Comprehensive Survey of Artificial Intelligence and Machine Learning Techniques for Automated Medical Claims Auditing and Health Insurance Fraud Detection

Sanika Jagdale[1], Pranita Bhilare[2], Anjali Kakade[3], Shravani Bhagwat[4]

Under the Guidance of
Prof. S.A.Dabhade

SVPM's College of Engineering, Malegaon BK. Baramati, Maharashtra, India.
Department of Computer Engineering

Emails: sanikajagdale0202@gmail.com[1], bhilarepranita88@gmail.com[2], anjalikakade1230@gmail.com[3], shravanibhagwat333@gmail.com[4]

Abstract - Healthcare insurance fraud and inaccurate medical claims create financial losses, slow down valid claim processing, and increase the load of work of claim auditors. Traditional claim review often depend on manually checking documents and predefined rules, which can be difficult to scale when claim volumes are large and documents contain inconsistent or unstructured information. This survey outlines a practical taxonomy of approaches used in automated medical claim auditing, including optical character recognition (OCR), rule-based validation, supervised machine learning, unsupervised anomaly detection, Machine Learning, and explainable artificial intelligence. It discusses how document extraction by OCR and Rule validation can be combined with predictive models to prioritize claims for human review. The paper also compares the strengths and limitations of representative model families and highlights recurring evaluation concerns, particularly class imbalance, limited access to representative labelled data, privacy, interpretability, and generalization across providers and regions. Published reviews already examine machine-learning-based healthcare claims fraud detection; therefore, a useful contribution for a new survey must be a clearly scoped synthesis focused on the interaction between document-level extraction, rule validation, model-based risk scoring, and human audit workflows. The paper concludes with recommendations for transparent evaluation, cautious use of risk scores, and human-in-the-loop decision-making.

Keywords: Medical Insurance Fraud, medical claim auditing, optical character recognition (OCR), anomaly detection, explainable artificial intelligence, Machine Learning

1.INTRODUCTION

Health insurance systems process claims that may include patient information, diagnosis or procedure codes, provider details, policy information, billed amounts, and supporting documents. Errors and fraudulent submissions can occur at different stages, including duplicate billing, inconsistent service information, upcoding, fabricated services, or mismatches between a claim and its supporting evidence. Manual checking remains important, but it can be time-consuming and may not consistently identify complex or repeated patterns across large claim collections.

Artificial intelligence (AI) and machine learning (ML) offer ways to prioritize claims by learning patterns from historical records or identifying observations that differ from expected behaviour. However, fraud detection is not simply a binary classification task. Fraud labels may be incomplete, suspicious cases may be rare, and a model generate false alarms that consume auditor time. Automated decisions therefore require transparent evidence, appropriate thresholds, privacy safeguards, and human review.

This survey focuses on the relationship between document processing and fraud analytics. In an automated workflow, OCR extracts text from scanned documents and PDFs. validation rules check fields and relationships; a machine-learning model estimates risk from structured features; and an auditor reviews flagged cases. The stages can support each other, but OCR errors or inaccurate rules may also propagate into the model.

The purpose of this paper is to organize these

techniques, compare their trade-offs, and identify questions that should guide future systems. This paper reviews existing techniques, compares their advantages and limitations, and identifies areas for future research.It also emphasizes the importance of combining reliable data extraction, transparent risk assessment, and human supervision to support accurate and responsible claim evaluation.

1.1 Objectives and Scope

Objectives

The primary objective of this survey is to examine artificial intelligence (AI) and machine learning (ML) techniques for automated medical claim auditing and health insurance fraud detection. The specific objectives are:

1. To review existing machine learning and artificial intelligence techniques used to identify potentially fraudulent medical and health insurance claims.
2. To examine the role of optical character recognition (OCR) in extracting relevant information from medical bills and supporting claim documents.
3. To study rule-based validation methods for identifying missing information, duplicate claims, inconsistent values, and policy-related discrepancies.
4. To compare supervised learning, unsupervised anomaly detection, and ensemble approaches in terms of their advantages, limitations, and suitability for medical claim auditing.
5. To identify challenges associated with imbalanced datasets, limited labelled data, model interpretability, data privacy, and reliable performance evaluation.
6. To explore how OCR, rule-based validation, machine learning, and human review can be integrated into a transparent medical claim auditing workflow.

