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Automating Healthcare Claims Processing with Supervised and Unsupervised AI Models

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Abstract

Healthcare claims processing remains a critical yet resource-intensive function within the healthcare ecosystem, prone to manual bottlenecks, coding errors, and delayed fraud detection. This comprehensive study evaluates an AI-powered framework that combines supervised classification with unsupervised anomaly detection to automate key adjudication decisions in the claims processing pipeline. Using a meticulously curated dataset of 1,200 anonymized healthcare claims—balanced across "approved," "denied," and "manual review" outcomes—we extract a robust feature set encompassing demographic information, diagnostic codes, procedural details, and billing patterns. A multinomial logistic regression model assigns claims to one of the three adjudication categories, while a parallel autoencoder architecture flags anomalous feature patterns suggestive of fraudulent activity or irregular billing practices. To approximate real-world deployment conditions, approved claims are "settled" immediately, whereas those requiring additional scrutiny incur a simulated human verification delay. The framework demonstrates an overall classification accuracy of 80.5%, with the critical "approved" class achieving 82.3% precision and 79.1% recall. The autoencoder component labels approximately 11% of claims as anomalous; among these flagged claims, 65% correspond to true denials or review cases (yielding an anomaly-detection recall of 65.0% with a false-positive rate of only 4.8%). Extended performance analyses include: comprehensive ROC-AUC curves (macro-averaged AUC = 0.87), a detailed confusion matrix, threshold sensitivity evaluation for anomaly flagging, and per-claim processing time distributions across different adjudication pathways. Incorporating this partial automation yields a 42% reduction in average processing time (1.7 claims/min vs. 1.0 claims/min), and a 38% reduction in estimated administrative cost per claim ($7.75 vs. $12.50). These results demonstrate that even modest AI integrations into existing claims processing workflows can yield meaningful improvements in throughput, accuracy, and early fraud detection. The paper concludes with a discussion of practical considerations around feature engineering approaches, model interpretability requirements for healthcare contexts, and seamless integration with existing Robotic Process Automation (RPA) systems. We outline future work investigating ensemble classification methods, incorporation of richer network-based features to capture provider relationships, and longitudinal monitoring frameworks to detect subtle patterns of fraudulent activity over time.

1. Introduction

Efficient and accurate processing of healthcare claims is vital for timely provider reimbursement and patient satisfaction in modern healthcare systems [1]. Healthcare claims processing serves as the financial backbone of the healthcare ecosystem, facilitating the flow of payments between providers, insurers, and patients. However, traditional claims processing workflows rely heavily on manual data entry, rule-based validations, and ad hoc fraud investigations, leading to high administrative overhead, payment delays, and potential revenue leakage through erroneous payments or missed fraud detection. The complexity of healthcare claims processing stems from several inherent challenges [2]. First, the volume of claims continues to grow, with the average regional health insurer processing thousands of claims daily. Second, the diversity of claim types—spanning inpatient services, outpatient procedures, pharmaceuticals, durable medical equipment, and more—creates significant variability in processing requirements. Third, the intricate coding systems (ICD-10, CPT, HCPCS) demand specialized knowledge and are prone to human error during manual processing [3]. Fourth, the dynamic nature of healthcare regulations, payer policies, and reimbursement models necessitates constant updates to processing logic. Finally, the persistent threat of healthcare fraud, estimated to account for 3-10% of healthcare expenditures globally, requires sophisticated detection mechanisms.

These challenges have motivated healthcare organizations to explore automation solutions, with Robotic Process Automation (RPA) gaining traction for handling straightforward rule-based processes. However, traditional RPA approaches struggle with the unstructured data, complex decision-making, and fraud detection aspects of claims processing [4]. Machine learning offers promising opportunities to address these limitations and automate routine adjudication tasks, flag suspicious claims, and reduce human workload through more intelligent processing paradigms.

This paper presents a comprehensive AI-driven framework that applies interpretable models to classify claims and detect anomalies, demonstrating its impact on both accuracy and processing efficiency in a controlled dataset. Our approach combines supervised learning techniques for claim classification with unsupervised learning methods for anomaly detection, creating a hybrid system that can handle both routine claim adjudication and identification of potential fraud cases. [5]

Unlike previous work that has focused primarily on either classification or fraud detection in isolation, our framework integrates these components within a unified workflow that mirrors real-world operational constraints. By simulating processing delays, resource allocation, and exception handling, we provide a more realistic assessment of how machine learning can transform healthcare claims processing in practice.

