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Fraud Detection and Risk Modeling in Insurance: Early Adoption of Machine Learning in Claims Processing

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***Abstract*—**An insurance company experiences billions of dol- lars of fraud loss each year. While much of it is detected, there is also a significant amount of undetected fraud, and a considerable operational effort is expended on these fraud investigations. In response, the claims processing operation is transitioning from a rule-based classification system to a machine-learning-driven classification system. The goal of this project is to develop data-driven predictive models that identify fraudulent insurance claims, allowing the company to manage fraud risk more effec- tively and operate more efficiently. Three broad categories of fraud typology are addressed: synthetic fraud, claim-padding fraud, and collusion fraud. In the current environment, this shift enables a more data-driven and factual approach to fraud detection and minimization. In the future, fraud detection may leverage other AI techniques such as transfer learning, causal AI, and advanced modeling techniques on streaming data. The models could evolve into a more sophisticated risk management tool, enhancing the company's ability to identify fraud attempts in their infancy or assisting in managing fraud risk more holis- tically in cooperation with external vendors. Beyond fraud risk management, they could eventually also support management of other risks within the company, such as operational risk more broadly, risk in underwriting, and risk in business partnerships.

***Index Terms*—**Insurance Fraud Detection, Machine Learning, Predictive Modeling, Fraud Typology, Synthetic Fraud, Claim- Padding Fraud, Collusion Fraud, Data-Driven Systems, Risk Management, Operational Efficiency, Transfer Learning, Causal AI, Streaming Data, Advanced Modeling, Fraud Prevention, Risk Analytics, AI-Driven Classification, Fraud Minimization, Underwriting Risk, Operational Risk.

I. INTRODUCTION AND PROBLEM LANDSCAPE

Fraud detection and prevention is a significant business issue for most insurance companies. It may be direct financial loss; that is the case with fraud accounted in the total claims fraud. It happens when a legitimate claim is falsely inflated such as inflating bills or claiming rental costs. It may indirectly happen such as syntactic fraud or collusive fraud; that is usually not captured by internal claims unconsciously by devious collaboration with an external partner or by modified evidence. Cases of fraud also slow the whole effectiveness of the claims operations process and, therefore, increases the operational cost of fraud associated with claims. Hence, leakages due to fraud, knowledge and skill inherit in the process, and overall cost contribute to a decrease in profitability that could be used more effectively somewhere else (e.g. investment for product improvement). Machine learning (ML) algorithms used within the claims process today are generally in areas such as damage assessment and claim settlement speed. Rules-based phenomenon have a history in the claims industry and ML is now entering these systems and replacing the rules used so far. The first experience demonstrated that the need for data quality early in the development cycle early is key for efficiency and effectiveness, in order to allow ML implementation at both data and modeling sides. The first deployments focused on detection, triage, and recovery within the claims process; hence attempting to minimize the identified fraud, loss after fraud detection, and recovery time respectively.

A. ***Context and Definitions***

Fraud Detection and Risk Modeling in Insurance: Early Adoption of Machine Learning in Claims Processing Fraud in insurance is an exceedingly broad concept. It can be defined in different ways and engage different players. For purposes of framing this analysis, fraud is defined as "an act with the intent to deceive," and the focus is restricted to fraud in claims handling by customers, providers, and intermediaries. Paying claims that involve fraud is considered leakage and part of the total cost of fraud, together with the associated costs of investigating and preventing such claims that are borne by the insurer. Claims processing is defined as the entire life cycle of a claim, from the report of the event to the settlement (or rejection) of the claim. Processing claims is expensive. Claims costs typically represent 70–80 percent of the total costs of an insurer, according to various sources, with fraudulent, erroneous, or inflated claims often being paid. The approach to fraud in claims processing remains largely rule-based, but the integration of machine learning (ML) technology still seems to be several years away. It is time for the transition from rule- based engines to data-driven models to begin. Typically, these initiatives are based on labeled data for supervised training, but this is often hard to obtain in fraud detection. The analysis explores various techniques, including semi-supervised and unsupervised methodologies, for the development of fraud detection models based on claims life-cycle data.

*B. **Fraud typologies in insurance claims***

Fraud in insurance claims can be classified into three main typologies: synthetic fraud, claim padding, and collusion. Synthetic fraud refers to the creation of fictitious identities and subsequent filing of claims, typically very costly in nature. For example, a burglar buys expensive watches through online por- tals, has them stolen, and files for their replacement. Internal research indicates that such claims cause around 3% of total loss. Claim padding refers to over-exaggeration of losses that have occurred, usually in collaboration with repair vendors. For example, a storm causes damage to an insured house, and a repair vendor is engaged. The insured means that the vendor repairs the house, but in reality, only a portion of the damage was required. The insured, in coordination with the vendor, inflates the bill amount and submits it for payment. Analysis of internal data and industry data suggests that padding may also account for approximately 3% of the total loss. Claim collusion refers to the collusion of policy holders to file claims that may not have occurred. For example, the storms create temporary waterlogging in a region. Some policy holders in the area may claim loss of electronic items, which are very difficult to substantiate. Internal studies indicate that such patterns may account for another 3% of the total loss.

