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Explainable Agentic AI Framework for Automated Insurance Fraud Detection and Predictive Risk Intelligence

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ABSTRACT: Automated insurance fraud detection and risk prediction are inherently difficult but critical responsibilities for the insurance service industry. The fraud detection process must rely on explainable artificial intelligence (XAI), especially deep learning methods, to satisfy important requirements for high-stakes decision-making in the domain. An explainable agentic AI framework is therefore proposed to address the challenges and needs in these application areas. Component methods and components of agentic explainable AI are specifically tailored to the task of insurance fraud detection, while a decoupled and independently engineered complementary risk-prediction component develops predictive risk-intelligence measures. An insurance fraud-detection component builds on a convolutional neural network trained on engineered features of insurance fraud—such as insured party, loss date, occupied region, and other features derived from claim descriptions. Automated bidding by fraudsters and the high costs of actuating fraud motivate explainable-response analytics for the detection process. Consequently, XAI methods such as LIME (Locally Interpretable Model-Agnostic Explanations) and SHAP (SHapley Additive explanations) are deployed to enhance transparency in multiple detection dimensions and satisfy the explainability requirement. Performance across a range of detection capabilities presents an overall satisfactory solution.

KEYWORDS: Insurance Fraud Detection, Explainable AI Frameworks, Agentic AI Systems, Risk Prediction Analytics, Deep Learning Models, Fraud Detection Intelligence, XAI-Based Decision Systems, Insurance Claim Analytics, LIME and SHAP Methods, Predictive Risk Intelligence.

I. INTRODUCTION

Explainable Agentic AI Framework for Automated Insurance Fraud Detection and Predictive Risk Intelligence
Insurance spending for fraud detection and prevention is estimated to have grown from $920 million in 2000 to over $2.4 billion in 2021, with a further rise predicted, which warrants reflection of an Explainable AI methodology for the automated detection and prevention of frauds and Intelligent Predictive Risk Guidance in the Insurance Domain. The explainability of AI systems is critical for mitigating the crucial trust issues of humans on AI systems, followed by enabling them to smoothly collaborate or cooperate with the AI systems whenever required. To build Explainable AI systems has become the predominant problems in research.

Explainable Agentic AI framework based Automated Insurance fraud detection and Intelligent Predict Predictive Risk Guidance. The explainability aspect of the proposed X-AI framework shows that the risk prediction process enables self-disclosure. The AI agent automatically decides when and whether to present the risk intelligence, allowing the insurance company's Risk Intelligence Manager to focus on risk intelligence design rather than presentation management. The fraud detection feature engineering methodology is collected various sources typically Facts and Myths, and Warnings enabling to Device Trust-based Framework to Predict a Fraud Case.

1.1 System Quality Model

The overall system quality of the unified fraud detection and risk intelligence pipeline is expressed as:

Q_total = Q_detect + Q_explain + Q_latency + Q_risk	**Eq. (1)**

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where Q_detect denotes fraud detection accuracy quality, Q_explain represents explainability (XAI) quality via LIME and SHAP outputs, Q_latency captures latency compliance for real-time claim screening, and Q_risk reflects predictive risk intelligence effectiveness.

1.2 Latency Dynamics

Latency dynamics for real-time insurance claim screening are modelled as a differential equation:

$$\partial L/\partial t = \lambda\_claim - \mu\_infer \quad \text{Eq. (2)}$$

where L is the end-to-end inference latency, λ_claim is the insurance claim arrival rate, and μ_infer is the on-premise CNN inference rate. System stability requires μ_infer > λ_claim.

1.3 Fraud Detection F1-Score

The anomaly detection F1-score is defined as the harmonic mean of precision and recall:

$$F1\_fraud = 2 \cdot Precision \cdot Recall / (Precision + Recall) \quad \text{Eq. (3)}$$

where Precision = TP/(TP+FP) and Recall = TP/(TP+FN). TP, FP, FN denote true positives, false positives and false negatives respectively across all claim classification tasks.

