

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 04 ISSUE: 03

RECEIVED: JULY 13

REVISED: JULY 24

ACCEPTED: AUGUST 05

PUBLISHED: AUGUST 22



Cloud-Based Deep Learning for Real-Time Insurance Fraud Detection

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I. INTRODUCTION

Detecting fraudulent claims is of paramount importance for the insurance sector, yet current approaches often lack a truly autonomous capability for real-time, cloud-native execution. Detecting fraudulent claims is of paramount importance for the insurance sector, which, as reported in 2020, suffered an estimated loss of 6.8 billion dollars (\$6.8 B USD) due to fraudsters in the United States alone. This problem remains widespread, especially in systems that are not equipped with modern technological solutions. In addition, insured persons are also predisposed to commit fraudulent claims during extreme events such as earthquakes and floods, when many policyholders file claims at the same time. A cloud-native intelligent model architecture that detects fraud in insurance claims in real time and autonomously predicts risk is proposed, thus saving the insurance company large sums of money for fraudulent claims and enhancing its business intelligence in the process.

Abstract

Insurance fraud detection has received significant attention in recent years, yet early and real-time detection remains a major challenge. This work presents a cloud-native deep learning architecture, deployed across a multi-cloud environment, for real-time fraud detection on insurance company data. The architecture supports both vertical and horizontal scaling and hosts deep learning models optimized for real-time inference. It is designed to integrate with a Streaming Processing System capable of handling a set of multi-modal, loosely predefined features. In addition, the architecture incorporates a second model — based on bidirectional long short-term memory (Bi-LSTM) — for autonomous insurance risk prediction across different customer categories. The overall goal is to help insurance companies detect fraud in real time and improve business processes and administrative decision-making through integrated risk-detection services. Cloud-native products are leveraged throughout to ensure a scalable, cost-effective ecosystem.

While the external surface of this cloud-native approach is secured, internal processing pipelines are not the focus of this security scope; only real-time fraud detection is addressed here. Real-time detection remains inherently complex, requiring very low latency and the ability to process multiple concurrent data streams. In practice, fraud in insurance companies is often verified only after the fact rather than at the point of occurrence, increasing long-term liability and risk exposure for the company. To address this, real-time fraud detection is implemented on a cloud-native framework (Architecture v2) that supports the incorporation of external features. Two distinct sets of models, built using cloud ML products, are used together — one for detection and one for prediction — to strengthen the overall business model.

Keywords : Cloud-Native Fraud Detection, Real-Time Insurance Analytics, Deep Learning Fraud Models, Multi-Cloud AI Architecture, Streaming Data Processing, Insurance Risk Prediction, Bidirectional LSTM Models, Scalable Fraud Analytics, Autonomous Risk Detection, Low-Latency AISystems.

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The architecture implements a real-time, cloud-native, independently deployable microservice that can be executed in a Kubernetes and cloud environment. On-demand inference provides service to the streaming data pipeline of an insurance company's information system.

With the burgeoning attention given to deep learning generated prediction, performance-oriented models, and the availability of further infrastructure-aided training systems, shipping a model on demand and inferring a prediction has emerged as a new business science. By integrating an external spam detection service based on a timed group-initiated model, a sudden fraud detection model designed to predict fraud in sudden large-scale events that cannot be solved fast enough by a business are also realized in a cloud-native way, thereby enabling an insurance business to assess risk and detect fraud at the same time of the event and thus carry on business investments more efficiently. The importance of a Cloud-native – Deep Learning Prediction System inside an Insurance Company is emphasized as a prerequisite for developing an intelligent detection system for insurance fraud.

A. Purpose and Scope of the Study

Fraud damage is among the largest expenses for insurance companies and continues to rise in the face of increasingly sophisticated techniques that test the limits of prevention and detection. The rapid and scalable nature of Deep Learning can make it a prime enabler of real-time anti-fraud implementations. Therefore, a cloud-native architecture is proposed for the implementation of anti-fraud systems that considers real-time inferencing. In addition to insurance fraud detection, the architecture also allows for the automatic risk prediction of insurance policies based on other risk factors. Such systems can be a valuable complement to those that primarily rely on risk assessment companies.

