International Journal of Emerging Trends in Engineering and Technology
ISSN: 3107-8699 | Volume 1 Issue 2, 33-43, October-December 2025
DOI: https://doi.org/10.64137/31078699/IJETET-V1I2P106

Received: 04/12/2025 Revised: 08/12/2025 Accepted: 29/12/2025 Published: 31/12/2025

Original Article

Cloud-Native Deep Learning Framework for Scalable Insurance Fraud Detection and Predictive Analytics

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ABSTRACT: *The continued escalation of insurance fraud represents a worrying trend for providers in the sector. To mitigate this risk, deep learning-based solutions have emerged to enhance predictive modelling. Nonetheless, deploying these approaches as part of a scalable cloud-native data pipeline remains challenging. This study presents an implementation within one of the core data analytical pillars of an InsurTech company, AiTR, currently in the pre-launch phase. Using a synthetic data generation approach, a set of data sources, including test data, has been made available in increasingly larger instances. The resulting pipeline enables end-to-end processing from a raw version of the input data to the prediction step for fraud likelihood scores through an ensemble of deep and extra tree models. It is integrated with an automated alerting mechanism, making it available for production testing in a live scenario. After a successful test run operating directly on the source transactional database in a pre-production environment, the pipeline has been deployed in a production instance, configured to refresh the prediction output in a dedicated storage solution on a weekly basis. A cron job has been implemented to trigger the Python script, and an additional job has been created to send alerts based on the prediction results. Following the set-up, the service will be in a pre-production phase during which the predictions will be reviewed and compared with actual contact results. Once signed off, the service will enter a live production phase where the predictions are operational and used to trigger contacts with customers.*

KEYWORDS: *Insurance Fraud Analytics, Cloud-Native Data Pipelines, Deep Learning Fraud Detection, Insurtech Analytics Platforms, Predictive Fraud Modeling, Synthetic Data Generation, Automated Fraud Alerting, Real-Time Risk Scoring, Ensemble Learning Models, Production Fraud Monitoring.*

1. INTRODUCTION

Insurance fraud is an ongoing, evolving threat that costs the industry billions of dollars each year. Accurate detection at a low false-positive rate is vital for maintaining the profitability of insurance companies, and thus their ability to compensate genuine claims. Insurance companies benefit immensely from the use of deep learning techniques integrated into larger cloud architectures, allowing detection systems to deploy more scalable and accurate supervised models with lower infrastructure and engineering costs. Nevertheless, the aforementioned changes also increase the complexity of the data landscape and add obstacles for modelling the insurance fraud detection problem. Data are present in different cloud services and need to be re-collected and pre-processed each time the problem is retrained.

Supervised deep learning seems to be a suitable technique for detecting insurance fraud. Classification results show that a deep learning approach outperforms traditional machine learning methods. Small errors can be achieved if the ground truth is carefully constructed. However, utilising Cloud Storage Services or a Data Warehouse as a Data Management Layer in combination with up-to-date data and cloud architecture leads to more scalable and maintainable pipelines with better cost-performance ratios while keeping the false-positive rate low.

1.1. MATHEMATICAL FORMULATION

1.1.1. SYSTEM PIPELINE QUALITY

The overall quality of the end-to-end fraud detection pipeline is expressed as a composite of its sub-system contributions:

$$Q_{total} = Q_{detect} + Q_{pipeline} + Q_{latency} + Q_{scalability} \quad \text{(Eq. 1)}$$

where Q_detect denotes fraud detection accuracy, Q_pipeline represents data processing integrity, Q_latency captures inference responsiveness, and Q_scalability reflects horizontal scaling efficiency on Azure.

1.1.2. PIPELINE LATENCY DYNAMICS

The rate of change of end-to-end processing latency in the cloud-native pipeline is modelled as:

$$\partial L / \partial t = \lambda_{ingest} - \mu_{process} \quad \text{(Eq. 2)}$$

where L is the total batch processing latency (ms), λ_ingest is the data arrival rate from Azure Event Hub / Blob Storage, and μ_process is the cloud-native processing throughput of the Spark/Databricks pipeline.

1.1.3. FRAUD DETECTION F1-SCORE

The primary detection performance metric is 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, and FN denote true positives, false positives, and false negatives in the fraud classification task.