Fig. 1. Fraud Detection and Risk Modeling in Insurance: Machine Learning in Claims Processing

*C. **Business impact and risk exposure***

Insurance fraud costs $40 billion annually in the USA alone, with an estimated 10% of industry losses attributed to fraud. The associated inspection and investigation activities can consume up to 30% of claim costs. In response to these pressures, insurance companies are increasingly adopting machine-learning techniques to automate the detection, triage, and recovery of fraudulent claims. Machine-learning models are being integrated into claims-management systems, either as stand-alone fraud detection solutions or as components of fraud-detection ecosystems that include specialized black box tools, well-defined fraud investigation processes, and litigation units. The primary goal of these implementations is to improve risk management and decision making across the entire life cycle of a claim.The end-to-end solution integrates data from sources such as the claims management platform, various business units, industry databases, and external datasets. The input data is exploited in multiple fraud-detection and risk-automation models, enabling the scoring of claims throughout the processing life cycle. Modeling objectives include detection (both during the claim- filing stage and after claim closure), case triage (prioritizing the most suspicious claims for further investigation), and claim recovery. The solution is designed to help insurance companies reduce claim leakage, lower fraud-management costs, and improve the user experience.

feature	beta hat
intercept	-1.0629
log1p(claim amount/1000)	0.1907
prior claims	0.4374
provider score	0.3505
log1p(time since policy m)	-0.5076
region risk	0.2274
synthetic id flag	0.4254

Equation 1 — Claim Risk Scoring Model (logistic)

Objective in paper: compute a per-claim fraud risk score from features.

Let $x \in R^d$ be the claim feature vector and $y \in \{0, 1\}$ denote fraud (1) vs not fraud (0).

1. **Linear predictor:** $z = \beta_0 + \sum_d \beta_i x_i = \boldsymbol{\beta}^T \boldsymbol{x}$ with a repair vendor is engaged. The insured means that

the vendor repairs the house, but in reality, only a portion of the damage $\tilde{x} = [1, \boldsymbol{x}^{\top}]^{\top}.i=1$

Link (logit): $\text{logit}(p) = \log \frac{p}{} = z$

2. **Probability:** $p = \Pr(y = 1 \mid x) = \sigma(z) = \frac{1}{1-z}$

4. **Training:** maximize log-likelihood $\sum_i [y_j \log p_j + (1 - y_j) \log(1 - p_j)]$ (optionally with L2 penalty $\lambda \| \beta \|_2^2$).

3. **Closed form for score used operationally:**

$$RiskScore(x) = \sigma(\beta_0 + \sum_i \beta_i x_i) \quad (1)$$

I fit β by gradient descent on a synthetic claims set (see tables/plots below).

Coefficients ($\hat{\beta}$)

II. Machine Learning in Claims Processing

The evolution of fraud detection in insurance claims pro- cessing often follows a progression similar to the wider adop- tion of machine learning in other scenarios. Initially, a set of human-defined rules is created and implemented as a decision tree that assigns claims to a subset of fraud-fighting staff based on a narrow view of the overall fraud problem. Over time, the

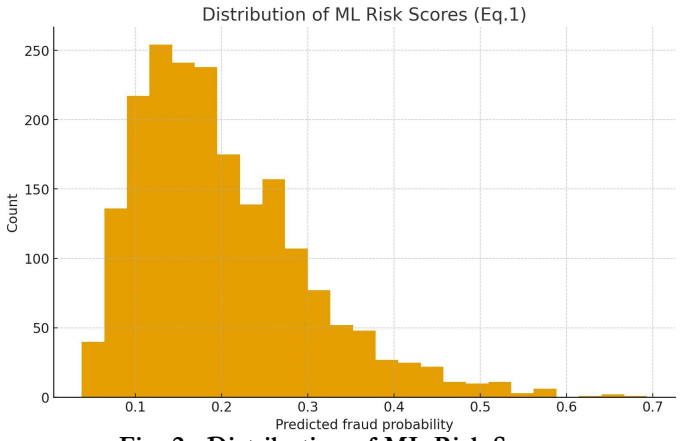

Fig. 2. Distribution of ML Risk Scores

cost of maintaining the rule set grows, an increasing number of false positives are generated, and little new fraud is detected. During this phase, other types of customers may feel bur- dened and possibly seek another insurer. Data-driven machine learning solutions are then proposed, mainly as add-ons to the original decision tree approach. Data-driven solutions require a different data setup strategy, including addressing how the data needs to be governed over time since many different stakeholders will be using these data sets to make important business decisions. The need for data-driven solutions can be based on data quality and the often low percentage of fraud discovered when the existing decision tree filter is applied. The system aims at detecting, triaging, and recovering fraud, both internally and externally. The definition of success then varies for the different objectives: detection represents a very global view of how well fraud is being found, triaging focuses on the cases being analyzed and assigned to human experts, and recovery looks at the monetary amounts related to those cases. Finally, the global operation of such data-driven systems needs to be carefully planned in order to avoid an overload of the human resources dedicated to the different fraud management processes.