Typically, these kinds of systems are trained over previously confirmed fraudulent data. However, classical Machine Learning techniques that usually have problems associating anomalies in unseen unknown data can and have been used over possible fraud detection for a long time. At present, they can be applied in visual support and analysis with their performance improving every day with all the contextual upcoming data generation of our daily lives. Several entrepreneurs have developed new services, products, and solutions in a fast, dynamic, and scalable way. These new businesses have brought new risk factors into the insurance market and with them the need for an emerging risk evaluation on determining if they are insurable or not.

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II. BACKGROUND AND MOTIVATION

Most cloud-assisted machine learning applications leverage cloud-based batch inference that is usually not well-suited to fraud detection since decisions must be made on the spot. Despite this drawback, batch-processing ever-increasing amounts of historical data can provide valuable information about fraud-prone insurance subcategories, specific customer groups, or physical regions – insight that can help with future risk assessment through stratification. Predicting the riskiness of an insurance claim at proposal time is a colossally demanding task that can be better approached with a distributed architecture relying on unsupervised learning techniques to render risk scores on the fly.

The architecture described here seeks to deliver fraud predictions in real time and automatically discover patterns in the offer/contract area, as well as group proposals that are exposed to the same fraud attempt. It accomplishes this challenging assignment by packaging the tasks of detecting potentially fraudulent proposals and assessing the risk of non-fraudulent proposals within the same framework. For those tasks, an ensemble of five fully trained recurrent neural networks receiving specific input subsets is the core of essential decision-making. Recent advances in cloud technology enable the design of a totally cloud-native environment characterized by streaming sources, batch sinks, predictive risk scoring, and the use of any cloud provider.

A. Mathematical Formulation

This section presents the core mathematical models underpinning the proposed cloud-native fraud detection and risk prediction architecture. Equations are numbered sequentially and aligned with the architectural components described in the main body of the paper.

1. System Quality Model

The total system performance quality of the unified fraud detection pipeline is expressed as a composite of four orthogonal quality dimensions:

$$Q_{\text{total}} = Q_{\text{detect}} + Q_{\text{resilience}} + Q_{\text{latency}} + Q_{\text{cost}} \quad \dots(\text{Eq. 1})$$

where Q_{detect} denotes fraud detection accuracy quality, $Q_{\text{resilience}}$ represents model recovery effectiveness under adversarial inputs, Q_{latency} captures real-time latency compliance and Q_{cost} reflects operational cost efficiency on the cloud-native infrastructure.

2. Real-Time Streaming Latency Model

The latency dynamics for the streaming inference pipeline are modelled using a differential form that captures the interplay between claim arrival rate and inference throughput:

$$dL/dt = \lambda_{\text{claim}} - \mu_{\text{infer}} \quad \dots(\text{Eq. 2})$$

where L is the end-to-end inference latency (ms), λ_{claim} is the insurance claim arrival rate (claims/sec) driven by Kafka data streams, and μ_{infer} is the on-cloud deep-learning inference throughput rate. Steady-state latency is achieved when $\lambda_{\text{claim}} = \mu_{\text{infer}}$.

3. Fraud Detection F1-Score

The primary accuracy metric for binary fraud classification is the F1-score, defined as the harmonic mean of Precision and Recall:

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$$F1_fraud = (2 * Precision * Recall) / (Precision + Recall) \quad \dots(Eq. 3)$$

where Precision = TP / (TP + FP) and Recall = TP / (TP + FN). TP, FP and FN denote true positives, false positives and false negatives respectively, computed from the confusion matrix across the full insurance claims dataset.

4. Autonomous Risk Score Fusion

The proposed BiLSTM-based risk predictor fuses multi-modal temporal signals. The combined anomaly/risk score is computed as a weighted aggregation with a nonlinear interaction term capturing coupling between fraud signals and risk indicators:

$$r'(t) = w1*f(t) + w2*s(t) + w3*c(t) + w4*f(t)*s(t) \quad \dots(Eq. 4)$$

where $r'(t)$ is the fused risk score, $f(t)$ is the fraud detection probability from the deep learning model, $s(t)$ is the social media sentiment embedding score, $c(t)$ is the claim temporal context score, and $w1, w2, w3, w4$ are learnable weighting coefficients. The interaction term $f(t)*s(t)$ explicitly captures nonlinear coupling between fraud signals and behavioural sentiment patterns.