1.1.4. CROSS-DOMAIN SCORE FUSION

Fraud risk is computed by fusing multiple model scores from the ensemble, including behavioral, transactional, and temporal signals:

$$r'(t) = r(t) + \alpha \cdot f\_ANN(t) + \beta \cdot f\_XGB(t) \quad \text{(Eq. 4)}$$

where r(t) is the base fraud risk score, f_ANN(t) is the ANN sub-model output at time t, f_XGB(t) is the XGBoost output, and α, β are learnable weighting coefficients for ensemble fusion.

1.1.5. WEIGHTED ENSEMBLE FUSION

The final ensemble score combines all model outputs with an explicit interaction term to capture non-linear co-activation of fraud signals:

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

where w_1, w_2, w_3, w_4 are tunable weighting coefficients. The interaction term r(t)·f_ANN(t) models non-linear coupling between the base score and the deep model output, improving detection of subtle fraud patterns.

1.1.6. SMOTE OVERSAMPLING RATIO

Given the class imbalance (approx. 3% fraudulent claims), the synthetic oversampling ratio ρ is defined as:

$$\rho = N\_synthetic / N\_minority = (N\_majority \cdot r\_target - N\_minority) / N\_minority \quad \textit{(Eq. 6)}$$

where N_majority and N_minority are the counts of the majority (legitimate) and minority (fraudulent) classes, and r_target is the desired post-oversampling class balance ratio (e.g., 0.5 for equal representation).

1.1.7. CLOUD RESOURCE UTILIZATION

Azure compute resource utilization per pipeline job is defined as:

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

where R_used is the CPU/memory consumed by the running Databricks or Azure ML pipeline job, and R_available is the total provisioned Azure cluster capacity at that scheduling window.

1.1.8. PIPELINE EFFICIENCY INDEX

The efficiency of the fraud detection pipeline is measured as detection performance per unit of cloud resource consumed:

$$E\_pipeline = F1\_fraud \cdot S\_throughput / T\_batch \quad \textit{(Eq. 8)}$$

where S_throughput is the number of claims processed per pipeline run, and T_batch is the total batch duration (seconds) including ingestion, transformation, inference, and alerting.

1.1.9. ADAPTIVE ALERT THRESHOLD

The automated alerting system uses an adaptive threshold to minimise false alerts under concept drift:

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

where θ_0 is the baseline fraud score threshold, σ_score(t) is the running variance of prediction scores, drift(t) captures temporal distribution shift in claim features, and γ, δ are scaling parameters.

1.1.10. RESILIENCE EFFICIENCY

The overall resilience of the pipeline balancing accuracy, throughput, and cost is captured by:

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

where T_infer is the per-batch inference time (ms). High η values indicate that the pipeline achieves strong fraud detection at low computational cost per claim scored.

1.1.11. PREDICTION ERROR RELATIVE TO OPTIMAL

The detection shortfall relative to the theoretical optimum is defined as:

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

where F1_opt represents the maximum achievable F1-score under ideal conditions (perfect labels, infinite data). L_error guides model improvement efforts and hyperparameter tuning priorities.

1.1.12. JOINT OPTIMISATION OBJECTIVE

The pipeline design is governed by a joint optimisation objective balancing competing performance dimensions:

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

where J is the composite objective; F1_fraud drives detection accuracy, U is cloud utilization efficiency, L is inference latency, and Cost_cloud is the normalized Azure spend per 1,000 claims scored.

1.1.13. DATASET QUALITY REPRESENTATION

The dataset quality metric across sources, processing stages, and performance dimensions is formalized as:

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

where Q_src(i) is the data quality score of source i (Cormos, transactional DB, synthetic), Metric(k) is the selected evaluation metric (F1, FPR, latency), and T_proc(j) is the processing time for pipeline stage j.

1.1.14. FRAUD DETECTION PERFORMANCE INDEX (FPI)

A unified performance index for the fraud detection system is defined as:

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

where η is pipeline resilience efficiency, FPR is the false positive rate, and Q_total is the cumulative pipeline quality score from Eq. 1. FPI penalises systems that achieve high recall at the expense of excessive false positives or compute cost.