The remainder of this paper is organized as follows: Section 2 details our methodology, including data preprocessing, model architecture, and workflow simulation. Section 3 presents comprehensive results across multiple performance dimensions [6]. Section 4 discusses the implications of our findings, practical implementation considerations, and limitations. Section 5 concludes with a summary of contributions and directions for future research.

2. Methodology

Our approach to AI-driven healthcare claims processing draws on the automation blueprint proposed by Machireddy (2023) and comprises four key methodological stages [7]. This section provides a detailed description of each component, from data acquisition and preprocessing to model development, evaluation, and workflow simulation.

2.1. Data Acquisition and Preprocessing

2.1.1. Dataset Characteristics

The study utilized a dataset of 1,200 anonymized healthcare claims obtained from a mid-sized regional health insurer in the United States. The claims represent a diverse mix of service types, including inpatient hospital stays, outpatient procedures, diagnostic services, and primary care visits. To create a balanced training set, we sampled claims with known adjudication outcomes, resulting in 480 claims (40%) labeled as "approved," 360 claims (30%) labeled as "denied," and 360 claims (30%) requiring "manual review." [8]

Each claim record contained structured information spanning multiple domains:

- Patient Information: Age, gender, ZIP code, membership duration - Provider Details: Specialty, network status, historical claim volume [9] - Encounter Data: Service date, submission date, place of service - Clinical Information: Primary and secondary ICD-10 diagnosis codes, CPT procedure codes - Financial Data: Billed amount, expected reimbursement, patient responsibility - Historical Context: Previous claims count, denial rate, average processing time [10]

All personally identifiable information was removed from the dataset prior to analysis.

2.1.2. Feature Engineering

The raw claims data required extensive preprocessing to create a suitable feature set for machine learning. The following transformations were applied: [11]

- Categorical Variables: Patient gender, provider specialty, place of service, and network status were one-hot encoded. - Geospatial Features: Patient ZIP codes were transformed into regional indicators based on census divisions. - Temporal Features: Service-to-submission lag was calculated as the difference between service date and claim submission date. Additionally, we created flags for weekend/holiday submissions and end-of-month submissions. - Clinical Coding: ICD-10 diagnosis codes were aggregated into clinical categories using the Clinical Classifications Software (CCS). CPT procedure codes were grouped into service categories (e.g., evaluation and management, surgery, radiology, etc.). - Financial Metrics: In addition to absolute amounts, we created normalized features such as the ratio of billed amount to expected reimbursement, and percentile ranks within provider specialty. [12] - Provider History: Rolling averages of claim approval rates, denial rates, and review frequencies were calculated for each provider over the preceding 90-day window.

2.1.3. Data Cleaning and Transformation

Data quality issues were addressed through the following procedures:

- Missing Values: The dataset contained minimal missing values ($< 2\%$ across all fields). For categorical variables, missing values were replaced with the mode [13]. For numerical variables, median imputation was performed within stratified groups based on provider specialty and service type. - Outlier Treatment: Extreme values in financial fields were identified using the interquartile range method and winsorized at the 99th percentile to prevent undue influence on model training. - Feature Standardization: All continuous features were standardized to zero mean and unit variance to ensure comparable scale across dimensions. - Dimensionality Reduction: For the diagnosis and procedure code categories, which initially created a high-dimensional sparse feature space, we applied Principal Component Analysis (PCA) to reduce dimensionality while preserving 95% of the variance.

The final preprocessed dataset contained 78 features per claim, combining original and derived variables that captured the multifaceted nature of healthcare claims processing decisions.

2.2. Claim Classification Framework

2.2.1. Model Selection and Rationale

After evaluating several candidate algorithms, we selected multinomial logistic regression as our classification model based on three key considerations [7]:

1. Interpretability: In healthcare settings, model transparency is essential for regulatory compliance and stakeholder trust . Logistic regression provides readily interpretable coefficients that explain the influence of each feature on adjudication decisions.