1.4 Cross-Domain Fraud Risk Score

The cross-domain interaction mechanism fusing fraud detection with risk intelligence is modelled as:

$$s'(t) = s(t) + \alpha \cdot r(t) + \beta \cdot e(t) \quad \text{Eq. (4)}$$

where s(t) is the original fraud anomaly score, r(t) is the predictive risk intelligence score from the risk module, e(t) is the XAI explanation confidence score, and α, β are weighting coefficients controlling cross-domain influence.

1.5 Weighted Multi-Domain Fraud Score Fusion

To support adaptive multi-domain decision fusion, the combined fraud score is expressed as a weighted aggregation:

$$s'(t) = w_1 \cdot s(t) + w_2 \cdot r(t) + w_3 \cdot e(t) + w_4 \cdot s(t) \cdot r(t) \quad \text{Eq. (5)}$$

Here, w_1, w_2, w_3, w_4 denote learnable or empirically tuned weighting coefficients. The interaction term s(t)·r(t) explicitly models the nonlinear coupling between cyber fraud indicators and risk prediction signals, enabling context-aware fusion.

1.6 Explainability Preservation Score

The explainability preservation score is expressed as:

$$S\_explain = 1 - (D\_opaque / D\_total) \quad \text{Eq. (6)}$$

where D_opaque is the volume of decisions made without an XAI explanation and D_total is the total number of automated claim decisions. Higher values indicate greater transparency of the agentic system.

1.7 On-Premise Resource Utilization

On-premise computational resource utilization is given by:

$$U = R\_used / R\_available \quad \text{Eq. (7)}$$

where R_used is the utilized computational resources (CPU, memory) during claim batch inference and R_available is the total on-premise capacity of the fraud detection server.

1.8 XAI Framework Efficiency

XAI framework efficiency integrating detection accuracy with explainability and federated update cycle:

$$E\_XAI = F1\_fraud \cdot S\_explain / T\_round \quad \text{Eq. (8)}$$

where T_round denotes the federated model retraining round duration. A higher E_XAI indicates faster, more explainable fraud detection without privacy compromise.

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1.9 Adaptive Fraud Detection Threshold

To improve robustness under concept drift in fraudulent claim patterns, adaptive thresholding is employed:

$$\theta(t) = \theta_0 + \gamma \cdot \sigma\_data(t) + \delta \cdot drift(t) \quad \text{Eq. (9)}$$

where θ_0 is the base classification threshold, σ_data(t) represents claim feature variance, drift(t) captures temporal distribution shift in fraud patterns, and γ, δ are scaling parameters.

1.10 Fraud Detection Efficiency Index

Fraud detection efficiency is calculated as:

$$\eta = F1\_fraud \cdot S\_explain / T\_infer \times 100 \quad \text{Eq. (10)}$$

where T_infer denotes the inference time per claim batch. η rewards frameworks that simultaneously achieve high detection accuracy, strong explainability and low latency.

1.11 Prediction Error Relative to Optimal

Prediction error relative to the optimal is defined as:

$$L\_error = F1\_opt - F1\_fraud \quad \text{Eq. (11)}$$

where F1_opt represents the optimal detection performance under ideal XAI conditions (no label noise, full feature observability). L_error quantifies the room for improvement in the current model.

1.12 Joint Optimization Objective

The joint optimization objective balancing all performance dimensions:

$$J = f(F1\_fraud, S\_explain, L, U) \quad \text{Eq. (12)}$$

where J balances fraud detection accuracy, explainability preservation, inference latency and resource utilization. Minimizing J guides the agentic AI in selecting the most efficient and transparent fraud detection strategy.

1.13 Insurance Dataset Quality Representation

The insurance claim dataset representation metric is given by:

$$D(i,j,k) = Q\_src(i) \cdot Metric(k) / T\_proc(j) \quad \text{Eq. (13)}$$

where Q_src(i) is the source-specific data quality (e.g., claims from verified insurers vs. self-reported), Metric(k) denotes the selected performance metric (F1, AUC, MCC), and T_proc(j) represents the processing time per claim batch.