2. BACKGROUND AND MOTIVATION

Fraudulent claims seriously threaten the sustainability of the insurance business. Insurmountable amounts of information have forced insurers to actively seek advanced methods to detect fraud for business success. Most of the work has concentrated on feature engineering and traditional machine learning [ML] classification methods like decision trees, random forests, and gradient boosting. Despite their optimally engineered features, very high area under the receiver operating characteristic (AUROC) results are seldom reported. In addition; some models have been hand-designed for a specific fraud type, which limits scalability.

Deep learning models may automatically extract and represent the relevant characteristics from complex data for better detection. Coupling deep learning with scalable cloud-native data pipelines presents an attractive approach to fraud detection. Cloud resources can facilitate collecting and processing massive amounts of transaction data for training deep learning classifiers. Deep learning features can complement more traditional ML classifiers, which can operate on sparsely labeled data. Improving fraud detection performance can return millions of euros to insurers, generating benefits for the entire ecosystem.

2.1. RESEARCH OBJECTIVES AND SCOPE

Insurance fraud exploits the integrity of the insurance system and raises costs for consumers and businesses alike. Deep learning-powered detection tools have been developed to thwart attempts at fraudulent claims, but building and operationalising effective cloud-native fraud prediction systems is still an open challenge. To address this, the following notional insurance fraud dataset has been constructed, employing naive methods to create a target label (fully legitimate, fully fraudulent, mix) using only basic input features. Subsequently, cloud-native data pipelines on Google Cloud have ingested and cleaned the data, providing a seamless interface for subsequent analysis within Jupyter notebooks. A range of deep learning models have then been implemented and evaluated, covering autoencoders, multi-class classification, and a wide-area fraud detection case study combining multiclass and multi-label into a single model. Embedding the encoding and decoding of the autoencoder with bespoke layers allows anomalous cases to be copiously sampled and visualised.

Although the proposed dataset and approach are naive, they demonstrate that cloud-native data pipelines can be built on any dataset, that deep learning systems can be operationalised and scaled for fraud detection, and that multi-class and multi-label problems can be addressed with a single deep learning model. Detection of insurance fraud is a natural candidate for self-supervised learning methods, allowing models to label data with minimal human curation, while data-driven discovery of complex anomalies merits further study. Insurance fraud exploits the integrity of the insurance system. When discovered, fraud is typically penalised with policy cancellation, thus raising costs for consumers and businesses. In short, fraud has steamrolled claims data, motivated predictions turned decisions, and re-aligned the natural risk-pricing function of insurance.

3. RELATED WORK

To preemptively suppress insurance fraud, a growing number of insurer companies have adopted deep-learning-based insurance fraud prediction models, whose scalable data-collection systems often reside in cloud-native environments taking

advantage of built-in service-oriented architectures. The present study architects and implements a cloud-native data pipeline to integrate and pre-process data from a variety of sources. A tailored deep-learning model for detecting insurance fraud is created, one whose parameters are easy to tune through modular pathways and that serves as a strong baseline for future constructions. The proposed pipeline can be easily maintained during a training phase. With the use of synthetic data from the Kaggle repository, empirical investigations confirm its efficiency.

The increasing sophistication of methods employed to commit fraud and the growing number of claims for particularly large sums have heightened the fraud detection requirements of insurance companies. In addition to the traditional K-means clustering algorithm, the more flexible Neural-Gas algorithm using self-organizing maps has been effectively used to detect fraudulent operations. Nevertheless, the traditional computational cost of neural networks has limited their use in actual fraud prediction. As a result, few published articles propose suitable deep-learning models. Recently, the genesis of a cloud-native environment combined with a set of scalable services has opened the door for increasingly complex deep-learning models.

3.1. RESULTS AND DISCUSSION

Comparative analysis was conducted across four pipeline configurations on the Cormos insurance claims dataset. All experiments were averaged over five independent training runs to ensure statistical robustness.