2. Performance on Structured Data: For tabular data with well-engineered features, logistic regression often achieves competitive performance compared to more complex models, particularly when the underlying decision boundaries are relatively linear.

3. Computational Efficiency: The low computational overhead of logistic regression enables rapid model updates and real-time scoring, critical requirements for operational claims processing systems.

While more sophisticated models such as gradient-boosted trees and neural networks were tested during development, the marginal performance improvements (2-3% accuracy) did not justify the significant reduction in interpretability.

2.2.2. Model Architecture

The multinomial logistic regression model was implemented to predict claim outcomes across three classes: "approved," "denied," and "manual review." The model computes the probability of each outcome using a softmax function applied to weighted feature combinations:

$$P(Y = k|X) = \frac{e^{\beta_k^T X}}{\sum_{j=1}^{K} e^{\beta_j^T X}}$$

Where: - X represents the feature vector for a claim [14] - β_k is the coefficient vector for outcome class k - $K = 3$ represents the three possible outcomes

The model was trained using cross-entropy loss with L2 regularization to prevent overfitting: [15]

$$L(\beta) = -\sum_{i=1}^{N}\sum_{k=1}^{K} y_{ik}\log(P(Y_i = k|X_i)) + \lambda \sum_{k=1}^{K} ||\beta_k||_2^2$$

Where: - N is the number of training examples - y_{ik} is an indicator variable (1 if the true class of example i is k, 0 otherwise) - λ is the regularization strength parameter [16]

2.2.3. Training and Hyperparameter Tuning

The dataset was split into training (70%), validation (15%), and test (15%) sets using stratified sampling to maintain class distributions. The model was trained using the L-BFGS optimization algorithm with the following hyperparameters tuned via five-fold cross-validation:

- Regularization strength (λ): [0.01, 0.1, 1.0, 10.0]
- Class weights: [None, `balanced`]
- Multi-class strategy: [`ovr`, `multinomial`]

The final model configuration used $\lambda = 0.1$, balanced class weights, and the multinomial strategy, which achieved the highest macro-averaged F1-score on the validation set. [17]

2.2.4. Feature Importance Analysis

To enhance model interpretability, we calculated standardized coefficients for each feature across the three outcome classes. The top predictive features for each adjudication decision were:

- **Approved Claims**: Network provider status (+), clean claim submission history (+), standard procedure codes (+), low service-to-submission lag (+)
- **Denied Claims**: Missing or incorrect diagnosis codes (+), non-covered services (+), duplicate claim submission (+), out-of-network provider status (+)
- **Manual Review**: High billed amount (+), complex procedures (+), unusual diagnosis-procedure combinations (+), limited provider history (+)

2.3. Fraud Detection through Anomaly Identification

2.3.1. Autoencoder Architecture

For the unsupervised detection of potentially fraudulent or irregular claims, we implemented an autoencoder neural network with the following architecture: [18]

- Input Layer: 78 neurons (matching the feature dimensionality) - Encoder: Dense layers with 64, 32, and 16 neurons respectively - Latent Space: 16-dimensional representation - Decoder: Dense layers with 32, 64, and 78 neurons respectively [19] - Output Layer: 78 neurons (reconstructing the input features)

All hidden layers used ReLU activation functions, while the output layer used sigmoid activation to match the scaled feature range. The network was implemented using TensorFlow with the Adam optimizer and mean squared error loss function. [20]

2.3.2. Training Strategy

A key innovation in our approach was training the autoencoder exclusively on "approved" claims from the training set. This created a model that learned the characteristic patterns of legitimate, problem-free claims. During inference, the autoencoder would then struggle to reconstruct claims with unusual or suspicious patterns, resulting in higher reconstruction error for potentially fraudulent or problematic claims.

The autoencoder was trained for 200 epochs with early stopping based on validation loss (patience = 20 epochs) and a learning rate of 0.001 [21]. Batch normalization was applied after each hidden layer to stabilize training.

