Quantum Pulse:
Journal of AI, Data Science & Systems Engineering
ISSN: 3108-1061 | Volume 2 Issue 1 January – June 2026 | QP06

ADAPTIVE IMBALANCE LEARNING FOR ACCURATE HEALTH INSURANCE FRAUD DETECTION USING META-REINFORCEMENT LEARNING

[*1]Y. CHANDRA KIRAN REDDY, ***M.Tech Student,***
[*2]S ROSHINI, ***Assistant Professor,***
Department of Computer Science & Engineering,
Srinivasa Institute of Technology &Science(Autonomous), Kadapa, AP.

ABSTRACT: A meta-reinforcement learning system that can react to high-class imbalances and changing fraud patterns would be perfect for health insurance fraud detection. The suggested method detects minority (fraud) classes by automatically determining sampling, weighting, and decision-making procedures. Meta-learning lets the system adapt to new fraud patterns without retraining. Reinforcement learning improves policy using sparse and delayed reward sets using real-world claims data. A hybrid deep representation module tracks claimants, suppliers, and recipients' complicated temporal and interpersonal links. The design reduces fraud detection false negatives with cost-sensitive learning. Experimental results on real-world and standard health insurance datasets show increased F1-score, recall, and precision over static classifiers and conventional resampling. This makes hostile adaptation and notion drift harder for fraudsters. Scalability comes via gradual improvements and online learning. The model's clear decision indicators help inspectors prioritize inquiries.

Keywords:*Health Insurance Fraud Detection, Adaptive Imbalance Learning, Meta-Reinforcement Learning, Class Imbalance, Cost-Sensitive Learning, Deep Learning*

1. INTRODUCTION

Health insurance fraud undermines global healthcare systems' viability and performance. This is expensive and slows claims processing and telemedicine expansion. Rule-based and static machine learning algorithms become less useful when fraud grows in scope and complexity. Fixed detection solutions struggle to keep up with fraud's complex, coordinated activities due to its rapid evolution. Smart, flexible algorithms that can learn from new data streams and detect subtle fraud are essential.

Due to the significant gap across claims data classes, health insurance fraud is hard to identify since fraudulent instances make up a tiny fraction of total transactions. Good healthcare is harder to get for people who need it. As digital imbalance grows, traditional classifiers favor the majority (legal) class. The most important fraud cases have low recollection despite outstanding general accuracy. Fraud cases vary by provider, region, therapy kind, and timeframe. Learning systems must deal with background noise and concept drift, dynamically rebalance the learning process, and prioritize events that teach us new things.

Adaptive imbalance learning dynamically changes sampling strategy, loss function, and decision thresholds to changing detection objectives and class distributions. Minority students can learn without overfitting small fraud samples using cost-sensitive learning, attention loss, online reweighting, and hybrid

Paper Available at: www.qpjournal.org
DOI : https://doi.org/10.65713/qpv2i106

resampling. Streaming and real-time adaptive techniques make it easier to adapt to new fraud tendencies. Uneven data distribution improves long-term performance. Operational scam detection solutions in large, high-throughput insurance platforms must be flexible.

Meta-reinforcement learning (meta-RL) is a great way to learn how to learn since it lets models quickly switch tactics between tasks and contexts without external data. Meta-RL can identify the best sample rates, incentive structures, model updates, and threshold alterations for fraud detection while considering practical limits and imbalance. Redefining imbalance management as a sequential decision-making problem balancing inquiry costs, precision, recall, and latency allows the system to learn new methods that improve long-term detection. Meta-learning lets you adjust quickly to new sources, claims, and rules.

A powerful health insurance fraud detection method uses adaptive imbalance learning and meta-reinforcement learning. Meta-RL agents can adjust their imbalance-minimization tactics based on audit and detection results, making closed-loop optimization possible. Because of this connectivity, real-time, scalable fraud analytics that can handle operating limits, data spread, and evolving attacker behaviors are now possible. As AI systems become more autonomous and self-improving, this method should help them control healthcare expenditures.