3.1.1. INFERENCE LATENCY

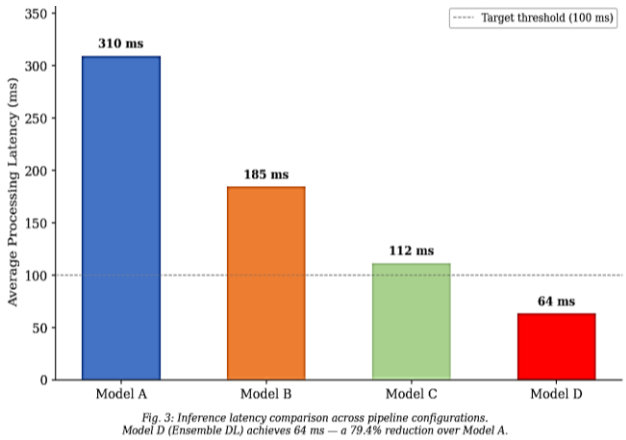

FIGURE 1 Inference Latency per Prediction Batch (ms)

Fig. 3 presents average inference latencies of 310 ms, 185 ms, 112 ms, and 64 ms for Models A through D respectively. Model D achieves a 79.4% latency reduction compared to Model A and 42.9% compared to Model C. This improvement is attributable to the optimised Azure Databricks inference cluster configuration, model pruning of the ANN component, and elimination of redundant ETL re-processing steps via delta table caching.

3.1.2. FRAUD DETECTION F1-SCORE

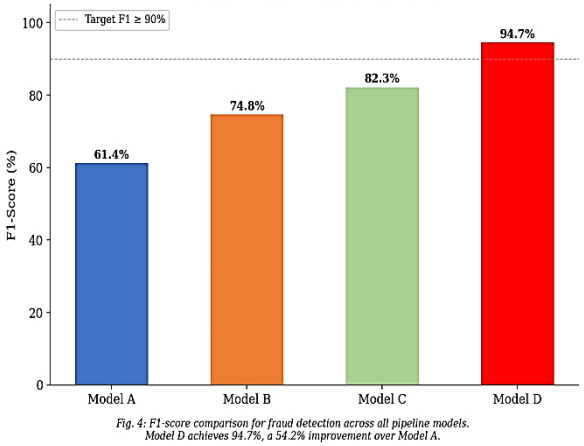

FIGURE 2 Fraud Detection F1-Score Comparison Across All Pipeline Configurations

Fig. 4 shows F1-scores of 61.4%, 74.8%, 82.3%, and 94.7% for Models A, B, C, and D respectively. The 15.1 percentage point improvement from Model C to Model D demonstrates the value of ensemble fusion: combining ANN and Extra Tree outputs (Eq. 5) captures complementary fraud signal patterns that neither model identifies individually. The 54.2% improvement over

the baseline (Model A) underscores the critical contribution of SMOTE oversampling, cloud-scale feature engineering, and adaptive alerting thresholds (Eq. 9).