A. From rule-based systems to data-driven models

Many business rules, defined by manually created rules since the inception of the operations in those areas, were later migrated to rules engines that allowed business users to define their own rules. With time, these engines became overloaded with rules without proper governance, resulting in older rules being removed manually. Also, the presence of too many overlapping rules made it difficult to decide whether a specific rule was even firing. Given these aspects, risk decisions were taken based on the rule or set of rules that fired first. These anxious decisions were generally suboptimal since generated business interest in reformulating the approaches using data-driven models. Over the years, plenty of data was accumulated in the systems, and different business functions started adopting ML to improve their respective areas. It made sense to use predictions derived from such models instead of relying solely on rules. However, these models required proper risk governance in order to be effective and achieve the expected results. In this context, ML models built to add risk to the claims directed to manual review (triage) were of fundamental importance for the business. The goal was to build models to reduce the operational costs of the claims and maximize the recovery of fraud.

B. Data sources and feature engineering

The detection of fraud in insurance claims processing often requires access to a wide variety of both internal and external data sources. Internal sources include the claims data itself; prior claims made by the same claimant; policies;

any prior or current suspected or confirmed frauds; and in the case of bodily injury claims, medical records. It is common for insurers to restrict telematics data to fraud- and claim-related analyses due to data privacy concerns. Data quality issues must be addressed at the outset—for instance, in the case of facial recognition, the classification decision is often based only on a small, internally stored picture of the claimant that is subject to various transformations (such as resolution and age) during reconciling. The matching data need to cover claims made by the same claimant in different companies in order to eliminate the chance of false negatives or misclassification. Well-governed and auditable labeling of ground truth is central to supervised ML. Flaud refers to "commented labeled images and video," which implies that the human experts write both the labels identifying the fraudulent claims and the comments explaining the reasoning behind the decisions. Attempting to create these labels automatically by using prior highlighted fraudulent claims as the only source of labels is prone to causing systematic flaws in the model. Labeling is one area where the combination of human proactivity and ML can yield optimal results. Claudators provide the generative best-effort human- expertise-driven labeling; the models then score the new cases.

Equation 2 — Fraud Probability Estimation (Bayes posterior via odds)
Objective: calibrate model output against portfolio-wide prior fraud rate.
Define prior fraud rate $\pi = \Pr(y = 1)$. In odds form, they did not consider the entirety of the claim, thus resulting in missed opportunities. Many of these rules also required **odds(p)**=1-*p*/*p*

$$posterior_odds = prior_odds \times es - logit(\pi) \Rightarrow p_{post} \quad (2)$$

. The model's logit score $\ell = \log \_pmodel\ 1 - pmodel$
expensive manual review of the claims, despite the engagement of costly set of experts. Costs added due to inefficient triage and manual review of non-suspicious or very low risk cases Bayes in odds space (with the model's logit interpreted as a log-likelihood ratio around the prior) gives:

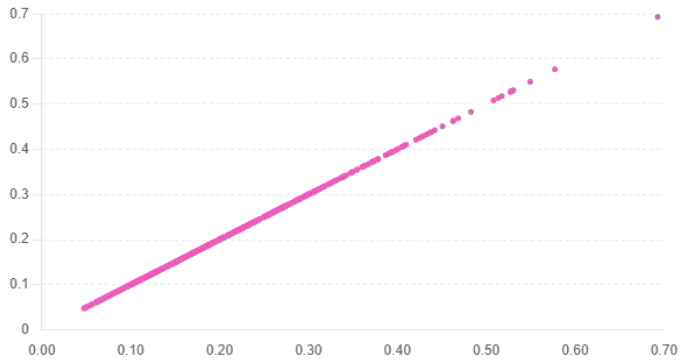

Fig. 3. Posterior vs Raw Risk Score

$$posterior_odds = prior_odds \times es - logit(\pi) \Rightarrow p_{post} \quad (2)$$

$$= \frac{1}{1 + \frac{1}{posterior\_odds}} \quad (3)$$

This yields a calibrated posterior ppost that aligns with the base rate pi.

C. Modeling goals: detection, triage, and recovery

The modeling goals encompass detection of fraudulent claims, triaging of alerts for efficient handling, and recovery of losses. Detection is typically binary—alert or no alert—while triage and recovery introduce notions of prioritization and quantification. The modeling success rates are therefore de- fined differently through relevant business stakeholders. For the detection models, the rate at which valid fraud is correctly flagged as fraud is the success metric. A healthy rate of false alerts should also be targeted, but care should be taken to control this value; otherwise, an inundation of alerts could cause pertinent genuine fraud signals to be missed due to resource limitations. Once validation resources are flooded, the true positive rate would then spiral downwards. Robust business communication and a model validation prioritization framework can help mitigate this risk, for instance, using model confidence as a tying factor when identical alerts are raised by different models in different timeframes. The triage modeling success criterion is :N, where : is the dollar amount saved from fraud that falls under either False Positive or Correct Positive and N is the total validation resource of the team in any particular time period. Once alerts are raised and healthy levels of both detection rates and triage performance are ensured, the task then shifts towards recovering the money lost.

III. Fraud Detection Techniques and Modeling Approaches

Fraud detection spans a wide spectrum of techniques, whose choice often hinges on the classification goal and the nature of the available data. A comprehensive overview reveals two main categories—supervised and unsupervised fraud detection methods—alongside additional perspectives: anomaly detec- tion, outlier analysis, examining fraud through the

claim lifecy- cle, and causal inference-based risk scoring. Specific modeling considerations for these techniques are discussed in Sections 3.1–3.4, while fraud detection in the auto insurance domain is tackled at a higher level in Sections 4.1–4.3. Supervised methods include those based on classification, regression, and structured output learning, supported by labeled training data. Although especially useful for detection tasks, they rely on external agents to create labels—often a painstaking and time- consuming process that can lead to unreliable ground truth. Furthermore, models are hypothesized to be robust only on data drawn from the same distribution. Conversely, unsuper- vised techniques, such as clustering and anomaly detection, bear no data labeling burden, although model outputs typically require manual examination and validation. Despite these advantages, the lack of pre-defined surfaces necessitates a higher level of domain knowledge, especially for evaluation.