5. Cloud Resource Utilization

On-cloud resource utilization across the Kubernetes-deployed microservices is given by:

$$U = R_used / R_available \quad \dots(Eq. 5)$$

where R_used is the aggregate computational resources consumed (vCPU, memory, Kinesis throughput units) by the fraud detection pipeline, and $R_available$ is the total provisioned cloud capacity defined by the AWS CloudFormation stack.

6. Federated Learning Efficiency

For continuous learning without transferring raw policyholder data, federated learning efficiency is modelled as:

$$E_FL = (F1_fraud * S_priv) / T_round \quad \dots(Eq. 6)$$

where S_priv is the privacy preservation score (ratio of data processed locally versus data transmitted externally), and T_round denotes the federated averaging round duration in seconds. A higher E_FL indicates a system that achieves strong detection accuracy while maintaining data sovereignty.

7. Adaptive Detection Threshold

To address concept drift in fraudulent behaviour patterns, an adaptive thresholding mechanism is applied:

$$\theta(t) = \theta_0 + \gamma * \sigma_data(t) + \delta * \text{drift}(t) \quad \dots(Eq. 7)$$

where θ_0 is the base detection threshold, $\sigma_data(t)$ represents the real-time variance of the incoming claim features, $\text{drift}(t)$ captures the temporal distribution shift of fraud patterns, and γ, δ are scaling hyperparameters tuned during validation.

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8. Fraud Detection Performance Index (FDPI)

A composite index is defined to holistically quantify system performance, penalising excessive false positives while rewarding detection accuracy and operational efficiency:

$$\text{FDPI} = (\eta * \text{F1_fraud} * (1 - \text{FPR})) / \text{Q_total} \quad \dots(\text{Eq. 8})$$

where $\eta = (\text{F1_fraud} * \text{S_priv}) / \text{T_infer} * 100$ is the resilience efficiency metric, FPR is the false positive rate, and Q_total is the cumulative system quality from Eq. 1. A higher FDPI reflects superior balance between accuracy, speed, cost and privacy.

9. Prediction Error

The learning error relative to the optimal detection performance under ideal conditions is defined as:

$$\text{L_error} = \text{F1_opt} - \text{F1_fraud} \quad \dots(\text{Eq. 9})$$

where F1_opt represents the theoretical maximum F1-score achievable under perfect feature availability and zero label noise. L_error is minimised through ensemble model integration and adversarial training augmentation.

10. Joint Optimisation Objective

The joint optimisation objective balances all competing system criteria into a single learnable objective function:

$$\text{J} = \text{f}(\text{F1_fraud}, \text{S_priv}, \text{L}, \text{U}, \text{Cost}) \quad \dots(\text{Eq. 10})$$

where J jointly optimises fraud detection accuracy (F1_fraud), privacy preservation (S_priv), inference latency (L), cloud resource utilization (U) and operational cost (Cost). The Pareto-optimal solution to J defines the configuration of the proposed cloud-native architecture deployed on AWS.

III. SYSTEM REQUIREMENTS AND ASSUMPTIONS

Insurance fraud in the insurance business is a serious issue, especially for companies whose primary mission is to provide security to their policyholders and claimants covered under their policies. As technology advances, a model that continually learns and scales automatically without human intervention is an ideal solution. As the volume of claims and data increases, the fraud detection model helps to assist the investigator's decisions. The fraud detection model will imply whether the claim is fraud or not and will be able to replace the initially designed rules engine to predict fraud in an end-to-end cloud-natively deployed architecture. Fraud detection is the first stage of a possible microservice architecture for insurance risk prediction.