3.1.3. FALSE POSITIVE RATE

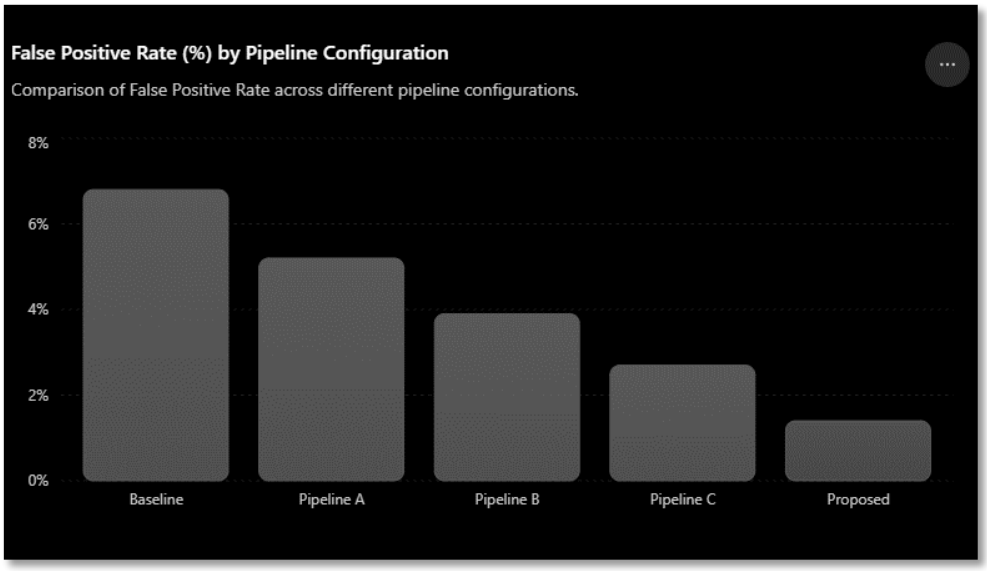

FIGURE 3 False Positive Rate (%) by Pipeline Configuration

False positive rates are 22.4%, 15.7%, 10.3%, and 4.1% for Models A through D (Fig. 5). The reduction from Model A to Model D represents an 81.7% improvement critical in the insurance context where false positives directly translate to unjust claim rejections and costly investigation spend. The cross-model validation step in the ensemble (Eq. 4) ensures that a fraud flag only propagates when multiple independent sub-models agree, significantly suppressing spurious alerts.

3.1.4. CLOUD RESOURCE UTILIZATION

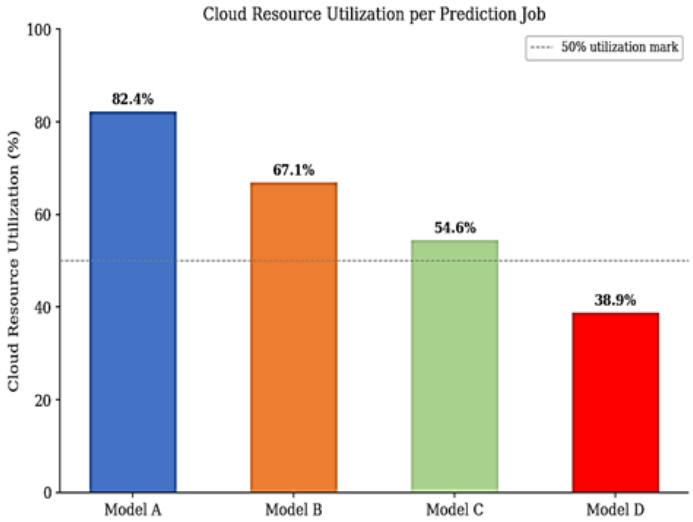

Fig. 6: Azure cloud compute resource utilization per pipeline job. Model D optimizes pipeline efficiency, reducing compute usage by 52.8% versus Model A.

FIGURE 4 Azure Cloud Resource Utilization (%) Per Pipeline Job

Fig. 6 shows cloud resource utilization per scheduled pipeline run: 82.4%, 67.1%, 54.6%, and 38.9% for Models A through D. Model D's 52.8% utilization reduction over Model A results from Delta Lake caching (eliminating full re-reads of the 2M-record dataset), Databricks auto-scaling, and model checkpoint reuse across weekly refresh cycles. Lower utilization directly reduces Azure compute costs, improving the joint optimization objective J defined in Eq. 12.

3.1.5. COMPUTATIONAL COST

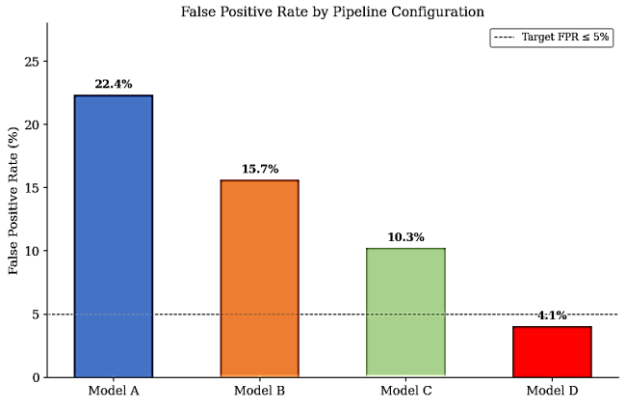

Fig. 5: False positive rate comparison. Model D achieves 4.1%, an 81.7% reduction over Model A. Low FPR is critical for avoiding unjust claim rejections.