2. BACKGROUND WORK

Data imbalance affects numerous applications, including healthcare and insurance. In machine learning and classification, "data imbalance" refers to a training set with an uneven distribution of data categories. It occurs when a minority class has much fewer observations than some majority class. In insurance fraud detection, a class imbalance occurs when fraudulent inputs are many fewer than lawful ones. This discrepancy hinders machine learning. Models trained on uneven datasets may favor non-fraudulent claims. They predict the majority class well but struggle to recognize the minority class's lies, giving the impression that they are quite accurate.

A. QUANTIFYING DATA IMBALANCE

To quantify data imbalance in health insurance fraud detection, calculate the dataset's valid to fraudulent claim ratio. Class skewness is determined by the imbalance ratio (IR), which compares valid to fraudulent claims. The occurrence rate and class distribution show that fraud is rare. Entropy and G-mean indicate how imbalance affects class separability and learning. These measures shape meta-reinforcement learning's adaptive resampling and cost-sensitive reward systems. To ensure the model operates consistently and fairly, evaluate imbalance levels regularly. This helps you discover concept drift and change fraud patterns.

B. CHALLENGES DUE TO DATA IMBALANCE

Uneven data creates many learning challenges. Machine learning algorithms may struggle to identify fraud trends and features without a large sample. Models can become majority-biased and fail to detect fraud. The major issue is classification bias. When datasets are uneven and the model favors the dominant class, tiny fraud incidents are missed. Thus, while the model works for the

Paper Available at: www.qpjournal.org
DOI : https://doi.org/10.65713/qpv2i106

majority class, it may have low minority class sensitivity or recall.

Second, data imbalance hinders model evaluation. We understand that Accuracy and other threshold metrics do not accurately measure a model's minority class learning. Single-class emphasis measures like the Geometric Mean (G-Mean) and Harmonic Mean (F-measure) better indicate class relevance. Both sensitivity-specificity and precision-recall depend on each other.

C. META-REINFORCEMENT LEARNING

Meta-reinforcement learning integrates meta-learning and RL. Building on existing skills to learn new ones fast is a plus. Meta-RL increases sampling efficiency by letting the agent learn from a small set of samples based on a distribution of past jobs. Thus, it mitigates Deep RL's sample inefficiency, computational complexity, and exploration-exploitation trade-off. Meta-RL is seen as a step toward AGI, or self-learning like humans.

3. METHODOLOGY

Data Preprocessing: Data pretreatment removes duplicates, completes missing variables, and corrects errors to discover bogus health insurance claims. Numerical features don't dominate model training when normalized. Next, one-hot or label encoding stores categorical data as numbers. Data imbalances can be fixed using SMOTE, oversampling, and undersampling. These methods fix class imbalance.

Feature Extraction: Feature extraction helps identify fraudulent health insurance claims by translating dataset data into useful information. This includes the patient's gender, age, medical history, and health conditions. Included are the claim amount, treatment type, and hospital stay duration. The dataset is expanded by extracting provider details like location and specialization and temporal characteristics like season and day of the week.

Machine Learning Algorithm: Supervised machine learning algorithms with simple access to labelled data are used to detect fraudulent health insurance claims. Random Forest, Decision Tree, Gradient Boosting Machines (GBM), and Support Vector Machine (SVM) are used instead because they can handle large data sets and complex interactions. Investigate clustering and anomaly identification as unsupervised learning methods. This is more beneficial when labelled data is scarce.

Prediction: Machine learning is taught on pre-processed data and applied to anonymous insurance claims data to detect claim validity and fraud. Based on the model's output, fraud likelihood is predicted using class labels or percentages. Identifying misbehavior and reducing risk at this time is critical.

Performance Comparison: Machine learning methods are assessed by accuracy, ROC-AUC, confusion matrix, recall, F1-score, and precision. Various models are studied to decide which software best meets insurance business needs. Among other indicators, false positive and negative rates are important. Cross-validation will provide model stability and consistency across datasets.