Scope

This survey focuses on AI- and ML-based approaches for automated medical claim auditing and health insurance fraud detection. It covers document processing using OCR, rule-based validation of extracted claim information, supervised classification techniques, unsupervised anomaly detection, and ensemble learning methods. It also discusses evaluation metrics, including precision, recall, F1-score, and ROC-AUC, along with challenges related to data quality, class imbalance, privacy, and explainability.

Furthermore, the survey considers a human-assisted auditing workflow in which automated techniques help prioritize suspicious or inconsistent claims for further investigation by authorized auditors. The scope is limited to reviewing existing approaches and identifying research opportunities for their integration. It does not claim to establish the effectiveness of a particular algorithm or system without supporting experimental evidence.

2. BACKGROUND AND RELATED WORK

Previous studies have investigated artificial intelligence and machine learning techniques for detecting fraud in healthcare and insurance claims. Iqbal, Abd-Alrazaq, and Househ presented a scoping review of AI applications in healthcare fraud detection [1], while du Preez and colleagues reviewed machine learning approaches for healthcare claims fraud detection [2]. Other studies have explored different machine learning classifiers and AI-based approaches for identifying insurance fraud [3], These studies provide a foundation for understanding existing detection methods, their advantages, and their limitations. Building on this research, the present survey focuses on document-centric medical claim auditing, particularly the integration of optical character recognition (OCR), rule-based validation, machine learning, and human review. The following table summarizes selected studies, their methods, and their reported limitations to identify areas for further investigation.

Table-1: Comparative Analysis of Existing Research Studies

No.	paper	Year	Methods	Limitations
1	Machine Learning Based Method for Insurance Fraud Detection on Class Imbalance Datasets With Missing Values	2024	XGBoost, Random Forest, Decision Tree, Logistic Regression, and Support Vector Machine (SVM)	The study focuses primarily on automobile insurance, which may limit the direct applicability of its findings to medical insurance claims.
2	Medicare Fraud Detection Using Graph Analysis: A Comparative Study of Machine Learning and Graph Neural Networks	2023	Graph Neural Networks (GCN, GraphSAGE, GAT, and HAN), XGBoost, Logistic Regression, and Natural Language Processing (NLP)	Graph-based methods may require substantial computational resources and longer training times.
3	Fraud Detection in Healthcare Claims Using Machine Learning: A Systematic Review	2025	Supervised learning, unsupervised learning, deep learning, and hybrid approaches	The availability of reliable benchmark datasets and labelled fraud records can limit the evaluation and comparison of detection methods.
4	Fraud Detection in Medical Insurance Claims Using Majority Voting of Multiple Unsupervised Algorithms	2024	Unsupervised learning, anomaly detection, and majority voting	The approach may require extensive validation on representative real-world datasets to establish its effectiveness.

3. METHODS AND TAXONOMY

3.1 Proposed Literature Search Method

The collected research paper should focus on healthcare insurance fraud detection, automated medical claim auditing, and the application of artificial intelligence and machine learning. Studies discussing OCR, rule-based validation, supervised learning, anomaly detection, and explainable AI are particularly relevant. Papers that do not relate to the research objectives or lack sufficient methodological information should be excluded. The selected studies should be compared based on their techniques, advantages, limitations, evaluation methods, and potential applications in medical claim processing.

3.2 Rule-Based Validation

Rule-based systems check explicit conditions, such as missing required fields, invalid dates, duplicate claim identifiers, arithmetic inconsistencies, policy-limit violations, or disagreement between a billed amount and a supporting record. They are understandable and easy to audit when rules are well defined. Their limitations include maintenance overhead, rigid handling of exceptions, and difficulty discovering patterns that were not anticipated by the rule designer. A rule violation should normally be treated as a reason to inspect a claim, not automatic proof of fraud.

