships between features and targets	Insurance_Claim_Data.xlsx (15,000 records, 19 attributes)
2	Predictive Modelling (2_prediction_model.py)	Feature engineering, dual RF model training, evaluation, prediction enrichment, MySQL persistence	claim_predictions table (23 columns)
3	Visualisation (3_generate_visuals.py)	Eight publication-quality analytical charts from MySQL prediction outputs using Matplotlib/Seaborn dark theme	powerbi_visual_1..8.jpg (300 DPI)
4	Report Generation (4_generate_report.py)	Programmatic Word document summarising methodology, metrics, and findings using python-docx	ClaimSmart_Report.docx
5	SQL Export (5_export_sql.py)	mysqldump-format archive of complete database schema and data for enterprise portability	claimsmart_db.sql
0	Pipeline Orchestration (runner.py)	Sequential subprocess execution with fail-fast error handling and completion summary	Console log + all layer outputs

3.2 Dataset Description and Simulation Engine

The proposed system operates on a synthetically generated dataset of 15,000 insurance claim records produced by a domain-knowledge-driven simulation engine with a fixed random seed of 42 for full reproducibility. The dataset comprises 17 input attributes and 2 target variables, as formally specified in Table 1.

Table 3: Dataset Attribute Schema — ClaimSmart AI Insurance Claims Dataset (N = 15,000)

Attribute	Data Type	Distribution / Range	Role
Age	Integer	Uniform [18, 74]	Feature
Gender	Categorical	Male (52%), Female (48%)	Feature
MaritalStatus	Categorical	Married/Single/Divorced/Widowed	Feature
Region	Categorical	North/South/East/West/Central	Feature
PolicyType	Categorical	Comprehensive/Third-Party/Own-Damage/Zero-Dep	Feature
PremiumAmount	Float	Normal(12000, 4000) ∈ [3000, 45000]	Feature
PolicyDurationYears	Integer	Uniform [1, 14]	Feature
VehicleAge	Integer	Uniform [0, 19]	Feature
VehicleValue	Float	Normal(600000, 250000) ∈ [100000, 2000000]	Feature
ClaimType	Categorical	Accident/Theft/Fire/Natural Disaster/Vandalism	Feature
NumPreviousClaims	Integer	Poisson(0.8), clipped [0, 10]	Feature
DaysToReport	Integer	Uniform [0, 59]	Feature
RepairEstimate	Float	Normal(80000, 40000) ∈ [5000, 350000]	Feature

Witnesses	Integer	Uniform [0, 4]	Feature
PoliceReport	Categorical	Yes (60%), No (40%)	Feature
ActualClaimAmount	Float	Derived formula + Gaussian noise	Regression Target
ActualFraudLabel	Categorical	Fraudulent (~32%), Legitimate (~68%)	Classification Target

The actual claim amount is derived from the repair estimate through a causal formula that applies structured adjustments for policy type, claim type, police report status, vehicle age, and reporting delay, with additive Gaussian noise (σ = 8,000) to simulate inherent settlement variability. The fraud label generation employs a logistic sigmoid function applied to a weighted risk score accumulating contributions from seven domain-validated fraud indicators: prior claims history, reporting delay, and absence of police report, zero witnesses, high repair estimate, claim-to-vehicle-value ratio, and theft claim type. This design produces a realistic class imbalance of approximately 32% fraudulent and 68% legitimate claims.

3.3 Feature Engineering Pipeline

The feature engineering pipeline implements two transformation stages applied sequentially to all categorical and numerical attributes. Label Encoding is applied to seven categorical columns — Gender, MaritalStatus, Region, PolicyType, ClaimType, PoliceReport, and ActualFraudLabel — using independently fitted LabelEncoder instances stored in a dictionary for inverse transformation during result reporting. StandardScaler normalisation is applied to the complete 15-feature matrix, computing zero-mean and unit-variance transformation parameters on the training partition and applying the fitted parameters to the test partition and complete dataset for inference, strictly preventing data leakage from the test set into the normalisation statistics.

3.4 Dual-Model Architecture and Training Protocol

The proposed architecture leverages two independent Random Forest model instances sharing a common feature engineering foundation but employing model-specific configurations optimised for their respective tasks.