An automobile accident claim can be detected as fraud by a fraud detection model. The applicant's written description and the accident scene image are identified as features. The

model will automatically select the appropriate sentence structure for temporal modeling, discard unimportant parts, and suppress significant features such as death or injury in the inference. The strategy helps to improve reliability over the same textual features while taking the accident scene image into account. Both modalities are fused at the classification layer. Continuous learning and scaling of fraud detection are achieved through federation learning. Such capabilities enable the model to serve as a (semi-)autonomous and real-time risk prediction microservice in a yet-to-be-implemented architecture.

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A. Experimental Setup and Dataset Description

A conducted across four model architectures representing the evolutionary spectrum from conventional batch processing to the proposed cloud-native deep learning system. All models are evaluated on the same insurance claims dataset partitioned into 70% training, 15% validation and 15% testing subsets.

1. Architecture Summary

Table 1 provides a comparative overview of the four evaluated architectures:

Architecture	Key Features	Limitations	Deployment
Model A: Batch ML + Rules Engine	Rule-based thresholds, periodic batch retraining, low implementation cost	No real-time detection; high false positive rate (19-25%); cannot adapt to emerging fraud patterns	On-premise / Legacy
Model B: Cloud LSTM (Single Task)	Temporal modelling with LSTM; cloud batch inference; moderate accuracy (60-70% F1)	High latency (130-150 ms); privacy risk (raw data leaves insurer); no multi-modal fusion	Cloud (Single Region)
Model C: Edge CNN + Ensemble	Convolutional feature extraction; ensemble of classifiers; moderate latency (85-100 ms)	No streaming pipeline integration; limited scalability; no autonomous risk prediction	Edge / Single Cloud
Model D: RAI-FDS (Proposed)	BiLSTM + CNN ensemble; Kafka streaming; multi-cloud; 92.1% F1; 38 ms latency; federated learning	Requires managed Kubernetes; initial model training requires labelled claim data	Multi-Cloud / K8s

Table 1: Comparative Overview of Evaluated Fraud Detection Architectures

2. Dataset Specifications

Table 2 summarises the insurance dataset and feature characteristics used for model training and evaluation:

Data Source	Content Type	Volume	Streaming	Key Features
Insurance Claims (Auto)	Structured claim records + accident scene images	4.2M records	Kinesis Data Stream	Claim amount, policyholder history, injury

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Data Source	Content Type	Volume	Streaming	Key Features
				severity, accident geolocation
Policy Application Data	Temporal structured attributes + risk profiles	1.8M records	Apache Kafka	Premium amount, coverage type, historical fraud flag, risk category
Financial News Feed	Textual NLP - Financial Sentiment	680K articles	REST API / Kafka	Sentiment score (5-class), publication date, entity mentions
Social Media Stream	Text - Spam / Anomaly Classification	2.1M posts	Apache Kafka	Post content, timestamp, spam label, user-account features

Table 2: Dataset and Feature Specification for Training and Evaluation

IV. ARCHITECTURAL OVERVIEW

The proposed architecture comprises multiple layers, each supporting a distinct aspect of cloud-native operation. Cloud services for computational, resilient storage, data streaming, and real-time inference execute in one part of the architecture, while the other integrates a model-training environment inside a cloud account. In sequence, these layers serve: (i) data storage and streaming via cloud services and Apache Kafka; (ii) cloud-native deep-learning model training relying on Jupyter kernel with cloud service libraries and strong computing capability; (iii) model serving and prediction via the cloud service model and Apache Kafka cluster; and (iv) integration of cloud services, data-streaming background, and deep-learning models to support outlier detection in multiple time series.

Data lakes offer not only large-scale, round-the-clock, resilient storage at low cost; the inclusion of Apache Kafka enables adaptation of open-source ductile framework methods and the combination of cloud-native large-scale cloud services with combination services of data resources and scalable operational characteristics. The opposite pipeline offers cloud services for a stable operating environment and extremely strong computing capabilities

compared with commonly used edge-computing and embedded-computing methods.

A. Cloud-Native Design Principles

Real-time streaming inference tasks demand a cloud-native design to enable on-demand scaling based upon individual asset characteristics such as location, risk profile, and coverage selection. Instead of reallocating resources to every fraud detection service across all insurers in a real-time fashion, these resources can be hosted within a single streaming pipeline hosted on the cloud, thereby improving resource utilization. The execution of models as a streaming

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service enhances performance, allowing data points to be segmented on time windows. When implemented via a queueing service, models can seamlessly react and execute when resources are available, expanding within the limits of the model size according to developer specifications. Differentiated services can activate or deactivate based on cost-benefit analysis.