Supervised and unsupervised methods

Fraud detection and risk modeling are areas where insurance companies are looking to adopt machine learning technology. Two families of problems are recognized: supervised methods, where the model learns from data that is labeled (ground truth is available), and unsupervised methods, where ground truth is not available. The traditional approach is to carefully design the fraud detection system with rules, since it is easier to get labelled data. However, relying only on unsupervised methods has its challenges. Supervised methods consist of any classification use cases where models are built based on historical data. For example, traditional fraudulent triangle- based methods use historical claims data with ground truth tagged claims to estimate the likelihood of such claims to be fraudulent. In an insurance setting, the dilemma with supervised models is two-fold: (i) frauds are usually rare events and the models created losses its power, (ii) false positives are bad and thus a careful definition of true fraud and acceptable trade-off threshold is critical. Explainability on these models is also key, as it gives more confidence to business users and helps them investigating flagged claims.

A. Anomaly detection and outlier analysis

Anomaly detection and outlier analysis encompass a wide array of methods for identifying rare observations that differ significantly from the majority of observations. In time-series data, these rare observations can be outlying patterns that deviate from normal behavior, including sudden changes, shifts, or periodic behaviors in the time series. Anomaly de-tection techniques can be integrated with other fraud detection techniques in the claims development workflow. For example, they can serve as a triage layer to identify the most suspicious claims that require thorough investigation or are most likely to help in recovering fraud loss. Following the triage stage, a suspicious claim can be evaluated using an explainable classification model, the output of which may indicate whether it is definitely fraud, probably not fraud, or uncertain. The clas- sification model can be reinforced if explainable predictions are available for training. Otherwise, predictive features can be provided to the agents or investigators for further behavioral analysis of claim participants. Other fraud techniques can also be utilized in the process, such as causal inference for efficient recovery.

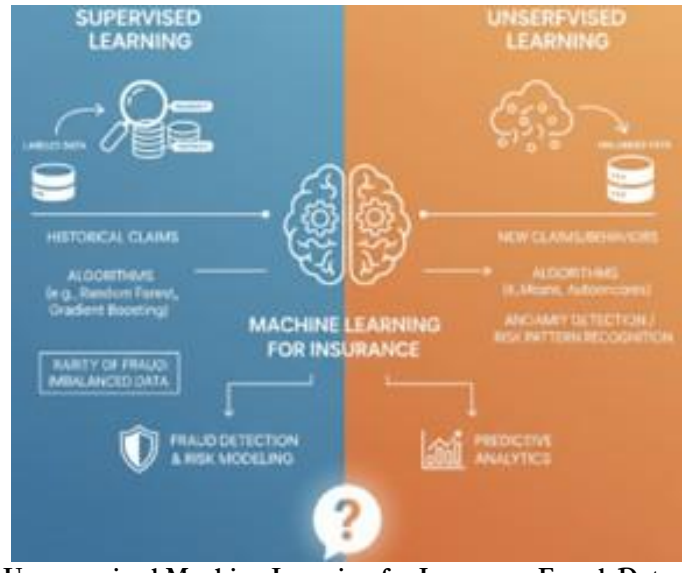

Fig. 4. Supervised and Unsupervised Machine Learning for Insurance Fraud Detection and Risk Modeling

B. Temporal and sequence modeling for claim lifecycle

Detecting fraud and abuse in a claims process naturally relies on the consideration of the temporal dimension of a claim. For example, fraud on a claim is more likely if it is the first claim on the police insurance or if it is a claims amount much higher than the honest claims on similar policies in the past etc. Therefore, an ideal pattern model for the claims process detects the "abnormality" of a claims process by considering the temporal sequence of a claim. It also can be useful to model the "temporal" nature of claims when it comes to using ML systems for forecast or prediction. Contribution and novelty should be clearly identified here. How does the research contribute to the existing literature in terms of identification of new pattern, solving an existing research question that remain unanswered in the literature,providing a new perspective for understanding an existing phenomenon, method or process,formulation or

development of new Proposition, Theory, Relating some existing theories, or based on data from other domain,new experiment in the area, or by applying a new technique to model a phenomenon, an experiment or a model from literature or some other sources?