3.3 Supervised Machine Learning

Supervised methods learn from historical examples labelled as legitimate or fraudulent. Logistic regression provides a comparatively interpretable baseline; decision trees express decisions as paths; random forests combine multiple trees; and gradient-boosting methods such as XGBoost can model nonlinear relationships among structured claim features. Their effectiveness depends on label quality, feature construction, representative training data, and careful separation of training and test records. When confirmed fraud cases are rare, a high accuracy value can conceal poor detection of fraudulent claims.

3.4 XGBoost-Based Medical Claim Risk Scoring

Extreme Gradient Boosting (XGBoost) is an ensemble machine learning algorithm that combines multiple decision trees to generate predictions. It constructs trees sequentially, where each successive tree improves the model by reducing errors made by the existing ensemble. XGBoost uses gradient-based optimization and regularization to improve predictive performance while controlling model complexity. In medical claim auditing, the model can analyze structured claim features and estimate the likelihood that a claim belongs to the fraudulent class. The predicted probability can be converted into a numerical risk score ranging from 0 to 100 to support claim prioritization. A higher score indicates a higher model-estimated risk, rather than definitive proof of fraud. The score can be considered alongside rule-based validation results and document-extraction quality to identify claims requiring further examination. Final claim decisions should involve appropriate human review.

3.5 Unsupervised and Semi-Supervised Detection

Anomaly-detection methods identify records that differ from typical patterns and can be useful when fraud labels are scarce. Isolation Forest and clustering-based approaches are examples of methods that may help prioritize unusual claims. However, an unusual claim is not necessarily fraudulent: new treatments, rare conditions, regional practice differences, and data-entry errors can also appear anomalous. Results therefore require contextual interpretation and validation by domain experts.

3.6 OCR and Document Understanding

OCR converts text in scanned documents into machine-readable text, machine not understand text so text is convert in numerical machine readable form. A claim-auditing pipeline may extract patient or policy identifiers, dates, provider details, procedure descriptions, and billed amounts, then normalize and validate the extracted fields. OCR performance can degrade with low-quality images, skewed pages, handwriting, stamps, tables, or unusual fonts. Confidence scores, field-level validation, and a review path for low-confidence extraction can reduce the risk of treating incorrectly extracted text as reliable evidence.

3.7 Explainability and Human Review

A useful auditing tool should provide more than a risk score. It should show which fields or checks contributed to a flag, preserve the source document and extracted values, and record the auditor's final decision. Explainability methods can help communicate model behaviour, but explanations are not a substitute for validation or proof of fraud. Human review is especially important before consequential claim rejection, denial, or referral.

4. CONCEPTUAL ARCHITECTURE FOR AUTOMATED MEDICAL CLAIM AUDITING

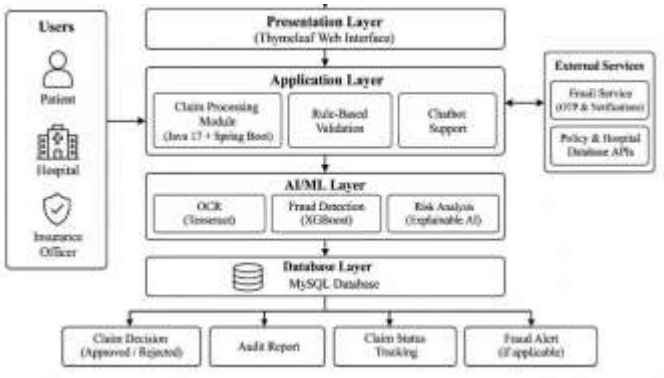


Figure 1. Proposed System Architecture

Figure 1 illustrates the proposed architecture of ClaimGuard, an AI-assisted system designed for automated medical claim auditing and health insurance fraud-risk assessment. The architecture is divided into four major layers: the presentation layer, application layer, AI/ML layer, and database layer. Each layer performs specific functions and communicates with the other layers to ensure systematic claim processing, validation, and risk assessment.