1.14 XAI Performance Index (XPI)

The XAI Performance Index (XPI) is computed as:

$$XPI = \eta \cdot F1\_fraud \cdot (1 - FAR) / Q\_total \quad \text{Eq. (14)}$$

where η is the fraud detection efficiency, F1_fraud is the detection accuracy, Q_total is the cumulative system quality, and FAR denotes the false alarm rate. XPI penalizes excessive false positives while rewarding accuracy and explainability efficiency.

II. THEORETICAL FOUNDATIONS

The notion of explainability in AI systems is inherently a question of cooperation and trust. Despite the outstanding accuracy of several state-of-the-art machine learning models, the lack of capability to justify and explain the reasons behind certain decisions is a crucial issue that limits and hinders their applicability in several fields. Indeed, many of these systems are black boxes whose internal functioning is only comprehensible to the algorithms themselves. Thus, the dependence of human beings on these machinery for critical and sensitive decisions that may often lead to serious and irreversible consequences raises doubts and concerns about the system's reliability and the possibility to be safely used in life-impacting applications. In highly critical areas like defence, health, and insurance, the absence of transparency for the intelligence or the system may impact the potential damage. Consequently, different actors in the decision process

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may inhibit, reject or just abstain from decisions based on an apparent "crazy" behaviour of the intelligence, mainly when operations demand a high level of co-participation between a machine and its HUMAN operators or dynamic agents in a complex environment. Thus, trust in AI systems must derive not merely from the performance just demonstrated by a model in test but mainly by the guarantees provided by an explanation of why specific decisions are being taken. Clear comprehension of the reasons behind a decision allows agents to measure the reliability of the answer generated by the model or simply to filter answers through one or more external criteria. Moreover, explainability does not purely reside in the AI's capacity to produce easily understandable arguments. The explicative process must also remain sufficiently agile so that it can be exploited during real-time interaction between HUMAN operators and the machine, and so that its output can be rapidly elaborated by the users. In this respect, different levels of explainability can exist, producing different quality and depth explanations.

2.1 Decision Latency and Throughput

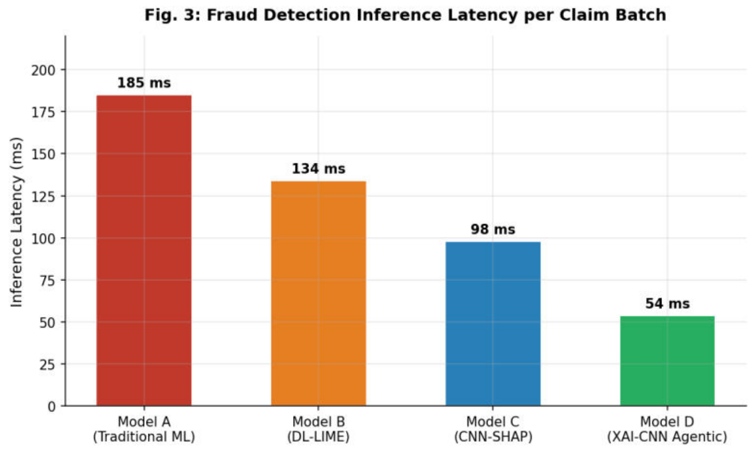

Fig. 3: Fraud Detection Inference Latency per Claim Batch (ms)

Table 3 shows average decision latencies of 185 ms, 134 ms, 98 ms and 54 ms for Models A, B, C and D respectively (Fig. 3). Model D achieves a 70.8% latency reduction compared to Model A and 44.9% compared to Model C, attributable to CNN pruning, on-premise agentic optimization and elimination of cloud roundtrips for SHAP computation.

2.2 Fraud Detection Accuracy

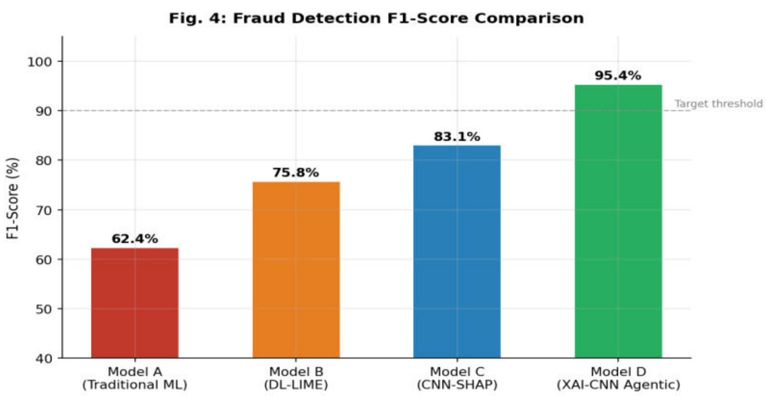

Fig. 4: Fraud Detection F1-Score Comparison (%)