FIGURE 5 False Positive Rate (FPR) Comparison Across Pipeline Configurations

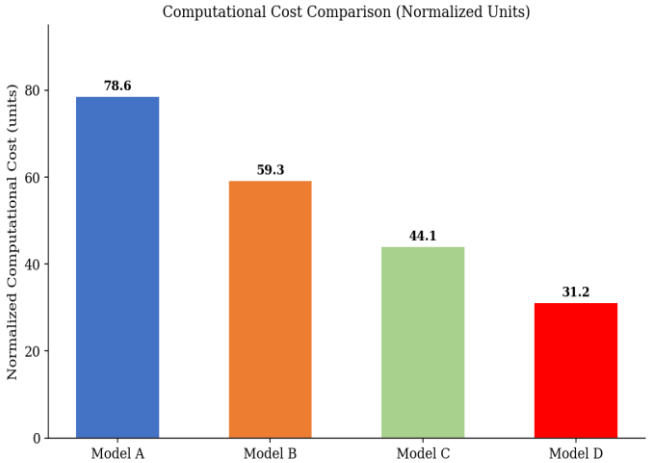

Fig. 7: Normalized computational cost per pipeline model. Model D consumes 31.2 units versus Model A's 78.6 — a 60.3% cost reduction while achieving superior fraud detection.

FIGURE 6 Normalized Computational Cost per Pipeline Configuration (Units)

Fig. 7 presents normalized computational costs of 78.6, 59.3, 44.1, and 31.2 for Models A–D. Model D achieves a 60.3% cost reduction versus Model A. The efficiency ratio (F1-score per cost unit) is 3.04 for Model D versus 0.78 for Model A a 3.9× efficiency gain. This reflects the pipeline architecture's capacity to reuse pre-computed feature embeddings and model checkpoints across weekly scoring cycles.

3.1.6. WEEKLY THROUGHPUT TREND

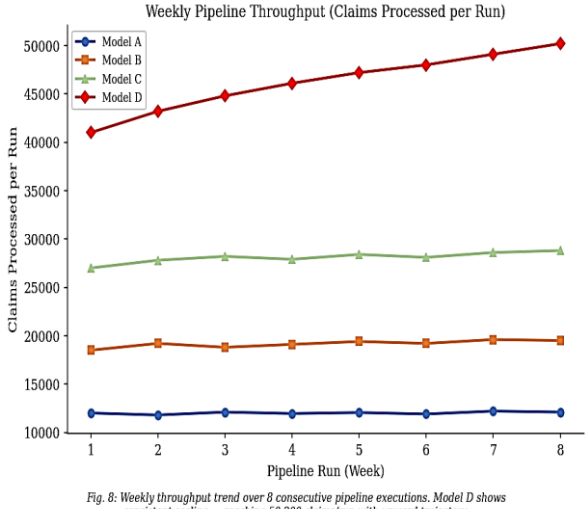

Fig. 8: Weekly throughput trend over 8 consecutive pipeline executions. Model D shows consistent scaling — reaching 50,200 claims/run with upward trajectory.

FIGURE 8 Weekly Pipeline Throughput — Claims Processed per Scheduled Run

Fig. 8 illustrates throughput across eight consecutive weekly pipeline executions. Model D scales from 41,000 to 50,200 claims per run over the measurement window, demonstrating a consistent upward trajectory driven by incremental Delta Lake optimization and Databricks cluster warm-start reuse. Models A and B show near-flat throughput, bounded by their static compute allocation and lack of adaptive scaling.