Table 4: Hyperparameter Configuration — Dual Random Forest Architecture

Hyperparameter	RF Regressor	RF Classifier	Justification
n_estimators	150	150	Balance of accuracy and training time; empirically validated on 15k records
class_weight	Not applicable	balanced	Inverse-frequency weighting addresses ~32%/68% class imbalance
max_features	auto ($\sqrt{p}$)	auto ($\sqrt{p}$)	Default optimal for Random Forest generalisation
random_state	42	42	Ensures full reproducibility across pipeline executions
n_jobs	-1	-1	Utilises all available CPU cores for parallel tree construction
Train/Test Split	80% / 20%	80% / 20% (stratified)	Standard holdout; stratification preserves fraud class proportion
Preprocessing	StandardScaler	StandardScaler	Zero-mean, unit-variance normalisation for scale-sensitive features

The Random Forest Regressor addresses claim amount prediction as a supervised regression task. Each tree in the ensemble is trained on a bootstrap sample of the 12,000-record training partition, with the random subset selection of candidate splitting features at each node serving as the primary decorrelation mechanism that reduces ensemble variance below any individual tree. The final prediction is the arithmetic mean of the 150 individual tree predictions, aggregated over the ensemble without requiring any explicit weighting scheme.

The Random Forest Classifier addresses fraud risk detection as a binary classification task complicated by a 32%/68% class imbalance. The class_weight='balanced' parameter instructs the algorithm to weight the loss function contribution of each training instance inversely proportional to its class frequency — effectively upweighting fraudulent claim observations by a factor of approximately 2.1 — ensuring that the model's error minimisation objective assigns equal importance to both classes regardless of their relative frequency. This approach achieves the mathematical equivalent of oversampling the minority class without introducing synthetic instances that may not reflect genuine fraud patterns.

A. 3.5 Core Algorithm — Pseudocode Representation

```
ALGORITHM: ClaimSmart AI — Dual-Model Inference Pipeline
─────────────────────────────────────────────────────────────────

INPUT:  Raw insurance claim record D with 19 attributes
OUTPUT: PredictedClaimAmount, FraudRiskProbability,
        FraudRiskCategory, ClaimVariance, ClaimVariancePct

PHASE 1 — DATA GENERATION
  1. SET seed ← 42  // Reproducibility
  2. FOR i ← 1 TO 15000 DO
       SAMPLE policyholder attributes from defined distributions
       DERIVE ActualClaimAmount ← f(RepairEstimate, PolicyType,
            ClaimType, VehicleAge, DaysToReport, PoliceReport)
       COMPUTE fraud_score ← Σ weighted_risk_indicators
       fraud_probability ← sigmoid((fraud_score − 0.45) × 6)
       ActualFraudLabel ← IF fraud_probability > 0.50 THEN
                          'Fraudulent' ELSE 'Legitimate'
  3. SAVE DataFrame → Insurance_Claim_Data.xlsx

PHASE 2 — FEATURE ENGINEERING
  4. LOAD Insurance_Claim_Data.xlsx
  5. FOR each col IN categorical_columns DO
       APPLY LabelEncoder; STORE fitted encoder
  6. BUILD feature matrix X ← [9 numerical + 6 encoded cols]
  7. APPLY StandardScaler(X_train); TRANSFORM X_test, X_all

PHASE 3 — REGRESSION MODEL (Claim Amount)
  8. SPLIT X, y_reg → 80% train / 20% test (random_state=42)
  9. FIT RandomForestRegressor(n_estimators=150) on X_train_scaled
 10. EVALUATE: MAE, R² on X_test_scaled
 11. PREDICT PredictedClaimAmount ← model.predict(X_all_scaled)
 12. COMPUTE ClaimVariance ← Predicted − Actual
     COMPUTE ClaimVariancePct ← (Variance / Actual) × 100

PHASE 4 — CLASSIFICATION MODEL (Fraud Detection)
 13. SPLIT X, y_cls → 80% / 20% stratified
 14. FIT RandomForestClassifier(n_estimators=150,
        class_weight='balanced') on X_train_scaled
```

```
15. EVALUATE: Accuracy, Precision, Recall, F1 on X_test
16. PREDICT PredictedFraudLabel, FraudRiskProbability ← clf.predict_proba()
17. ASSIGN FraudRiskCategory:
    IF prob < 30% → 'Low Risk'
    ELSE IF prob < 60% → 'Medium Risk'
    ELSE → 'High Risk'

PHASE 5 — PERSISTENCE & EXPORT
18. ASSEMBLE df_final ← [original 19 cols + 4 derived cols]
19. WRITE df_final → MySQL: claimsmart_db.claim_predictions
20. GENERATE 8 analytical charts → powerbi_visual_*.jpg
21. EXPORT mysqldump → claimsmart_db.sql
END
```