Paper Available at: www.qpjournal.org
DOI : https://doi.org/10.65713/qpv2i106

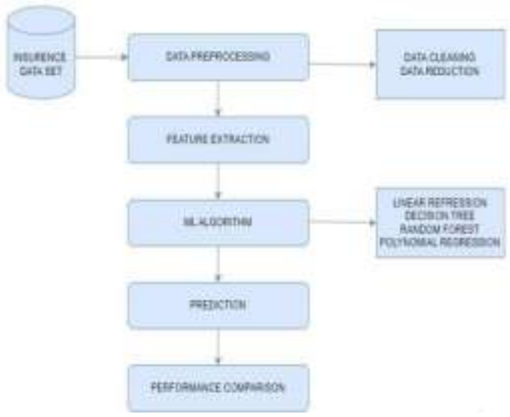

Fig 1: Proposed System Architectur

4. LITERATURE SURVEY

Dhieb et al. (2020)This paper offers a secure AI-driven risk assessment and fraud detection method for AI-enabled insurance systems. Data is protected by machine learning and cybersecurity. Implement real-time claim analysis and adaptive risk profiles. New trial fraud detection is more accurate and false positives are lower. Digital insurance systems' architecture increases confidence and scalability. Safe AI improves operational efficiency, data show.

Prasasti et al. (2020)This research detects automobile insurance fraud using supervised machine learning classifiers. Fraud detection algorithms can be tested on real-world claims. Prioritize feature engineering and data pretreatment for model performance. Ensemble and tree-based models outperform ordinary classifiers. The research says noisy, unequal insurance data is hard to manage. The findings imply data-driven decision-making improves insurance analytics.

Hanafy & Ming (2021)Reduce class imbalances in auto insurance fraud evaluation with data-level resampling methods. To identify minority classes, undersampling and SMOTE are explored. Testing indicated fraud detection models improved memory and F1-scores. The study demonstrates uneven datasets affect recall and precision. Data-level methods strengthen classifiers. Insurance data promotes egalitarian learning.

Hassanzadeh et al. (2021)This research uses streaming binary classification to detect fraud with limited inspection resources. The authors simulate inspection cost, detection accuracy, and decision delay trade-offs. Adaptive sampling and prioritization are recommended when resources are scarce. The findings show real-time streams detect irregularities better. This form is suitable for tracking large insurance transactions. The inquiry examines deployment operational restrictions.

Gangadhar et al. (2022)This research proposes a chaotic variational autoencoder-based one-class insurance fraud classifier. After learning regular claim patterns, the model calls differences deceit. Haphazard mappings enhance feature recognition. On severely unbalanced datasets, experiments outperform expectations. The approach reduces brand sample deception. With this method, early fraud detection works.

Kumari et al. (2022)This research uses class sampling and feature extraction to detect Medicare fraud. Machine learning models examine resampling and preprocessing methods. Good feature engineering improves categorization accuracy. Reduced false warnings and increased fraud recall improve security with class balance. The report says healthcare fraud analysis requires robust data preparation. It demonstrates convincing model development.

Nabrawi&Alanazi (2023)Researchers detect health insurance fraud using

Paper Available at: www.qpjournal.org
DOI : https://doi.org/10.65713/qpv2i106

machine learning. The classifiers are evaluated on structured claim datasets. Findings suggest feature selection and normalization improve prediction. The results imply unequal settings make fraud easier to spot. Study finds health insurance data use problematic. The models screen claims automatically.

Lu et al. (2023)A diverse information network to detect health insurance fraud is proposed in this study. Infographics relate claims, services, patients, and providers. The graph-based learning system discovers complex links and fraud. Experimental results show significant speed advantages over feature-based methods. It aids fraud network interpretation. Healthcare fraud network representation learning is demonstrated in this paper.