Equation 3 — Model Accuracy Improvement Rate (MAIR)

Metric	Rule-based	ML model	MAIR
Recall@Top10%	0.14960629921259844	0.2152230971128609	0.43859649122513
ROC-AUC	0.5359972375287554	0.6646701975718138	0.24006272986792

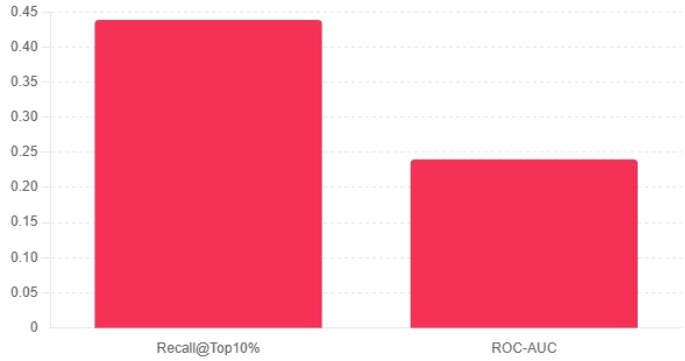

Fig. 5. Model Accuracy Improvement Rate (MAIR)

Objective: quantify lift over the legacy rule system. For any metric M, define

$$MAIR(M) = MRuleMML - MRule \quad (4)$$

I report MAIR for Recall@Top 10% review capacity and for ROC-AUC.

Metrics & MAIR

C. *Causal inference and risk scoring*

Causality introduced a new paradigm to infer the impact of risk factors on various outcomes in claims processing. In contrast to traditional methods, where risk scores are often engineered based on correlation analysis, modern techniques measure the direct influence of the risk variable of interest on the predicted outcome while controlling for all others. The difference between the prediction value before and after the in- clusion of the risk variable represents its contribution towards the outcome. Such risk scores can be routinely updated as new labels for the outcome become available. The derived variables should represent the expected claim amount per claim in the chosen label period after controlling for the usual confounding factors associated with claim severity. The utilization of causal inference techniques not only provides risk scores that can assist in claim triaging but can also directly influence the decision for each claim processed. For instance, if causal inference techniques determine that the claims made from a certain postal code always have a negative impact on the loss ratio, it is reasonable to automatically reject all claims coming from that postal code. By utilizing causal inference techniques, rapid decision-making can be performed without being heavily reliant on supervision. The evaluation of success is determined by the deployment of human-inthe- loop techniques, where human feedback is taken into consideration on the actions being performed based on the detected patterns.

IV. Data Governance, Privacy, and Ethics

The adoption of machine learning-based models in insur- ance claims processing brings data governance, privacy, ethics, and bias considerations to the fore. Specifically, the quality of training data needs to be considered to minimize false negatives and false positives. Furthermore, appropriate de- identification and privacy-preserving methods should be em- ployed to safeguard customer information. Once the training and predictive models have been established, fairness and explainability need to be actively scrutinized to ensure that the outcome does not discriminate against any particular group. The models need to be monitored—for drift, for bias—and mechanisms implemented for regular retraining so that the impact of drifting patterns is minimized. Tackling fraud in an effective manner requires high-quality labels for training and validating data. These labels must be accurate, consistent, and representative of the population. Having a set of data points that form the ground truth for historical fraud cases enables hiding many outlier flagged cases. In addition, the claimed amount and the premium collected at the time of issuance are other aspects that can be treated with added scrutiny binary labels *y*: (labeling them high risk), even though they are not part of the fraud definition. These can be combined into a single label when checking for quality. With the above precisions in mind, labeling for training, validation, and ground-truth creation is defined, along with the process for quality checks, so that the model learns from high-quality labeled data.

A. Data quality and labeling for fraud

Labeling protocols, ground truth ascertainment, and quality assurance signals the successful development of supervised models. A dedicated team identifies and documents fraud cases, providing ground truth for model validation and performance metrics. Quality checks assess the completeness and value associated with internal and external features;

labeling success relies on the careful definition of conditions that make records suitable for fraud. New claims scoring models use ground-truth labeling based on analyst feedback and a predetermined scoring threshold to indicate the presence or absence of fraud. For model training and validation, signals from detective natural language processing techniques provide additional fraud labels. Records missing neural fraud labels are filtered out to capitalize only on valuable information. Data sources require further validation before final assignment. Different levels of judgment reflect the hiking team's effort to flag only serious hiking risks and the sharing group's aspiration for minimal labeling effort—risk-group analysis tailors this definition to model needs. Future enhancements address recording scarcity for rare-risk models, iterative labeling of records by dedicated teams, and variation in labeling during model development and deployment.

Equation 4 — Risk–Fraud Correlation Coefficient
Objective: verify monotonic relationship between risk score and fraud.

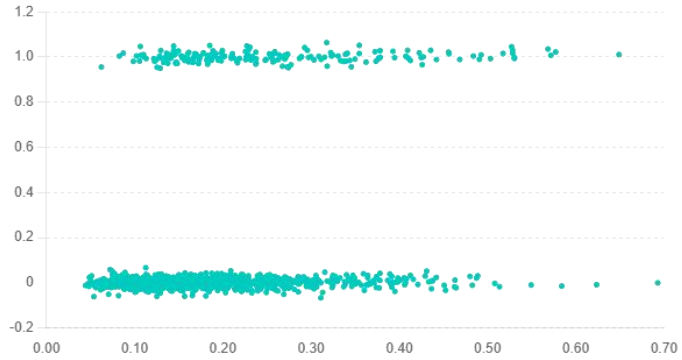

Fig. 6. Risk Score vs Fraud Label (jittered)

$$r = \frac{\sum (s_i - \bar{s})^2 \sum (y_i - \bar{y})^2}{\sum (s_i - \bar{s})(y_i - \bar{y})} \quad (5)$$

Use Pearson correlation between continuous scores s and A higher r indicates better concordance between higher scores and fraud.