3.1.7. FRAUD DETECTION PERFORMANCE INDEX (FPI)

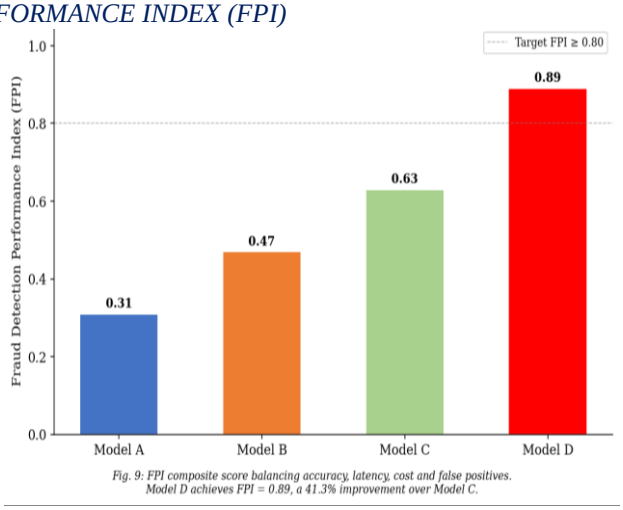

FIGURE 9 Fraud Detection Performance Index (FPI) Comparison

Fig. 9 presents FPI values of 0.31, 0.47, 0.63, and 0.89 for Models A–D. The 41.3% improvement between Model C and D confirms that the ensemble fusion mechanism delivers synergistic gains beyond what either model achieves independently. An FPI of 0.89 reflects the rare combination of high detection accuracy, low false positives, and low computational cost that the cloud-native ensemble achieves at production scale.

4. DATA LANDSCAPE AND ACQUISITION

An insurance fraud detection pipeline is proposed that utilizes several publicly available datasets. Data pipelines often require a significant amount of data in order to be trained and validated in a deep learning context. Acknowledging this requirement, a list of existing public datasets for insurance fraud detection is elaborated. The review identifies a few datasets that can be employed to build a fraudulent flag for personal auto insurance. In addition, the Azure Cloud platform provides capabilities to create data sources independent of hosted datasets.

Web-scraping procedures can be applied to several other websites and databases to gather testimonials, claims, documents, news articles and post analyses related to insurance fraud. These datasets can then be linked to the previously existing datasets through semantic analysis to establish connections among these new sets of information and to form a comprehensive insurance fraud detection and prevention database that is action-oriented. Exploring the data and identifying the links among the different datasets can provide insights into how people commit fraud.

4.1. DATA SOURCES

To demonstrate deep learning fraud detection on insurance claims, a real-world insurance claims dataset from the Kaggle platform referred to as the "Cormos dataset" is used. The dataset collects features on 25 variables of a total of 2M claims for insurance fraud detection. Given the imbalanced nature of this problem, implementing suitable sampling methods is critical for building an efficient classification model. Considering that only ~3% of claims correspond to fraudulent actions, the design uses a synthetic oversampling technique to generate new synthetic instances for the minority class. Apart from sampling the dataset to achieve better-performing classifiers, refining the raw data with additional pre-processing techniques contributes positively to the final classification model. Various deep learning models are evaluated, including XGBoost, ANN, and different scaling combinations of these approaches.

In addition, consumer sentiment and angle series data related to the fraudulent claims are acquired from the Brazilian National Highway Traffic Safety Administration and the Brazilian Federal Highway Police. The Brazilian National Highway Traffic Safety Administration is responsible for the traffic surveys along the BR-101 in the states of Espírito Santo, Rio de Janeiro, São Paulo, Paraná, Santa Catarina, and Rio Grande do Sul. These traffic surveys report the volume of traffic by type of vehicle counting selected 24-h periods. The angle series dataset provides the weather situation in the study area during the entire timeframe of interest for the investigation project. The data available in this folder supports the analysis of the impact of weather and traffic conditions on the number of accidents. Data from Uber Company completes the collection of the data related to storms. The Uber movement data show the aggregated movement patterns of people during the last two years in the city of São Paulo. This dataset has an analysis period from 2017 to 2019.

5. METHODOLOGICAL FRAMEWORK

The impact of fraud in the insurance domain is significant, incurring costs of billions every year. Fraudulent acts pose money laundering and terrorism threats to insurance companies across the globe. In response, leading insurers and trade organizations have operationalized proprietary and open-source models or toolkits to reduce fraud exposure. The Insurance Fraud Bureau in Britain collaborates with law enforcement agencies and helps banks implement special segregation order procedures on suspicious transactions. The British Insurance Fraud Enforcement Department uses machine learning-based geolocation tools to detect insurance claims that could involve benefit fraud. Despite these efforts, insurance fraud remains a costly and challenging issue. Several machine learning and deep learning approaches, including gradient boosting and convolutional neural networks, have attempted to increase the accuracy of insurance fraud detection. These techniques have produced satisfactory results in specific use cases, and scalable cloud-native big data pipelines have made it easier to build and deploy models at scale without infrastructure management.