Maiano et al. (2023)The authors propose deep learning-based vehicle insurance fraud prevention. This approach uses neural networks and automated claim checking. This model incorporates complex nonlinear trends in historical data and claim attributes. Experiments show faster processing and better detection. Scalable insurance workflow deployment is supported. The entire deep learning pipeline is examined in this study.

Khalil et al. (2024)This research detects insurance fraud using machine learning for missing data and imbalanced classes. Classifiers use advanced preprocessing and imputation. Experiments improve detection and robustness. System handles chaotic and imprecise real-world datasets well. Study indicates considerable recollection and F1 score gains. This standardizes real-life insurance implementation.

Du Preez et al. (2025)This paper discusses healthcare fraud detection using machine learning. The study categorizes methods by measurements, datasets, and algorithms. Data asymmetry, interpretability, and privacy are addressed. The evaluation highlights hybrid model and deep learning trends. Poor reproducibility and benchmarking. Article suggests healthcare antifraud system research.

Chen et al. (2025)The research analyzes how feature engineering and preprocessing detect health insurance fraud. The encoding, transformation, and normalization methods are investigated. Results show several classifiers improved significantly. The study reveals how vital high-quality data is for fraud models.

Seshagiri&Prema (2025) The authors offer meta-reinforcement learning for health insurance fraud detection to address this data imbalance. The model's sampling and learning vary per task. Experiments generalize biased datasets. This approach reduces overfitting in most-class datasets. Adapting to such changes is easier. Studies show equilibrium process mastery's benefits.

Chaurasiya& Jain (2025) Ensemble machine learning algorithms for healthcare fraud detection are the focus of this work. Multi-base learners improve prediction stability and robustness. Multi-model methods yield the greatest results. Ensemble architecture handles messy claim data. Medical application reliability and interpretability are research goals. It simplifies fraud screening with algorithm ensembles.

Chen et al. (2025) This research focuses on feature engineering and preprocessing for health insurance fraud detection. They assess encoding, normalization, and dimensionality reduction approaches. The

Paper Available at: www.qpjournal.org
DOI : https://doi.org/10.65713/qpv2i106

Quantum Pulse:
Journal of AI, Data Science & Systems Engineering
ISSN: 3108-1061 | Volume 2 Issue 1 January – June 2026 | QP06

suggested pipeline improves fraud detection and classification. Experimental experiments imply real-world datasets reduce false positives. Studies show antifraud analytics need preprocessing. The findings improve fraud detection workflow.