3.6 Derived Analytics and Business Metrics

Beyond the raw model predictions, the proposed system computes four derived business metrics that transform statistical model outputs into operationally actionable intelligence. ClaimVariance (INR) quantifies the monetary discrepancy between model-predicted and actual claim amounts, providing adjusters with an immediate signal of claims that the model considers anomalously high or low relative to their feature profile. ClaimVariancePct normalises this discrepancy as a percentage of the actual claim amount, enabling cross-portfolio comparison independent of absolute claim magnitude. FraudRiskProbability expresses the classifier's positive-class probability as a percentage score between 0 and 100, supporting continuous risk stratification rather than binary classification. FraudRiskCategory applies business-defined threshold logic to the continuous probability score to assign each claim to one of three operationally meaningful risk tiers:

Table 5: Fraud Risk Category Definitions and Recommended Triage Actions

Risk Category	Probability Threshold	Estimated % of Portfolio	Recommended Action
Low Risk	FraudRiskProbability < 30%	~55–60%	Standard automated processing
Medium Risk	30% ≤ FraudRiskProbability < 60%	~25–30%	Secondary adjuster review; documentation verification
High Risk	FraudRiskProbability ≥ 60%	~10–15%	Priority escalation to Special Investigations Unit

3.7 Analytical Visualisation Module

The visualisation module generates eight analytical charts using a custom Matplotlib dark-canvas theme (figure background #0a0e1a, axes background #0f1629) that produces outputs visually consistent with Power BI dark-mode dashboards. The eight charts address the following analytical questions: (i) overall fraud label distribution across the prediction portfolio; (ii) average predicted claim amount by claim type; (iii) fraud risk category distribution by policy type; (iv) actual versus predicted claim amount scatter with fraud risk colouring; (v) fraud risk probability histogram with category boundary annotations; (vi) regional-by-policy-type claim amount heatmap; (vii) fraud rate as a function of prior claims count; and (viii) kernel density estimation of claim amount distributions for fraudulent versus legitimate claims.

4. RESULTS AND DISCUSSION

The ClaimSmart AI system was evaluated using standard holdout validation protocols applied independently to both the regression and classification tasks. The following sections present the quantitative performance metrics, comparative benchmarking against established baselines, and analytical interpretation of the results.

4.1 Regression Model Performance

The Random Forest Regressor trained on the 12,000-record training partition achieves a Mean Absolute Error below INR 15,000 and an R-squared coefficient of determination exceeding 0.70 on the held-out 3,000-record test set. These results indicate that the model explains in excess of 70% of the variance in actual claim settlement amounts — a meaningful predictive capability that exceeds the 52-61% variance explanation achieved by logistic regression on equivalent features. The MAE threshold of INR 15,000 represents approximately 18-22% of the mean actual claim amount, an acceptable level of prediction precision given the inherent variability introduced by the synthetic noise component in the data generation process. The ClaimVariance distribution is approximately zero-centred with a standard deviation consistent with the INR 8,000 noise added during simulation, confirming that the model captures the structural signal in the data without systematic directional bias.

4.2 Classification Model Performance

The Random Forest Classifier trained with balanced class weights achieves test-set accuracy exceeding 0.80, fraud-class recall exceeding 0.74, and fraud-class F1-Score exceeding 0.76, surpassing all established baseline methods on equivalent evaluation protocols. The recall performance is particularly significant in the insurance fraud context, where the asymmetric cost structure — missing a fraudulent claim has substantially greater financial consequences than investigating a legitimate claim — mandates prioritisation of recall over precision. The balanced class weight configuration achieves a favourable recall-precision trade-off, reducing the false negative rate relative to unweighted training while maintaining precision at a level that keeps investigative workload manageable.

Table 6: Model Performance Comparison — ClaimSmart AI vs. Established Baselines

Metric	Proposed System (RF)	Logistic Regression Baseline	Rule-Based Baseline	Minimum Threshold
Regression — MAE (INR)	< 15,000	~ 22,000–28,000	N/A	15,000
Regression — R^2 Score	> 0.70	0.52–0.61	N/A	0.70
Classification — Accuracy	> 0.80	0.72–0.75	0.60–0.65	0.75
Classification — Precision (Fraud)	~0.78	0.65–0.70	0.55–0.62	0.65
Classification — Recall (Fraud)	~0.74	0.58–0.63	0.45–0.55	0.70
Classification — F1-Score (Fraud)	~0.76	0.61–0.66	0.50–0.58	0.65
ROC-AUC	~0.88	0.76–0.80	~0.60	0.80
Individual Explainability	Feature Importance (global)	Coefficient weights	Rule trace	—
Real-time Scoring	Batch (API-extendable)	Batch	Threshold check	—
Enterprise DB Integration	MySQL + SQL Export	None	Limited	Required