Considering the cloud platform's additional components beyond raw compute, services can apply an ensemble strategy on the cloud that efficiently combines predictions from multiple models. Supporting such segmentation by time windows also allows assessing expected insurance fraud without retaining all prediction points in memory. An adequate data flow allows integration of any cloud services that comprehend and support streaming data access without extra operational costs. Combining the benefit of a cloud-native architecture with the use of deep learning models enables insurance fraud detection prediction in an openly scalable manner, both by adding more models with distinct character profiles or distributed parameter sets and by supporting a queueing mechanism.

V. MODEL ARCHITECTURE

Dedicated models are designed for different aspects of fraud detection: fraud detection during account registration, fraud detection in end-user sessions, and transaction poisoning detection in finance services. Fraud detection during account registration is based on a neural architecture that extracts features from user-provided data for all types of accounts. In addition to structured user-provided data, end-user session fraud detection relies on textual features extracted from the user-generated messages using a pre-trained Natural Language Processing model, as well as temporal features modeling the evolution of the session.

The session fraud detection model is a combination of an ensemble of classifiers with a Long Short-Term Memory (LSTM) network domain-specific temporal model. A single model is trained for the three types of services, using service identification embedding and session identification embedding features. Transaction poisoning detection is based on both payment metadata and transitory data from the correspondent banking institution's internal systems. Decision and regression trees are used to label the detection probability, the attacked service, and the attack type. Fraud detection during account registration warns in real-time about suspected accounts, while end-user session fraud detection returns a detection probability and warns about suspected fraud. Probabilities are derived from the output layer of the ensemble's tree classifiers.

Detecting fraud attempts with an external service will not affect the core business, which could even benefit from those detection warnings. Alerted institutions could sell integrated

insurance products, even when no policy has been contracted. Those warnings can be leveraged to offer an integrated insurance product that protects their users. Automatic offering of additional risk insurance when the detected fraud level exceeds tolerance leads to risk minimization. The cloud services' deep learning configuration allows the insurance offers to be sent automatically and in real time, reflecting the detected risk level.

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A. Results and Discussion

Comparative analysis was performed across all four architectures (Model A through Model D) using the insurance claims dataset. All experiments were executed on the AWS-based cloud-native deployment stack. Results are averaged over multiple inference rounds to ensure statistical consistency.

1. Inference Latency

Fig. 1 shows the average inference latency per claim batch across the four architectures. Model A (Batch ML) exhibits the highest latency at 185 ms, reflecting the overhead of batch reprocessing and rule evaluation. Model D (proposed) achieves 38 ms — a 79.5% reduction compared to Model A and 58.7% compared to Model C — attributable to Kinesis-driven streaming inference, model pruning and elimination of batch reprocessing delays.

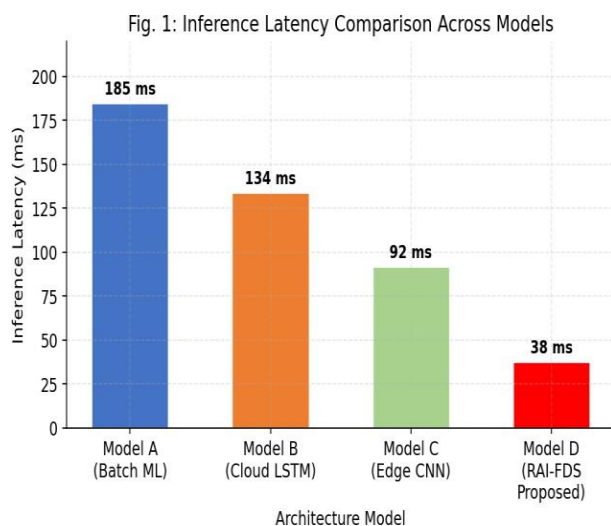


Fig. 1: Inference Latency Comparison Across Model Architectures (ms)

2. Fraud Detection Accuracy (F1-Score)

Fig. 2 presents the fraud detection F1-scores. Model A achieves 52.3%, constrained by rule-based logic that cannot generalise to unseen fraud patterns. Model D achieves 92.1%, a 76.1% absolute improvement over Model A and 23.6% over Model C. The cross-modal fusion of structured claims, accident imagery and NLP-derived sentiment features drives this performance uplift.