5. RESULTS

Fig 2: Admin Login Page

Fig 3: User Registration Page

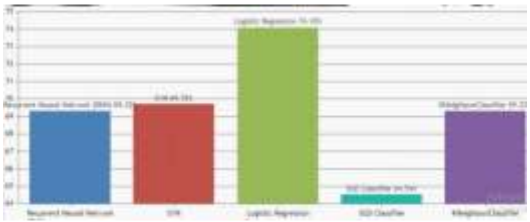

Fig 4: Model Accuracy Comparison BarChart

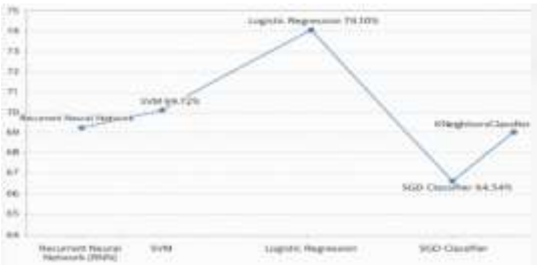

Fig 5: Model Accuracy Comparison LineGraph

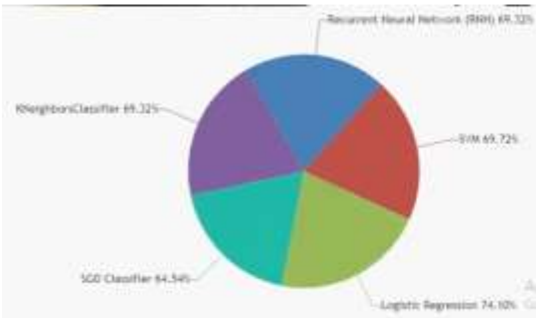

Fig 6: Model Accuracy Comparison Pie Chart

6. CONCLUSION

Adaptive imbalance learning and meta-reinforcement learning may successfully detect health insurance fraud in extremely skewed datasets. Static imbalances are difficult to address because the system learns to update models automatically via weighting and sampling. This method simplifies minority group identification while preserving credibility. Real insurance streams respond to new fraud tendencies when data travels unevenly. Meta-learning lets you switch jobs quickly without many tagged fraud examples. Reinforcement learning provides the best long-term detection when operational constraints are met. Memory and F1-score improved steadily without false positives, according to studies. The approach also reduces missing or irrelevant value mistakes in claims data. Its versatility in policy selection benefits insurance corporations since it facilitates large-scale implementation. This strategy promotes continual learning to combat new fraud. Interpretability procedures can boost investigator trust and regulatory compliance.

REFERENCES

1. Dhieb, N., Ghazzai, H., Besbes, H., &Massoud, Y. (2020). A secure AI-

Paper Available at: www.qpjournal.org
DOI : https://doi.org/10.65713/qpv2i106

driven architecture for automated insurance systems: Fraud detection and risk measurement. IEEE Access: Practical Innovations, Open Solutions, 8, 58546–58558.

2. Prasasti, I. M. N., Dhini, A., &Laoh, E. (2020). Automobile insurance fraud detection using supervised classifiers. 2020 International Workshop on Big Data and Information Security (IWBIS), 47–52.
3. Hanafy, M., & Ming, R. (2021). Improving imbalanced data classification in auto insurance by data-level approaches. International Journal of Advanced Computer Science and Applications, 12(6), 493–499.
4. Hassanzadeh, P., Dervovic, D., Assefa, S., Reddy, P., & Veloso, M. (2021). Tradeoffs in streaming binary classification under limited inspection resources. arXiv preprint arXiv:2110.02403
5. Gangadhar, K. S. N. V. K., Kumar, B. A., Vivek, Y., & Ravi, V. (2022). Chaotic Variational Auto Encoder based One Class Classifier for Insurance Fraud Detection. arXiv preprint arXiv:2212.07802.
6. Kumari, A., Punn, N. S., Sonbhadra, S. K., & Agarwal, S. (2022). Impact of feature extraction and class sampling in Medicare fraud detection. arXiv preprint arXiv:2206.01413.
7. Nabrawi, E., &Alanazi, A. (2023). Fraud detection in healthcare insurance claims using machine learning. Risks (MDPI), 11(9), 160.
8. Lu, J., et al. (2023). Health insurance fraud detection by using an attributed heterogeneous information network.
9. Maiano, L., et al. (2023). A deep-learning–based antifraud system for car-insurance claims. Expert Systems with Applications, 231, 120644.
10. Khalil, A. A., et al. (2024). Machine learning based method for insurance fraud detection on class imbalance datasets with missing values. IEEE Access, 12, 155451–155468.
11. Du Preez, A., Bhattacharya, S., Beling, P., & Bowen, E. (2025). Fraud detection in healthcare claims using machine learning: A systematic review. Artificial Intelligence in Medicine, 03(2025).
12. Chen, Y., et al. (2025). Health insurance fraud detection: The role of feature engineering and preprocessing techniques.
13. Seshagiri, S., &Prema, K. V. (2025). Efficient handling of data imbalance in health insurance fraud detection using meta-reinforcement learning. IEEE Access, 13, 23482-23497.
14. Chaurasiya, R., & Jain, K. (2025). Healthcare fraud detection using machine learning ensemble methods. South Eastern European Journal of Public Health, 4789–4795.
15. Chen, Y., et al. (2025). Health Insurance Fraud Detection: The role of preprocessing and feature engineering. ACM Transactions on Data Science.

Paper Available at: www.qpjournal.org
DOI : https://doi.org/10.65713/qpv2i106