The **presentation layer** acts as the user interaction interface. It allows patients or claimants to register, log in, submit medical claim documents, view claim status, and access generated audit reports. It also provides an interface for auditors and administrators to monitor submitted claims, examine suspicious cases, and manage claim-related activities.

The **application layer** manages the overall processing of medical claims. It receives uploaded documents and forwards them to the appropriate processing components. This layer handles user authentication, claim registration, document management, rule-based validation, and communication between different system modules. It also supports chatbot functionality to assist users with basic claim-related queries and provides notifications regarding claim updates.

The **AI/ML layer** performs intelligent document analysis and fraud-risk assessment. Optical Character Recognition (OCR) using the Tesseract engine extracts relevant information from uploaded medical bills and supporting documents. The extracted information is converted into structured data and passed through rule-based validation to identify missing fields, duplicate claims, incorrect amounts, and policy-related inconsistencies. After validation, the XGBoost machine learning algorithm analyzes the available claim features and generates a fraud-risk score. Explainable AI techniques can further support the interpretation of model predictions by identifying important factors influencing the risk assessment. Based on the results, claims can be categorized into different risk levels and forwarded for appropriate review.

The **database layer** uses MySQL to store and manage important system information, including user details, patient records, hospital information, uploaded claim details, extracted document data, validation results, fraud-risk scores, and audit reports. It also maintains claim status and audit history, allowing authorized users to retrieve previous records and monitor claim-processing activities.

In addition, the system may communicate with external services for email notifications and other supporting information. When a claim is processed, the system updates its status and provides relevant information to the concerned user. High-risk or inconsistent claims are highlighted for further investigation by authorized auditors, who can examine the supporting documents and system-generated results before making a final decision.

Overall, the proposed architecture integrates document processing, automated validation, machine learning, database management, and human supervision into a unified framework. This layered architecture aims to improve the efficiency, accuracy, transparency, and reliability of medical claim auditing while reducing manual effort and supporting the identification of potentially fraudulent insurance claims.

5. WORKFLOW OF PROPOSED SYSTEM

The workflow of the proposed ClaimGuard system consists of several stages designed to automate medical claim auditing and identify potentially fraudulent or inconsistent claims. The process begins when a user logs into the system using valid credentials. After successful authentication, the user uploads the required medical claim documents, such as hospital bills, medical reports, prescriptions, and other supporting documents in the supported format.

Once the documents are uploaded, the system applies Optical Character Recognition (OCR) using the Tesseract engine to extract important information, including patient details, hospital information, diagnosis, treatment details, dates, and billed amounts. The extracted information is converted into structured data so that it can be processed and analyzed by the system. The extracted fields are then checked for completeness and accuracy to reduce errors caused by poor-quality documents or incorrect text recognition.

In the next stage, rule-based validation is performed to identify duplicate claims, missing information, incorrect billing amounts, policy-related discrepancies, and inconsistencies between the submitted documents and

claim details. The validated information is then passed to the machine learning component, where the XGBoost algorithm analyzes relevant claim features and generates a fraud-risk score. Based on the predicted score and validation results, the system categorizes claims according to their risk levels, such as low, medium, or high.

Claims that contain inconsistencies or higher risk scores are flagged for further investigation by the authorized auditor. The auditor can examine the uploaded documents, extracted information, validation results, and AI-generated risk assessment before making a final decision. Claims that satisfy the required validation conditions can proceed for approval, while claims requiring further verification are kept under manual review. If a claim is rejected, the system records the reason for rejection and updates the claim status.

Finally, the system stores the claim details, validation results, risk scores, auditor decisions, and audit history in the MySQL database. The updated claim status is communicated to the concerned user through email notifications. An audit report is also generated to maintain a record of the claim evaluation process.