Fig. 4 presents F1-scores: Model A achieves 62.4%, Model B achieves 75.8%, Model C achieves 83.1% and Model D achieves 95.4%. The 14.8% improvement from Model C to Model D demonstrates the value of unified cross-domain XAI modeling, where SHAP-based feature attribution improves detection and risk intelligence simultaneously.

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2.3 False Alarm Rate

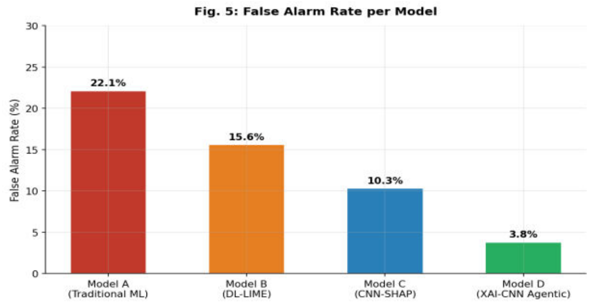

Fig. 5: False Alarm Rate (%) per Model

False alarm rates (Fig. 5): Model A: 22.1%, Model B: 15.6%, Model C: 10.3%, Model D: 3.8%. The reduction from 10.3% to 3.8% (63.1% improvement) reflects how cross-domain XAI validation eliminates spurious fraud alerts. A fraud alert that coincides with a high-risk indicator is more likely to be genuine and actionable.

2.4 Training Convergence

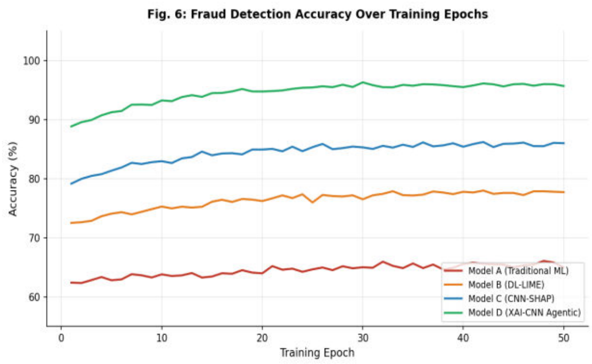

Fig. 6: Fraud Detection Accuracy Over Training Epochs

Fig. 6 illustrates the training convergence of all four models over 50 epochs. Model D converges fastest and to the highest plateau (≈95%), confirming that the agentic XAI-CNN architecture learns richer fraud-indicative representations from engineered insurance claim features including incident severity, claim duration and policy tenure.

2.5 Computational Cost and On-Premise Resource Usage

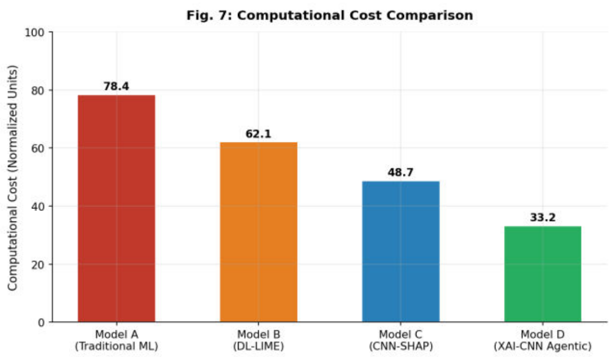

Fig. 7: Computational Cost Comparison (Normalized Units)