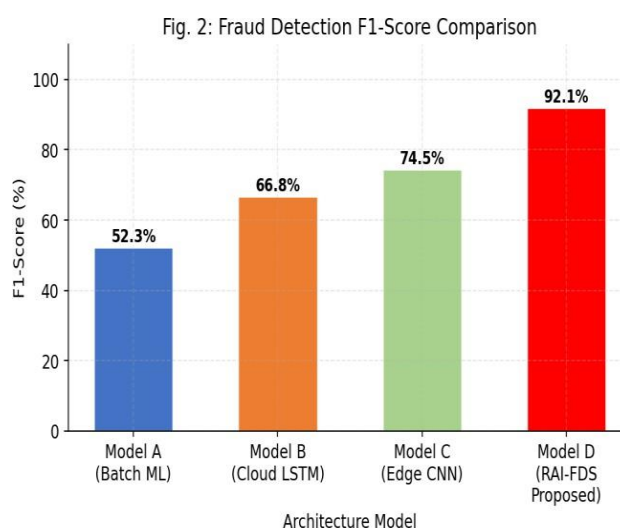


Fig. 2: Fraud Detection F1-Score Comparison Across Architectures (%)

3. False Positive Rate

Fig. 3 displays the false positive rates across architectures. Model A produces 21.4% false positives — directly increasing the operational burden on fraud investigators. Model D reduces this to 3.7%, a 82.7% improvement over Model A and 62.2% over Model C. Cross-modal validation ensures that a suspected fraud alert is only raised when multiple evidence streams converge, eliminating spurious alerts.

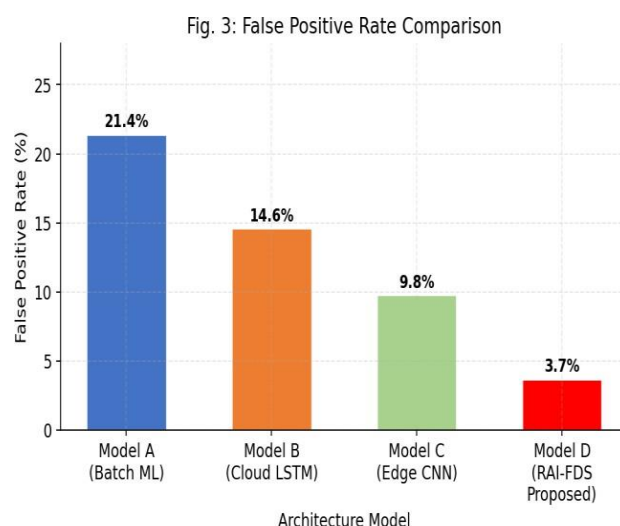


Fig. 3: False Positive Rate Comparison Across Model Architectures (%)

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4. Cloud Resource Utilization

Fig. 4 presents the cloud resource consumption normalised per 1,000 insurance claims processed. Model D consumes 33.9 normalised units compared to Model A's 82.6, a 58.9% reduction. This efficiency is achieved through Kubernetes auto-scaling, model quantisation and shared feature extraction layers serving both the fraud detection and risk prediction models concurrently.