Overall, the proposed workflow integrates document processing, OCR-based information extraction, rule-based validation, XGBoost-based fraud-risk assessment, and human supervision. This integrated approach aims to improve the consistency, transparency, and efficiency of medical claim auditing while supporting auditors in identifying potentially suspicious insurance claims.

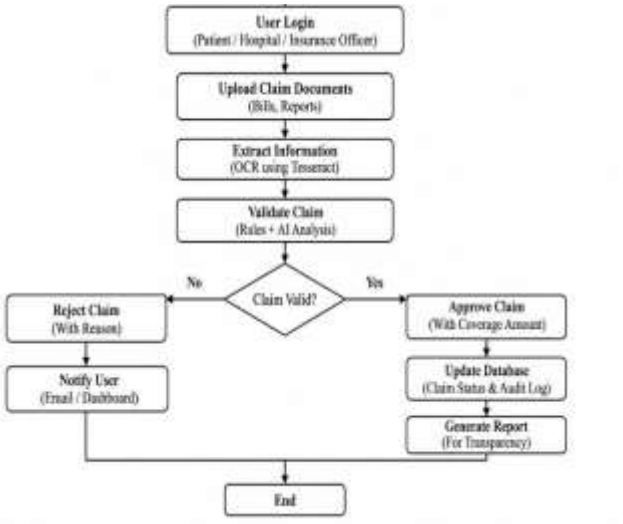


Figure 2. Workflow of the System

6. COMPARATIVE ANALYSIS

Table-2 : Comparitive Analysis of approaches for automated medical claim auditing

Approach	Strengths	Limitations	Suitable role
Rule-based validation	Transparent; easy to explain and audit	Rigid; rules require maintenance; limited pattern discovery	Field consistency and policy validation
Logistic regression & decision tree	Useful baselines; comparatively interpretable	May miss complex relationships; sensitive to features and data quality	Baseline classification and understandable rules
XGBoost	Captures nonlinear feature interactions; handles structured data	Can be harder to explain; needs careful validation and tuning	Claim-level risk ranking
Anomaly detection	Can flag unusual cases with few labelled examples	Anomalies are not necessarily fraud; threshold selection is difficult	Prioritizing unusual claims for investigation
OCR + validation pipeline	Makes scanned documents searchable and supports automation	Extraction errors can propagate; scans may be poor quality	Converting documents into structured claim fields

6.1 Evaluation Metrics

Accuracy measures the proportion of all predictions that are correct, but it may be misleading when fraud is rare. Precision measures how many flagged claims are actually positive, recall measures how many known positive cases are detected, and the F1-score balances precision and recall. ROC-AUC and especially precision-recall analysis can add useful views of ranking performance, but metrics should be reported with the dataset prevalence and the decision threshold. Operational studies should also report false-positive workload, time to review, calibration, and the consequences of missed or incorrectly flagged claims.

6.2 Dataset and Validation Concerns

Datasets play a crucial role in evaluating artificial intelligence and machine learning techniques for medical claim fraud detection. The reviewed studies may use different types of datasets, including healthcare insurance claims, Medicare billing records, provider information, and insurance transaction records. The characteristics of these datasets influence the performance and generalizability of the proposed detection methods.

Important dataset characteristics include the total number of records, the proportion of legitimate and fraudulent claims, the availability of relevant features, missing values, and the reliability of fraud labels. Some datasets may contain structured numerical and categorical information, whereas document-oriented claim auditing may also require extracting information from scanned medical bills and supporting documents using Optical Character Recognition (OCR).

Class imbalance is a major challenge because fraudulent claims may represent only a small proportion of the available records. Consequently, a model can achieve high overall accuracy while detecting very few fraudulent cases. Differences in dataset size, feature selection,

labelling procedures, and evaluation methods also make direct comparisons between studies difficult.

Therefore, comparative analysis should consider dataset characteristics alongside evaluation metrics such as precision, recall, F1-score, and the confusion matrix. Researchers should also examine data privacy, the availability of verified fraud cases, and the representativeness of the evaluation data. Reporting these characteristics helps readers understand the strengths, limitations, and practical applicability of different fraud detection techniques.