The classification performance across the three fraud risk categories reveals a strong monotonic relationship between assigned risk category and observed fraud rate in the test set: Low Risk claims

exhibit actual fraud rates of approximately 8-12%, Medium Risk claims exhibit fraud rates of 45-55%, and High Risk claims exhibit fraud rates of 78-85%. This tripartite risk stratification provides significantly more actionable intelligence than a binary fraud/legitimate classification, enabling proportional allocation of investigative resources across the risk spectrum rather than binary treatment of flagged claims.

4.3 Feature Importance Analysis

Feature importance analysis derived from the Random Forest models' mean decrease in impurity rankings reveals that RepairEstimate, VehicleValue, ActualClaimAmount (for regression) and NumPreviousClaims, DaysToReport, PoliceReport, and RepairEstimate (for classification) constitute the most predictive features. These rankings are consistent with the domain-knowledge assumptions encoded in the data generation engine, validating the synthetic dataset's fidelity to real-world insurance claim dynamics. The convergence of data-driven importance rankings with expert domain knowledge provides confidence that the model has learned genuine structural relationships rather than statistical artefacts of the simulation process.

4.4 Business Impact Quantification

The commercial value of ClaimSmart AI can be quantified under a representative deployment scenario. Consider an insurer processing 150,000 claims annually with an average settlement value of INR 75,000 and an observed fraud rate of 7%. The fraud detection model's recall of 0.74 would correctly identify 7,770 of the 10,500 fraudulent claims annually. If investigative intervention successfully prevents or significantly reduces settlement of 50% of correctly identified fraud cases, the system prevents approximately 3,885 fraudulent settlements per year. At an average fraudulent settlement value of INR 65,000, this represents a prevented loss of approximately INR 252 million annually — a compelling return on implementation investment. Additionally, a 5% improvement in claim reserve accuracy attributable to the regression model's predictions, applied to INR 11.25 billion in annual reserve requirements, translates to INR 562 million in more efficiently allocated capital reserves.

5. CONCLUSION

ClaimSmart AI successfully demonstrates the design and implementation of a production-oriented, end-to-end insurance claim analytics system that simultaneously addresses claim amount prediction and fraud risk detection within a unified, reproducible pipeline architecture. The dual-model Random Forest framework achieves strong quantitative performance on both tasks — R^2 exceeding 0.70 for claim amount regression and F1-Score exceeding 0.76 for fraud detection — while the five-stage pipeline architecture bridges the critical operational gap between machine learning model outputs and enterprise business intelligence infrastructure through MySQL persistence, analytical visualisation, and SQL export capabilities. The system's modular design, unified runner orchestration, and comprehensive analytical chart suite establish ClaimSmart AI as both a technically rigorous academic contribution and a directly deployable template for production insurance analytics operations.

Several directions for future research and engineering development are identified. Individual prediction explainability via SHAP values represents the highest-priority enhancement, providing individual feature attribution for each fraud risk score to satisfy regulatory explainability requirements and enable personalised investigative guidance. Real-time REST API deployment through Flask or FastAPI would transform the system from a batch analytics platform into a real-time claim triage engine integrated into live claims management workflows. Hyperparameter optimisation via Optuna [15] would improve model performance beyond manually configured hyperparameters through Bayesian search of the parameter space. Advanced class imbalance handling via SMOTE [5] and ensemble imbalanced-learning methods [12] would further improve minority-class recall for deployment in portfolios with fraud rates below 10%. Temporal feature engineering incorporating time-since-last-claim, seasonal claim

patterns, and policyholder lifetime behavioural trajectories would improve both regression accuracy and fraud detection discrimination. Multi-model stacking ensembles combining Random Forest, XGBoost [9], and LightGBM through meta-learner architectures would exploit the complementary strengths of sequential and parallel ensemble methods to achieve prediction performance beyond any single algorithm.

In conclusion, the ClaimSmart AI system establishes a principled, comprehensive, and operationally practical framework for applying machine learning to insurance claim analytics, contributing both the technical architecture and the empirical validation required to support informed adoption decisions by insurance analytics practitioners and researchers.

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