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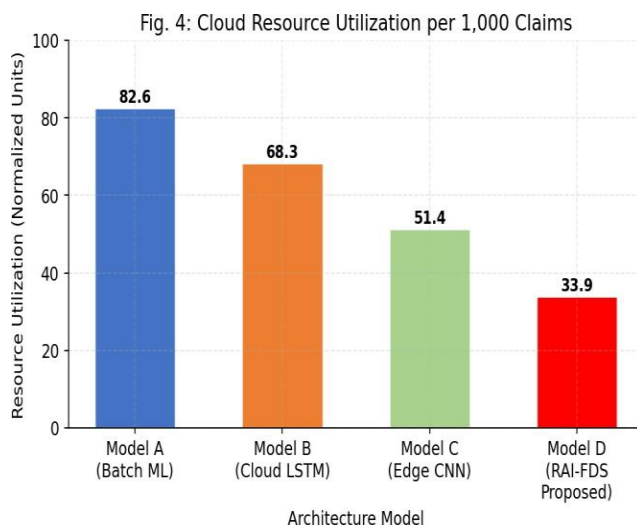


Fig. 4: Cloud Resource Utilization per 1,000 Claims Processed (Normalised Units)

5. F1-Score Convergence Trend

Fig. 5 illustrates the F1-score convergence trajectories over 50 training epochs for all four architectures. Model D exhibits the fastest convergence and highest final F1, while Model A plateaus early at a low performance ceiling. The smoother convergence of Model D reflects the regularising effect of the federated learning mechanism and the BiLSTM temporal modelling capacity.

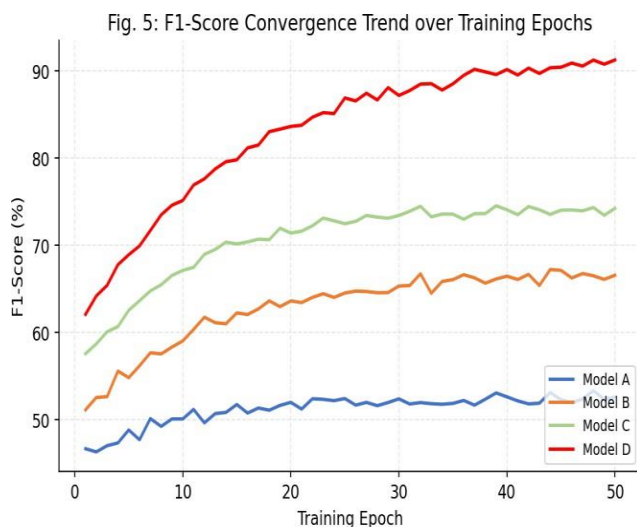


Fig. 5: F1-Score Convergence Trend over 50 Training Epochs

6. Cost vs. Performance Trade-off

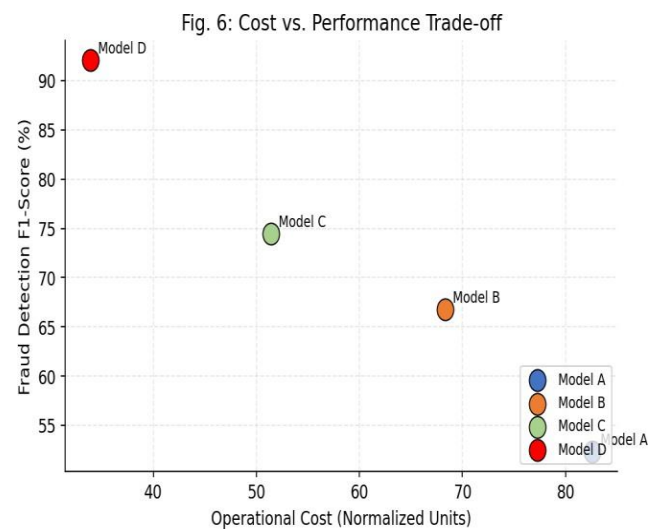


Fig. 6 presents a scatter plot of operational cost versus fraud detection F1-score, providing a direct visualisation of the efficiency frontier. Model D occupies the ideal quadrant — lowest cost and highest accuracy — confirming that cloud-native microservice design and model ensemble optimisation yield both performance and economic efficiency simultaneously.