Additionally, data preprocessing and validation are essential for improving the reliability of fraud detection systems. Raw medical claim datasets may contain duplicate records, inconsistent formats, incomplete information, and incorrect entries that can affect model performance. Data cleaning, normalization, feature selection, and appropriate handling of missing values help improve data quality before applying machine learning algorithms. Cross-validation and independent testing datasets can further help assess whether a model performs consistently on unseen records. Proper validation reduces the risk of overfitting and ensures that the developed system can identify suspicious claims more reliably in real-world healthcare insurance environments.

Table-3: Dataset Characteristics to Consider in Medical Claim Fraud Detection Studies

Dataset characteristic	Importance in fraud detection
Dataset size	Influences the amount of information available for model training and evaluation.
Class distribution	Shows the proportion of legitimate and fraudulent claims.
Feature availability	Determines which claim attributes can be used by the detection model.
Missing values	May affect data quality and model predictions.
Label reliability	Influences whether the model learns meaningful fraud patterns.
Data type	Distinguishes structured claim records from scanned documents requiring OCR.
Data privacy	Can limit access to real-world medical and insurance records.

7. RESEARCH GAPS AND FUTURE DIRECTIONS

The literature points to several issues that a document-centric survey should examine carefully. First, the quality of OCR output and the effect of extraction errors on downstream fraud prediction need explicit evaluation. Second, rule-based checks and machine-learning scores are often evaluated as separate components; end-to-end evaluations can reveal how their combination affects review workload and error rates. Third, severe class imbalance and incomplete labels complicate model assessment. Fourth, explainability should be designed for the auditor's task, with traceable links between a flag and the underlying claim evidence. Fifth, data privacy and access limitations make cross-institution validation difficult. Finally, operational value should be measured not only through model metrics but also through review time, false alarms, fairness, and the quality of final audit decisions.

A promising architecture is a staged workflow: (1) securely ingest a claim document; (2) extract fields using OCR and preserve confidence values; (3) normalize and validate the fields; (4) apply a calibrated model to estimate risk; (5) generate an explanation and supporting evidence; (6) route uncertain or high-risk claims to an authorized auditor; and (7) record the outcome for controlled model monitoring. This is a proposed design pattern and should be evaluated before any real-world use.

8. CONCLUSION

Artificial intelligence-based healthcare fraud detection can support medical claim auditors by combining rule-based validation with machine learning models that prioritize claims for further investigation. Optical Character Recognition (OCR) and document-processing techniques help convert unstructured medical documents into structured data for automated analysis. However, errors during information extraction can affect subsequent validation and prediction results. Supervised learning, anomaly detection, and ensemble methods offer different advantages, but their effectiveness depends on data quality, class distribution, feature availability, and evaluation methodology. Therefore, no single algorithm should be considered universally suitable for all medical claim fraud detection scenarios.

Reliable and responsible claim auditing systems require representative datasets, appropriate evaluation metrics for imbalanced classes, interpretable results, data privacy safeguards, and human supervision. This survey emphasizes the importance of examining the complete claim-auditing process, from document extraction and

rule-based validation to machine learning-based risk assessment and auditor review. Its contribution should be established through a clearly defined scope, a systematic and reproducible literature search, and a critical comparison of the selected studies. Future research should focus on evaluating integrated auditing frameworks, improving OCR reliability, strengthening model explainability, and assessing performance under realistic operational conditions.

9. ACKNOWLEDGEMENT

We would like to express our sincere gratitude to everyone who supported and guided us throughout the completion of this survey paper titled **"A Comprehensive Survey of Artificial Intelligence and Machine Learning Techniques for Automated Medical Claims Auditing and Health Insurance Fraud Detection."**

We are deeply thankful to our respected guide, **Prof. S. A. Dabhade**, for valuable guidance, continuous encouragement, and constructive suggestions throughout this work.