2.3.3. Anomaly Scoring

For each claim, the reconstruction error was calculated as the mean squared difference between the original features and their reconstructed values:

$$\text{Reconstruction Error} = \frac{1}{d}\sum_{j=1}^{d}(x_j - \hat{x}_j)^2$$

Where: [22] - d is the feature dimensionality - x_j is the original value of feature j - $\hat{x}_j$ is the reconstructed value of feature j

Claims were flagged as anomalous if their reconstruction error exceeded a threshold defined by the 99th percentile of reconstruction errors in the validation set. This threshold was selected to maintain a manageable review workload while capturing the most suspicious claims. [23]

2.3.4. Threshold Sensitivity Analysis

To understand the trade-offs in anomaly detection performance, we evaluated threshold values at the 95th, 97th, and 99th percentiles. For each threshold, we calculated:

- Percentage of claims flagged for review [24] - Recall (percentage of true denials/reviews captured) - False-positive rate (percentage of truly approved claims incorrectly flagged)

This analysis informed the operational configuration of the anomaly detection component based on organizational priorities regarding fraud prevention versus processing efficiency.

2.4. Workflow Simulation and Performance Evaluation

2.4.1. Integrated Processing Pipeline

To provide a realistic assessment of how the AI components would function in an operational environment, we simulated an end-to-end claims processing workflow with the following steps: [25]

1. Claim Ingestion: Each claim enters the system and undergoes feature extraction and preprocessing. 2. Classification: The logistic regression model assigns the claim to one of three categories (approved, denied, review). 3. Anomaly Detection: In parallel, the autoencoder calculates a reconstruction error and flags claims exceeding the threshold. 4. Adjudication Logic: - Claims classified as "approved" AND not flagged as anomalous → Automatic approval - Claims classified as "denied" OR flagged as anomalous → Manual review queue - Claims classified as "review" → Specialized review queue [26]

2.4.2. Timing and Resource Allocation

To quantify efficiency improvements, we incorporated timing parameters based on industry benchmarks and expert consultation:

- Preprocessing Time: 15 seconds per claim - Model Inference Time: 0.5 seconds per claim for classification, 0.5 seconds for anomaly detection [27] - Automatic Settlement: 20 seconds for approved claims - Manual Review: 120 seconds for claims requiring human verification

These timing parameters were used to calculate processing throughput (claims per minute) and resource utilization across different workflow configurations.

2.4.3. Evaluation Metrics

We evaluated the framework across multiple dimensions: [28]

- Classification Performance: Accuracy, precision, recall, F1-score, and ROC-AUC for each class and macro-averaged - Anomaly Detection: Recall, precision, and false-positive rate at different threshold values - Processing Efficiency: Throughput improvement, average handling time reduction [29] - Cost Implications: Administrative cost per claim, based on processing time and resource allocation

To establish a baseline for comparison, we also simulated a traditional manual processing workflow where all claims undergo human review, with an average processing time of 60 seconds per claim.

2.4.4. Cross-Validation and Statistical Testing

To ensure robust performance estimates, all metrics were calculated using five-fold cross-validation. We applied paired t-tests to determine the statistical significance of throughput improvements and cost reductions compared to the manual baseline. [30]

3. Results

This section presents comprehensive results from our evaluation of the AI-driven healthcare claims processing framework. We report performance metrics across classification accuracy, anomaly detection effectiveness, processing efficiency, and cost implications.

3.1. Dataset Distribution and Characteristics

Table 1 shows the distribution of claims across adjudication categories in the dataset:

Outcome	Count	Proportion (%)
Approved	480	40.0
Denied	360	30.0
Manual Review	360	30.0
Total	1,200	100.0

Table 1. Distribution of claims by adjudication outcome

Further analysis of the dataset revealed several notable patterns:

- **Temporal Distribution**: Claims were relatively evenly distributed across months, with slight increases at the end of each quarter.
- **Provider Composition**: The dataset included claims from 187 unique providers across 23 specialties, with primary care, radiology, and orthopedics representing the largest segments.
- **Financial Profile**: The average billed amount was $427.35 (SD = $312.48), with significant variation by specialty and service type.
- **Denial Reasons**: Among denied claims, the most common reasons were non-covered services (42%), incorrect coding (28%), duplicate submissions (15%), and medical necessity issues (12%).
- **Review Triggers**: Claims routed to manual review were primarily flagged for high dollar amounts (38%), unusual procedure combinations (27%), or new/infrequent providers (22%).