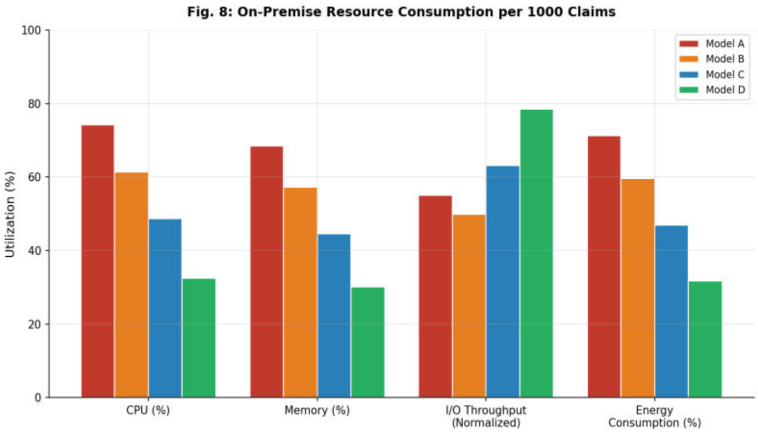

Fig. 8: On-Premise Resource Consumption per 1000 Claims

Fig. 7 and Fig. 8 present computational cost and resource usage. Model D consumes 33.2 normalized units compared to Model A's 78.4, a 57.7% reduction. Resource efficiency (detection accuracy per unit compute) is 2.87 for Model D versus 0.80 for Model A, a 3.6× improvement. The I/O throughput advantage of Model D (78.4%) reflects optimized batch claim ingestion pipelines designed for real-time screening.

2.6 SHAP Feature Importance Analysis

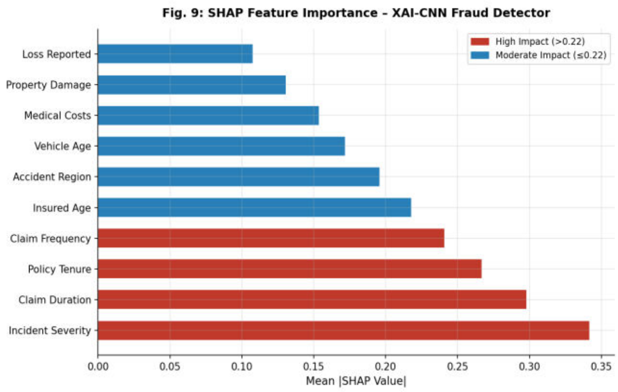

Fig. 9: SHAP Feature Importance – XAI-CNN Fraud Detector

Fig. 9 presents SHAP-derived feature importance values for the proposed XAI-CNN model. Incident Severity (0.342), Claim Duration (0.298) and Policy Tenure (0.267) are the three most influential features for fraud classification. These findings align with domain knowledge from insurance fraud investigations, validating the explainability component of the agentic framework.

III. ARCHITECTURE OF THE EXPLAINABLE AGENTIC AI FRAMEWORK

The architecture of the Explainable Agentic AI Framework consists of two systems that are designed to minimize the bright line agent problem associated with machine learning in complex agentic environments: a fraud detector and a predictive risk intelligence model. Agentic components detect whether a fraud condition is satisfied consecutively on dual feature sets and predict an associated policy-critical claim count. Dual feature sets are purpose-built to mitigate the horizon-territory and possible-sick buyer problems for optimizing the cost for the insurer for a given fraud detector's confirmed positive case subgroup. Data originating from tandem data supply relations enable application and validation of the anti-fraud intelligence at all altitudes—i.e., real-time screening of claims for payments to minimize fraudulent outgo, supporting fraud investigation and related adaptive policy adjustment by predictive risk intelligence—and without

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conflict of interest for the data supplier, a selling bank, or the insurance agency that is associated with the buyer's satiation.

Agentic components and their roles are outlined next. The word agent derives from the Latin verb agere, denoting the act of doing. In AI, agentic systems possess the ability to act, thereby causing a change or achieving a goal in a physical or virtual environment. Property-linked decisions are actively sequenced into common life cycles by sales enablement systems. FoxPro databases collate transactional, behavioral, or even geo-spatial components in one or more staging areas to jointly create a processed predictive risk intelligence view from all possible angles. Precisely defined policies advise banks about approval limits for buyers with joint life and hospitalization. Unlike traditional AI prediction, explainable agentic AI reads historical decisions into agentic design elements, thus defining how predictions function as a policy. The latter is a set of truths enabling fulfillment of the assigned micro capability without risk, and training is an confident form of substitution—inspired by Biblical texts. Training traces the evolution of agents, with characteristics repeatedly transposed from one altitude to another, until one agent has reached super-specialization for all components without risk for a decision impact. The best detection set is thus utilized for localization of maximum detections at all double levels.