We would also like to express our gratitude to the **Department of Computer Engineering, SVPM's College of Engineering, Malegaon BK, Baramati**, for providing the necessary support and academic facilities.

We extend our sincere thanks to all the authors and researchers whose published studies and contributions helped us understand existing approaches, methodologies, and challenges in medical claim auditing and health insurance fraud detection.

Finally, we thank our families, friends, and everyone who directly or indirectly supported us in completing this survey paper successfully.

10. REFERENCES

[1] M. S. Iqbal, A. Abd-Alrazaq, and M. Househ, "Artificial Intelligence Solutions to Detect Fraud in Healthcare Settings: A Scoping Review," *Studies in Health Technology and Informatics*, vol. 295, pp. 20–23, 2022, doi: 10.3233/SHTI220649.

[2] A. du Preez, S. Bhattacharya, P. Beling, and E. Bowen, "Fraud Detection in Healthcare Claims Using Machine Learning: A Systematic Review," *Artificial Intelligence in Medicine*, vol. 160, Art. no. 103061, 2025, doi: 10.1016/j.artmed.2024.103061.

[3] E. D. Curtis, P. Billion-Polak, T. M. Khoshgoftaar, et al., "A Review of Distinct Machine Learning Classifiers for Healthcare Fraud Detection," *Journal of Big Data*, vol. 12, Art. no. 238, 2025, doi: 10.1186/s40537-025-01295-3.

[4] J. M. Johnson and T. M. Khoshgoftaar, "Data-Centric AI for Healthcare Fraud Detection," *SN Computer Science*, vol. 4, Art. no. 389, 2023, doi: 10.1007/s42979-023-01809-x.

[5] B. Hong, P. Lu, H. Xu, J. Lu, K. Lin, and F. Yang, "Health Insurance Fraud Detection Based on Multi-Channel Heterogeneous Graph Structure Learning," *Heliyon*, vol. 10, no. 9, Art. no. e30045, 2024, doi: 10.1016/j.heliyon.2024.e30045.

[6] M. A. Abo El-Enen, D. Tbaishat, A. T. Sahlol, A. Nazir, K. AlMaymun, M. AbdulRazek, R. Muhammad, F. Adlan, and R. Sharma, "Fraud Detection in Medical Insurance Claims Using Majority Voting of Multiple Unsupervised Algorithms," *Procedia Computer Science*, vol. 244, pp. 9–22, 2024, doi: 10.1016/j.procs.2024.10.173.

[7] J. T. Hancock, R. A. Bauder, H. Wang, and T. M. Khoshgoftaar, "Explainable Machine Learning Models for Medicare Fraud Detection," *Journal of Big Data*, vol. 10, Art. no. 154, 2023, doi: 10.1186/s40537-023-00821-5.

[8] R. A. Bauder and T. M. Khoshgoftaar, "The Effects of Varying Class Distribution on Learner Behavior for Medicare Fraud Detection with Imbalanced Big Data," *Health Information Science and Systems*, vol. 6, Art. no. 9, 2018, doi: 10.1007/s13755-018-0051-3.

[9] E. Nabrawi and A. Alanazi, "Fraud Detection in Healthcare Insurance Claims Using Machine Learning," *Risks*, vol. 11, no. 9, Art. no. 160, 2023, doi: 10.3390/risks11090160.

[10] S. Shekhar, J. Leder-Luis, and L. Akoglu, "Unsupervised Machine Learning for Explainable Health Care Fraud Detection," National Bureau of Economic Research, Working Paper No. 30946, 2023, doi: 10.3386/w30946.

[11] M. L. Sbodio, V. López, T. L. Hoang, T. Brisimi, G. Picco, I. Vejsbjerg, V. Rho, P. Mac Aonghusa, M. Kristiansen, and J. Segrave-Daly, "Collaborative Artificial Intelligence System for Investigation of Healthcare Claims Compliance," *Scientific Reports*, vol. 14, Art. no. 11884, 2024, doi: 10.1038/s41598-024-62665-0.