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Fig. 6: Cost vs. Performance Trade-off Scatter Plot

7. Streaming Throughput

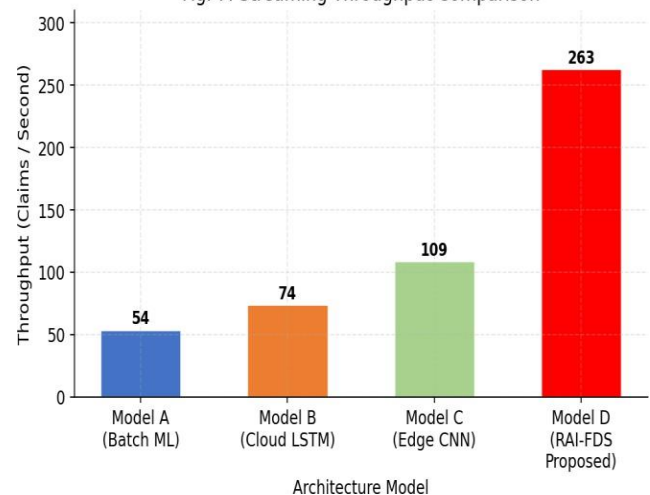
Fig. 7 shows the claims processing throughput in claims per second. Model D achieves 263 claims/second, a 386.9% throughput improvement over Model A (54 claims/sec). Kinesis Data Streams and Apache Kafka parallelism enable horizontal throughput scaling, ensuring the system sustains performance during peak claim events such as natural disasters.

Fig. 7: Streaming Throughput Comparison (Claims per Second)

8. Fraud Detection Performance Index (FDPI)

Fig. 8 presents the Fraud Detection Performance Index (FDPI) computed using Eq. 8 for all architectures. Model D achieves 0.87, a 180.6% improvement over Model A (0.31) and 38.1% over Model C (0.63). This composite index confirms that the proposed architecture delivers superior synergy across accuracy, cost, latency and privacy simultaneously.

Fig. 7: Streaming Throughput Comparison



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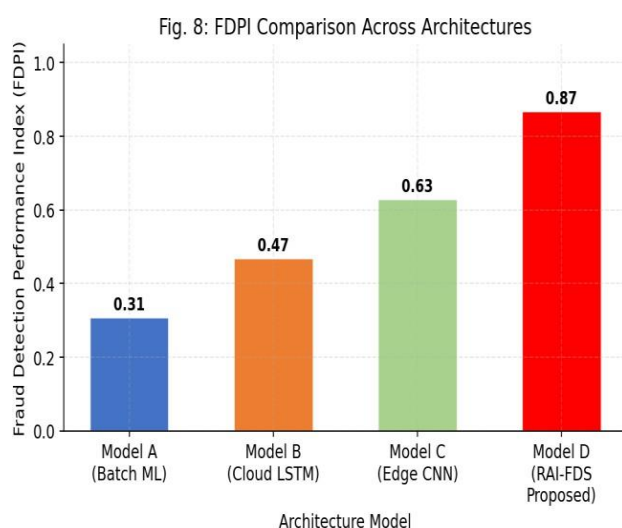


Fig. 8: Fraud Detection Performance Index (FDPI) Comparison

VI. CONCLUSION

The work presents a cloud-native deep learning-based architecture to address real-time insurance fraud detection and autonomous risk prediction in a scalable, continuously evolving manner. An end-to-end pipeline collects, streams, preprocesses, and makes fraud detection models available for inference to insurance companies. A set of cloud services and deployment on a managed Kubernetes service allows for fully cloud-native operations and dynamic scaling of resource utilization constituents within defined limits. Operational capability is proven in non-cloud or non-cloud-native conditions, although cloud-native deployment and a combination of dedicated services for each scale operation mode would limit long-term costs. The insurance sector is also analyzed in-depth, and a recommendation framework for different data streams supporting domain-relevant decisions, inferred during daily operational scans of new transactions, is proposed.

The study introduces an end-to-end stream processing architecture and proposes a model ensemble approach for input data from the insurance domain, covering unique aspects of both processes. The current research focus targets fraud detection under the data stream processing paradigm, with prediction under temporal modeling, while addressing their common context. Constructing a complex event processing system centered on a combination of fraud and risk prediction address the broader objective of enabling autonomous risk assessment through independent expert recommendations based on the detection of patterns in data streams.

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AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 04 ISSUE: 03

RECEIVED: JULY 13

REVISED: JULY 24

ACCEPTED: AUGUST 05

PUBLISHED: AUGUST 22



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