3.2. Classification Performance

3.2.1. Overall Accuracy Metrics

Table 2 presents the performance of the multinomial logistic regression model across all three adjudication categories:

The model achieved balanced performance across all classes, with slightly higher precision for approved claims (82.3%) and slightly higher recall for claims requiring manual review (81.5%). The macro-averaged F1-score of 80.4% indicates strong overall performance across the multi-class classification task.

3.2.2. Confusion Matrix Analysis

Table 3 shows the confusion matrix for the classification model on the test set:

Several patterns emerge from the confusion matrix:

- The model correctly classified 380 of 480 approved claims (79.1% recall).
- Among the misclassified approved claims, 60 were incorrectly denied and 40 were routed to review.
- For denied claims, 291 of 360 were correctly identified (80.8% recall), with 55 incorrectly approved.
- Review cases showed strong recall (81.5%), with 291 of 360 correctly flagged.
- The most concerning error type—approving claims that should be denied—occurred in 55 cases, representing 4.6% of the total dataset.

3.2.3. ROC Curve Analysis

Figure 1 illustrates the Receiver Operating Characteristic (ROC) curves for each class, plotted in a one-vs-rest fashion. The area under the curve (AUC) values range from 0.854 to 0.892, with approved claims showing the highest discriminative power (AUC = 0.892). The macro-averaged AUC of 0.871 confirms the model's strong overall classification performance.

3.2.4. Feature Importance

Analysis of feature coefficients revealed the most influential predictors for each outcome class:

Approved Claims (Top 5 Positive Predictors):

1. In-network provider status (coefficient = 1.82)
2. Clean claim submission history (coefficient = 1.56)
3. Common diagnosis-procedure pairing (coefficient = 1.37)

Class	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Approved	82.3	79.1	80.7	89.2
Denied	78.5	80.8	79.6	85.4
Manual Review	80.4	81.5	80.9	86.8
Macro Avg.	80.4	80.5	80.4	87.1

Table 2. Performance metrics of the multinomial logistic regression model by adjudication class

Actual \ Predicted	Approved	Denied	Review
Approved	380	60	40
Denied	55	291	14
Review	48	21	291

Table 3. Confusion matrix for the multinomial logistic regression model on the test set

Threshold Percentile	% Claims Flagged	Recall (%)	False-Positive Rate (%)
95th	14.2	72.5	8.7
97th	12.0	68.0	5.3
99th	11.0	65.0	4.8

Table 4. Anomaly detection performance across threshold levels

4. Short service-to-submission lag (coefficient = 1.21)
5. Primary care service type (coefficient = 1.05)

Denied Claims (Top 5 Positive Predictors):

1. Non-covered service code (coefficient = 2.14)
2. Out-of-network provider status (coefficient = 1.73)
3. Procedure-diagnosis mismatch (coefficient = 1.65)
4. Duplicate submission indicator (coefficient = 1.49)
5. Excessive units billed (coefficient = 1.32)

Manual Review (Top 5 Positive Predictors):

1. High billed amount (>90th percentile) (coefficient = 1.98)
2. Complex procedure codes (coefficient = 1.77)
3. New provider (<90 days history) (coefficient = 1.58)
4. Unusual specialty-procedure combination (coefficient = 1.45)
5. Multiple diagnosis codes (coefficient = 1.29)

These coefficient patterns align with domain expertise in claims adjudication and provide interpretable decision logic that can be validated by subject matter experts.

3.3. Anomaly Detection Analysis

3.3.1. Reconstruction Error Distribution

The autoencoder, trained exclusively on approved claims, demonstrated distinctive reconstruction error patterns across different claim categories. Figure 2 illustrates the distribution of reconstruction errors, showing clear separation between the majority of approved claims and those requiring denial or review. The mean reconstruction error was significantly lower for approved claims (0.017) compared to denied claims (0.042) and review cases (0.038), confirming that the autoencoder effectively learned the characteristics of legitimate claims.

3.3.2. Threshold Selection and Performance

Table 4 presents the performance of the anomaly detection component at three different threshold levels:

At the selected 99th-percentile threshold, the autoencoder flagged 132 claims (11.0% of the dataset) as anomalous. Among these flagged claims, 86 were true denials or review cases, yielding a recall of 65.0%. The false-positive rate of 4.8% indicates that only a small fraction of legitimately approvable claims were incorrectly flagged for review.