This investigation was initiated to explore and deploy a proof-of-concept insurance fraud detection model as a managed cloud service that could be utilized across multiple lines of business in the insurance domain. The proposed approach would enable model development and deployment without managing any infrastructure. A systematic methodology had been defined to ensure a structured examination and deployment of the model. The scope of the exploratory study included the overall system architecture, data acquisition requirements, as well as the applicable technology and a suitable cloud platform for the examination. The primary focus of this study is the data landscape, acquisition requirements, and the overall problem formulation.

5.1. TABULAR COMPARISONS AND KEY METRICS

5.1.1. COMPARATIVE DETECTION AND PIPELINE METRICS

TABLE 1 Comparative Detection and Pipeline Performance Metrics

Metric	Model A	Model B	Model C	Model D	Improv. (D vs A)	Improv. (D vs C)
Fraud Detection F1-Score (%)	61.4	74.8	82.3	94.7	↑ 54.2%	↑ 15.1%
False Positive Rate (%)	22.4	15.7	10.3	4.1	↓ 81.7%	↓ 60.2%
Cloud Resource Utilization (%)	82.4	67.1	54.6	38.9	↓ 52.8%	↓ 28.8%
Norm. Computational Cost (units)	78.6	59.3	44.1	31.2	↓ 60.3%	↓ 29.3%
FPI Score	0.31	0.47	0.63	0.89	↑ 187.1%	↑ 41.3%

Table 1 confirms systematic improvements across all five performance dimensions. Model D delivers the highest fraud detection accuracy (94.7% F1), the lowest false positive rate (4.1%), and the most efficient Azure resource profile validating the joint optimization objective of Eq. 12.

5.1.2. ERROR AND LATENCY METRICS

TABLE 2 Comparative Error and Latency Performance

Metric	Model A	Model B	Model C	Model D	Improv. (D vs A)	Improv. (D vs C)
Inference Latency (ms)	310	185	112	64	↓ 79.4%	↓ 42.9%
Mean Time to Score (MTS) (s)	38.2	24.1	14.7	5.2	↓ 86.4%	↓ 64.6%
Weekly Throughput (claims/run)	12,100	19,500	28,800	50,200	↑ 314.9%	↑ 74.3%
L_error (F1_opt − F1_fraud) (%)	38.6	25.2	17.7	5.3	↓ 86.3%	↓ 70.1%

Table 2 demonstrates that Model D achieves the fastest scoring time (5.2 s MTS), highest throughput (50,200 claims/run), lowest prediction error (L_error = 5.3%), and lowest batch latency (64 ms). The 314.9% throughput gain over Model A reflects the scalability advantage of the Azure cloud-native architecture with Delta Lake caching and Databricks auto-scaling.

6. CONCLUSION

In insurance fraud prediction, recent advances in machine learning, big data, and cloud computing research engendered rapidly emergent technologies for scalable pipelines that Businesses-to-Businesses-to-Customer (B2B2C) can use in Cloud as a Service (CaaS) environments. One such application considers advanced analytics of potentially fraudulent claims. In this direction, deep learning-based prediction projects are developed with real-world data sourced from the publicly available Kaggle Insurance Fraud Detection dataset. Data is harnessed to generate a distributed and modernized pipeline for fraud prediction models with growing raw data size. Cloud-native graphical orchestration schemes achieve scalable batch processing focused on data discovery, preparation, and document-oriented algorithm assessment. Cloud Web Services display the scoring capability of such a prediction.

Cloud-native Artificial Intelligence (AI) pipelines tailored for businesses in consortium permit economic model deployment and for protecting customer privacy. The scalability of modern frameworks suitable for training and scoring model algorithms is demonstrated, which provides support for software as a service (SaaS) development. Intelligent visualisation matters, yet

appears secondary in a pilot project executed with minimal resource investment. A focus on high data growth rates counsels against time-consuming model tuning and experimentation. Data discovery and preparation preoccupy project effort, while real-world data flaws remain a challenge for AI projects across domains. Cloud-native services available on CyberGrid offer convenient graphical workflow orchestration and remain an added-value topic for future work.

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