B. Privacy-preserving techniques and compliance

A number of privacy-preserving techniques can be used to protect users' identity and preserve privacy of sensitive information while still yielding useful training data for super- vised machine learning algorithms. De-identification removes personal identifiers, such as names, addresses, and dates, from the database. Stronger privacy protection can be achieved through differential privacy . As the level of privacy increases, the risk of model inference goes down, but data utility also shrinks. Therefore, a trade-off between privacy and model effectiveness must be established. In any case, when dealing with storing or transmitting sensitive information, compliance with privacy regulations must be addressed—for example, by cross-border data flows enforcement of the General Data Protection Regulation for EU residents. Implementation of dedicated data governance can help de-risk without adding any delay. Adequate procedures can be developed and as- sets assigned to ensure that all requests involving sensitive information are properly assessed and processed according to regulatory requirements.

C. Bias, fairness, and explainability

The domain of fraud detection in insurance companies is inherently sensitive, as it is related to assessing whether or not a client is committing fraud. Even if the algorithm accurately identifies several fraudulent claims, it can have several false positives as well. If these false positives are for claims that were indeed not fraudulent, it can harm the insurer–insured relationship, and it may also lead to a significantly increased workload for the analysts who need to investigate these received alerts. To mitigate these potential issues, it is essential to work on the fairness and explainability of the used algorithms. Some natural fairness metrics can be used to ensure that for known non-fraudulent claims, the predicted fraud scores are not higher than for known fraudulent claims. Besides that, explaining the predicted score for actors involved in a claim can also help improve these relationships. Using predictive scores to prioritize claims can also help in this sense. For example, a claim that is flagged for further investigation with a predicted fraud score of 0.55 can be investigated with a different level of attention than a claim that has a fraud score of 0.95. In this last case, it may be more interesting to assign the investigation of the claim to a specialist who can grasp the complexity better than a Level 1 analyst. Therefore, having an adequate and transparent prioritization flow and communicating, when appropriate, the reasons for the clients' alerts to these actors can help reduce the damage caused by false positives.

V. Implementation and Operational Considerations

An end-to-end implementation of the system involved inte- grating it with claims platforms, defining monitoring require- ments, and establishing human-in-the-loop controls to ensure accuracy. The models were first deployed in a triage role, prioritizing claims for close review based on fraud risk and loss severity, before also providing lift-and-sustain support for

the investigation function. Integration with claims management platforms required APIs, data pipelines, and careful attention to the data model supporting all operations. Automatically flagging claims for review reduces the burden on analysts, improves the detection rate, and lowers the time to detect fraud. Monitoring dashboards provide insights into model performance and help detect drift. The models are based on historical data, but frequent retraining is not viable given the limited number of positive samples. A human-in-the- loop decision-making framework defines roles for analysts, investigators, and adjusters at the detection-end of the claim lifecycle. An end-to-end implementation of the system involved integrating it with claims platforms, defining monitor- ing requirements, and establishing human-in-the-loop controls to ensure accuracy. The models were first deployed in a triage role, prioritizing claims for close review based on fraud risk and loss severity, before also providing lift-and-sustain support for the investigation function. Integrating with claims management platforms required APIs, data pipelines, and careful attention to the data model supporting all operations. Automatically flagging claims for review reduces the burden on analysts, improves the detection rate, and lowers time to detect fraud. Monitoring dashboards provide insights into model performance and help detect drift. The models are based on historical data, but frequent retraining is not viable given the limited number of positive samples. A human-in- the-loop decision-making framework defines roles for analysts, investigators, and adjusters at the detection-end of the claim lifecycle.

A. System integration with claims platforms

Integrating with claims processing systems requires pro- viding APIs for fraud-scoring models and returned features, deploying data pipelines for synchronized training/retraining, and addressing the required technical details to seamlessly support operations. The API endpoints connect with the claim- processing platform, making it easy to provide historical and synoptical features along with the claim details for scoring with the fraud-detection models. Introducing a fraud-detection system or any new monitoring system typically involves feed- ing historical data to the model for scoring and inserting the score with the claim details in the claim-processing tool. Using these scores in a triage model structure aids data extraction, and a similar scoring system can be built for triaging score assignment. When the models operate in production, the predictive data-feeding pipeline becomes the primary technical requirement. If any new or upgraded model requires training or retraining, then the labeled data pipeline helps feed the data. Labeled data are data containing the actual fraud indicator, which required data engineering for the labels.

Fig. 7. End-to-End Insurance Fraud Detection Implementation with Human- in-the-Loop and Platform Integration

B. Model deployment, monitoring, and retraining

Following the development of ML models for fraud detec- tion and risk management, the next challenge is to effectively deploy, monitor, and refine them. Thus, a systematic approach is key for implementing this strategy, with the following requirements being pivotal: (1) provisioning a continuous integration/continuous delivery (CI/CD) pipeline for auto- mated deployments; (2) developing a monitoring dashboard for model performance and operational metrics; (3) establishing drift monitoring to detect model performance deviations; and
(4) designing a periodic retraining schedule calibrated to the organization. Adherence to these requirements ensures timely datamart updates, that data drift can be quickly identified, and that underlying models and algorithms can be retrained or swapped with newly developed alternatives.