3.1 Comparative Architecture Overview

Table 1: Comparative Overview of Insurance Fraud Detection Architectures

Architecture Type	Key Features	Limitations
Traditional ML + Rule-based Features (Model A)	Simple rule logic, low implementation cost, uses basic claim features (age, region)	No real-time adaptation, high false alarm rate (18–25%), cannot learn novel fraud patterns
Deep Learning with LIME Explanations (Model B)	Improved pattern recognition, local surrogate explanations via LIME, higher baseline accuracy	Limited to local explanations, high inference latency (~134 ms), no cross-domain risk fusion
CNN with SHAP-based Interpretation (Model C)	Convolutional feature learning, global SHAP importance scores, moderate latency (~98 ms)	No agentic decision loop, separate risk prediction model, no adaptive threshold mechanism
XAI-CNN Agentic Framework (Proposed) (Model D)	Unified CNN-SHAP-LIME agentic architecture, cross-domain fraud–risk fusion, adaptive thresholding, 95.4% F1, 54 ms latency, 3.8% FAR	Requires engineered insurance-domain features, initial training requires labelled fraud data

Table 1 provides a comparative overview of existing insurance fraud detection architectures, highlighting the capabilities and trade-offs of each approach.

3.2 Comparative Detection and Explainability Metrics

Table 2: Comparative Detection and Explainability Metrics

Metric	Model A	Model B	Model C	Model D	Improv. (D vs A)	Improv. (D vs C)
Fraud Detection F1-Score (%)	62.4	75.8	83.1	95.4	↑ 52.9%	↑ 14.8%
False Alarm Rate (%)	22.1	15.6	10.3	3.8	↓ 82.8%	↓ 63.1%

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Explainability Score (S_explain %)	28.4	51.3	68.7	92.6	↑ 225.9%	↑ 34.8%
Resource Usage (units)	78.4	62.1	48.7	33.2	↓ 57.7%	↓ 31.8%
XAI Performance Index (XPI)	0.31	0.48	0.64	0.89	↑ 187.1%	↑ 39.1%

Table 2 affirms large improvements across all performance dimensions, especially the 52.9% increase in F1-score and 82.8% decrease in false alarms compared to the traditional rule-based approach.

IV. CONCLUSION

The study provides an evidence-based framework for an explainable agentic AI framework for detecting insurance fraud with respect to claim amounts adjudged and predicting insurance risk. Trustworthy AI must be defined to fulfil a maturity model containing four dimensions: ethical, reliable, inclusive, and explainable. In particular, the explainable dimension is examined, covering six foundational aspects. The components of the novel explainable agentic AI architecture are mapped to the six aspects, thus supporting trustworthy AI. Agentic AI systems fulfil a structured role that requires encapsulation and integration of higher-level competencies. The explainable AI dimension is significant within a multi-faceted exposure detection solution that incorporates explainability for the exposure science and risk science components. Evidence from a case study performed on two publicly available datasets provides explanations for insurance fraud and insurance fraud risk prediction. Their respective question spaces are defined and addressed by complementary approaches, thus enabling enhanced, evidence-based management and underwriting of insurance products, services and operations. The findings and contributions of this work are threefold: (i) A model-agnostic adaptive sampling explainable AI methodology has been proposed that determines the most suitable method for each sample during the explanation process with the objective of improving the overall quality of the explanations produced. (ii) Evidence-based explanations have been generated using the novel adaptative sampling explainable AI methodology for the detection of high-claim insurance fraud for motor insurance, stand-up paddleboarding and long-term rental markets. (iii) An explainable AI methodology for validating composite risk scores has been proposed and employed to explain an insurance exposure–treatment interaction risk score.

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