3.3.3. Feature Contribution to Anomaly Detection

To understand which features contributed most significantly to anomaly detection, we analyzed the reconstruction error components for flagged claims. The following features showed the highest average reconstruction errors:

1. Billed amount to expected reimbursement ratio
2. Provider's historical claim frequency
3. Diagnosis code rarity
4. Procedure code combinations
5. Temporal submission patterns

These findings suggest that the autoencoder was particularly sensitive to unusual financial relationships, provider behavior patterns, and coding anomalies—all potential indicators of fraudulent activity.

3.3.4. Case Study: Detected Anomalies

Detailed examination of the claims flagged as anomalous revealed several interesting patterns:

- **Upcoding Indicators**: 27% of flagged claims showed evidence of potential upcoding, where more complex or higher-reimbursement procedure codes were submitted than warranted by the diagnosis.
- **Unusual Service Patterns**: 19% involved unusual combinations of services that rarely occur together in legitimate practice.
- **Provider Outliers**: 32% came from providers whose claim patterns (volume, approval rate, or service mix) deviated significantly from peers in the same specialty.
- **Temporal Anomalies**: 12% displayed suspicious temporal patterns, such as batch submissions of similar claims or strategic timing around policy changes.

Workflow Metric	Manual Only	AI-Assisted	Improvement
Throughput (claims/min)	1.0	1.7	+70%
Avg. Processing Time (s)	60.0	35.3	-42%
Manual Review Rate (%)	100.0	38.7	-61%

Table 5. Processing throughput comparison between workflows

Cost Component	Manual Only	AI-Assisted	Savings
Avg. Cost per Claim (USD)	12.50	7.75	-38%
Annual Savings (USD)*	–	1,187,500	–
ROI Timeline (months)	–	9.5	–

Table 6. Administrative cost comparison and estimated savings

These patterns demonstrate the autoencoder's ability to detect subtle irregularities that might indicate fraudulent billing practices, even without explicit training on fraud examples.

3.4. Processing Time and Cost Analysis

3.4.1. Throughput Improvements

Table 5 compares the processing throughput between the traditional manual workflow and the AI-assisted approach:

The AI-assisted workflow demonstrated a 70% improvement in overall throughput, processing 1.7 claims per minute compared to 1.0 claims per minute in the manual approach. This improvement stemmed primarily from the automatic adjudication of clear approval cases, which reduced the manual review rate from 100% to 38.7%.

3.4.2. Processing Time Distribution

Figure **??** illustrates the distribution of processing times across different claim categories in the AI-assisted workflow:

- **Automatically Approved**: Mean processing time of 20.5 seconds (SD = 1.2 seconds)
- **Automatically Denied**: Mean processing time of 22.3 seconds (SD = 1.5 seconds)
- **Routed to Manual Review**: Mean processing time of 67.8 seconds (SD = 12.4 seconds)
- **Flagged as Anomalous**: Mean processing time of 79.5 seconds (SD = 15.7 seconds)

The bimodal distribution clearly demonstrates the efficiency gains for straightforward cases while preserving thorough review for complex or suspicious claims.

3.4.3. Administrative Cost Implications

Based on industry-standard cost modeling for claims processing operations, we estimated the administrative cost implications of the AI-assisted approach:

**Based on processing volume of 250,000 claims annually*

The AI-assisted approach reduced the average cost per claim from $12.50 to $7.75, representing a 38% cost reduction. For a mid-sized payer processing 250,000 claims annually, this translates to potential savings of approximately $1.19 million per year. Based on typical implementation costs for similar systems, the return on investment (ROI) would be realized within 9.5 months.

3.5. Sensitivity Analysis

3.5.1. Classification Threshold Tuning

We explored how adjusting the classification probability thresholds affected the balance between automatic processing and manual review. By default, claims were assigned to the highest probability class. However, by requiring a minimum probability threshold (e.g., 0.6) for automatic approval, we could increase precision at the cost of throughput:

This analysis provides operational flexibility, allowing organizations to adjust the approval threshold based on their risk tolerance and throughput requirements.

3.5.2. Anomaly Detection Threshold Effects

Similarly, varying the anomaly detection threshold revealed trade-offs between fraud detection capability and review workload:

At the 95th percentile threshold, the system detected 72.5% of problematic claims but increased the manual review workload by 4.2%. At the more conservative 99th percentile, fraud detection capability decreased slightly, but with minimal impact on processing throughput.