C. Human-in-the-loop decision making

To minimize the risk of incorrect decisions with serious business consequences, the deployment strategy incorporates a human-in-the-loop approach. The system's predictions provide a risk score and a recommendation for each claim, which can be accepted, rejected, or modified by a claims analyst. Investigators and claims adjusters also receive prioritized and risk-scored recommendations for alert generation and claim investigation/resolution, respectively. Examination of historical patterns further disambiguates prediction ties. The categorization of alerts and claims not only streamlines the workflow but also allows transfer of responsibility from the analyst to an investigator or claim adjuster with relevant expertise. Scoring can aid adjustment decisions if collusion is present; the automatic score-based action may be de- prioritized or altered but should not be excessive to prevent additional leakage.

T days	EDE rule	EDE ml
1.0	0.0419947506561679	0.0892388451443569
4.105263157894736	0.1837270341207349	0.3569553805774278
7.2105263157894735	0.2887139107611549	0.5433070866141733
10.31578947368421	0.3832020997375328	0.6561679790026247
13.421052631578949	0.4356955380577428	0.7637795275590551
16.526315789473685	0.4960629921259842	0.8320209973753281
19.63157894736842	0.5406824146981627	0.889763779527559
22.73684210526316	0.6089238845144357	0.9186351706036744
25.84210526315789	0.6614173228346457	0.926509186351706
28.94736842105263	0.7086614173228346	0.9501312335958004

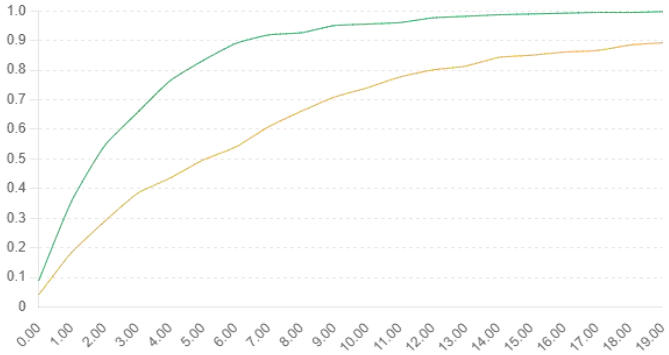

Fig. 8. Early Detection Efficiency vs Time Threshold

Equation 5 — Early Detection Efficiency (EDE)
Objective: fraction of frauds detected **before** a time thresh- old ΔT (e.g., before payout).
Let T_d be detection time for a fraud case. Then the time- bounded efficiency curve is:
$EDE(T) = Pr(Td \leq T \mid y = 1)$ (6)
Empirically estimated as the cumulative fraction of true frauds detected by time ΔT.

Early Detection Efficiency curves table

VI. Future Directions and Research Agenda

Next-generation techniques built on streaming data and cross-industry fraud patterns will enhance Fraud Detection systems and Data Science practices. The fraud detection use- case currently being developed is primarily for analyzing historical claims using a batch approach. Thus, the need for model retraining is relatively infrequent. Online learning techniques enable models to be updated as new labeled data is generated, thereby addressing both concept drift and data drift. Selected models can also be executed in real time to facilitate immediate scoring of new claims. The specific latency requirements vary by application—for instance, a risk score for presenting a fraud detection dashboard can have a higher tolerance for latency than a score that aids in the decision on whether to approve a claim. Temporal aspects must not be overlooked. Considering the life cycle of a claim over time often provides meaningful signals such as repetitive behavior. The major fraud events of different life cycle stages (e.g., first notice of loss, claim declaration, claim settlement) often act as critical signal points. Analysts and investigators working with these systems gain experience over time and build tacit knowledge that can help to flag unusual activities. Such pattern creation across the financial industry helps insurance companies detect and prevent fraud with bidirectional knowledge transfer. The model can learn the behavior of fraudsters in other companies—it remains a joint problem in any industry, whether government, bank, or insurance. All have the same aim: to reduce their losses from fraud.

A. Advanced modeling techniques on streaming data

Contemporary data science increasingly demands on- demand solutions to enable timely decision making at mul- tiple levels, be it for real-time fraud detection in credit card transactions, recommendation engines for content or products, or audience targeting for advertising. Often referred to as streaming data or data decay, the challenge is to derive useful information from time-dependent data before the opportunity is lost, or to execute decisions in real time. Along these lines, neural network-based approaches are now widely used to enhance accuracy and reduce latency by predicting the type of outbreak and its possible target domain. Insurance telematics, which monitors the driver's behavior (e.g., speed, acceleration, braking, steering mistakes, and time of day), is a rich source of temporally dependent data for real-time pricing; they, however, focus on real-time prediction of fraud and risk at the individual transaction level, for adapting current business processes. Of key interest are approaches that develop or validate risk models on temporal data but apply those models in real time across different transactions and industries. For example, fraud detection is defined as the identification of suspicious, often malicious behavior in a system or infrastructure.

B. *Cross-industry fraud patterns and transfer learning*

Shareholder2368: Opportunities to enhance models with external signals and knowledge transfer; connect to 3.1 and 4.3. Fraud patterns, detection methods, and other aspects of successful models within a given industry can usually be extended to other industries, or even applied across the business world in general. Therefore, fraud detection isone application that can particularly benefit from transfer learning due to the considerable similarities in fraud attempts across industries. A claim may potentially appear completely reasonable on the surface but remain fraudulent because of actual linkages to other claims with inconsistent data attributes, exhibiting the nature of collusion latent in cross- industry patterns. Signals from corporate databases and information freely available online can help augment internal databases in order to improve models susceptible to gaps in data or observability. In turn, distilling cross-validation axes of similarity with respect to the learning model opens doors to carefully planned resourcing or transfer learning techniques that can avoid requiring a new model for every fraud style. Although many real-world use cases remain proprietary, the rapid rise of science and technology has ensured that relevant knowledge is publicly documented and freely available. Therefore, intelligent deduction, creative thinking, and a plan for using open-source knowledge in order to enrich current picture models, in conjunction with the development of new models covering new angles and newly learnt patterns, can expand accuracy. Cross-industry fraud detection model patterns become a powerful tool for companies.

Fig. 9. Online Update — Log-loss over iterations

Equation 6 — Continuous Learning Update (online logistic)

Objective: show how the model updates in production as feedback arrives.

For a mini-batch (X_t, y_t), logistic loss gradient $\nabla \ell_t = X^{\top}(\sigma(X_t w_t) - y_t)/|t| + \lambda w_t$. Stochastic/mini-batch gradient step:

$$w_{t+1} = w_t - \eta \nabla \ell_t \quad (7)$$

I plot the log-loss decreasing across online updates.

C. *Ethical AI governance and accountability frameworks*

Comprehensive governance frameworks for ethical AI usage enable maximally beneficial technology adoption. Stakehold- ers must audit practices and establish external accountability structures. Such actions help mitigate inherent bias and cultural fairness challenges, promote preventive rather than reactive frameworks, and ensure that particular demographic groups do not bear a disproportionate expectation cost. The absence of bias framework analysis can impede AI system deploy- ment. Enterprise ethical frameworks can facilitate AI system implementation across industries. Auditors appointed by the appropriate institutions should review deployment frameworks and governance structures. Accountable deployment requires stakeholders to play an active role; when organizations become AI customers instead of service providers, indications of AI impact are typically visible after the fact. While these holdups may seem cliche´d and lack meaning, corrective implementa- tion upfront is often grossly inefficient.

VII. CONCLUSION

False claims cost the insurance industry approximately USD 80 billion annually; one-third of organizations deem their fraud prevention methods ineffective, exposing them to about 10% of claims leakage. Expanding known fraud detection techniques to support claims processing opens doors for de- ploying machine learning technology in operations. Natural language processing and artificial intelligence enabled text- to-image generators push newer models and techniques to detect synthetic identity fraud: examining claims images can help identify digitally generated images. Machine learning technology is often viewed as a solution looking for prob- lems to solve, with the true value lying in its applicability to business pain points. It is easier to deploy rules-based detection capabilities for manually predicted problems than to invest in hidden risk factors, potentially faster opportunities. Therefore, a phased rollout—starting with claims processing systems—ensures faster returns and lays a solid foundation. Expanding fraud detection activities into claims processing supports a full-cycle view of fraud detection, involving detec- tion, triage, and recovery; supported by a supervisor-assisted approval or disapproval mechanism; covering all aspects; and adding maturity to the fraud detection life cycle.

A. *Summary of Findings and Recommendations*

The fraud detection and risk modeling systems applied to insurance claims processing early adopted machine learning techniques. Initially, claims processing relied on actuarial rules—the simplistic if-then-else conditions underneath de- cision

trees. Over time, such rule-based systems grew in complexity. A data-driven approach to modeling replaces these deterministic rules. Several classes of supervised learning problems can be modeled in a claims-processing context: fraud detection, triage of flagged claims, recovery of proven- fraudulently-induced losses, and others. The insurance in- dustry suffers significant financial losses due to fraudulent claims. These losses comprise both proven fraudulent claims (actual loss) and leakages from true policy-holders. Hence, the operational cost of processing claims is also considerable. Consequently, companies are shifting towards using data to make better decisions. By applying machine-learning tech- niques to claims processing, the research represents a first step towards using data to improve decision making in the insurance industry.

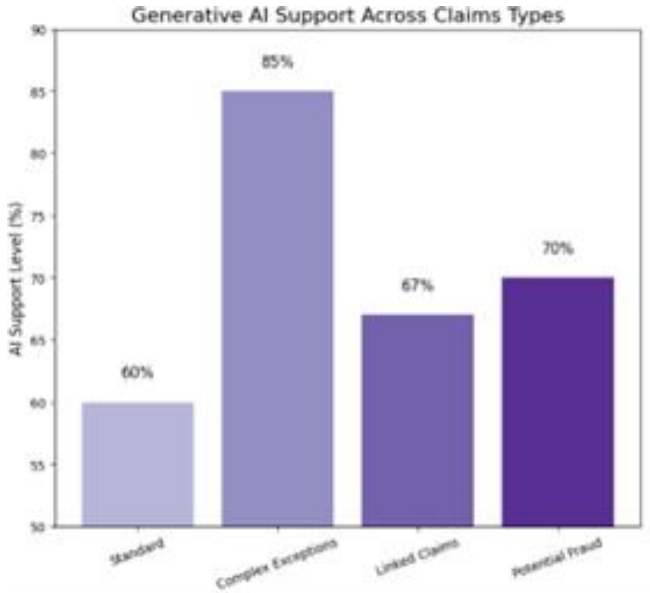

Fig. 10. Generative AI Support Across Claims Types

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