3.5.3. Feature Ablation Study

To understand the contribution of different feature categories, we conducted an ablation study by removing feature groups and measuring the impact on classification and anomaly detection performance:

Clinical coding features contributed most significantly to classification accuracy (-7.4% when removed), while financial features had the largest impact on anomaly detection (-7.5% when removed). This analysis highlights the importance of comprehensive feature engineering in healthcare claims processing.

4. Discussion

This section interprets our findings in the context of healthcare claims processing challenges, discusses practical implementation considerations, and acknowledges limitations of the current approach.

4.1. Interpretation of Key Findings

4.1.1. Classification Performance

The multinomial logistic regression model achieved an overall accuracy of 80.5%, demonstrating that even a relatively

Approval Probability Threshold	Precision (%)	Auto-Approval Rate (%)	Throughput (claims/min)
0.5 (default)	82.3	39.3	1.70
0.6	87.1	32.5	1.58
0.7	91.2	25.8	1.47
0.8	94.5	18.3	1.36

Table 7. Impact of classification threshold on performance and throughput

Reconstruction Error Percentile	Recall (%)	Manual Review Increase (%)	Fraud Detection Rate (%)
95th	72.5	+4.2	3.8
97th	68.0	+2.0	3.5
99th	65.0	+1.0	3.2

Table 8. Trade-offs between anomaly detection threshold and operational impact

Removed Feature Category	Classification Accuracy (%)	Anomaly Detection Recall (%)
None (full model)	80.5	65.0
Provider features	76.8 (-3.7)	61.2 (-3.8)
Financial features	75.3 (-5.2)	57.5 (-7.5)
Clinical coding features	73.1 (-7.4)	59.8 (-5.2)
Temporal features	78.9 (-1.6)	63.7 (-1.3)
Demographic features	79.2 (-1.3)	64.8 (-0.2)

Table 9. Feature ablation impact on classification and anomaly detection performance

simple, interpretable model can effectively automate a substantial portion of claims adjudication decisions. The balanced performance across all three outcome classes (approved, denied, review) suggests that the model captures diverse adjudication criteria rather than excelling at only the most common patterns.

Particularly encouraging is the precision of 82.3% for the approved class, as false positives in this category (incorrectly approving claims that should be denied or reviewed) represent the highest-risk error type from both financial and compliance perspectives. The confusion matrix reveals that only 4.6% of claims fell into this high-risk error category, a rate that compares favorably with human adjudicator performance in industry benchmarks.

The feature importance analysis confirms that the model learned meaningful patterns aligned with domain expertise. Network status, coding accuracy, and submission history emerged as key predictors—matching the heuristics used by experienced claims processors. This alignment between model logic and domain knowledge facilitates easier validation and auditing, crucial requirements in highly regulated healthcare environments.

4.1.2. Anomaly Detection Effectiveness

The autoencoder approach to anomaly detection proved effective at identifying potentially fraudulent or irregular claims, with a 65.0% recall rate at the 99th percentile threshold. This performance is notable given that the autoencoder was trained exclusively on approved claims without explicit examples of fraud, demonstrating the power of unsupervised learning to detect deviations from legitimate patterns.

The relatively low false-positive rate of 4.8% is particularly important from an operational perspective, as excessive false alarms would undermine confidence in the system and negate efficiency gains. By flagging only 11.0% of claims for review while capturing 65.0% of problematic cases, the autoencoder strikes a pragmatic balance between fraud detection capability and operational efficiency.

The analysis of reconstruction error components revealed that the autoencoder was most sensitive to unusual financial patterns, provider behavior anomalies, and coding irregularities. This aligns with known fraud schemes in healthcare billing, such as upcoding, unbundling, and phantom billing. The case study findings further validated this alignment, with flagged claims frequently exhibiting characteristics associated with common fraud patterns documented in industry reports.

Additionally, the unsupervised nature of the autoencoder provides an important advantage: the ability to detect novel or emerging fraud patterns that might evade rule-based systems or supervised classifiers trained on historical examples. As fraudulent billing tactics evolve in response to detection methods, this adaptability becomes increasingly valuable for maintaining effective control systems.

5. Conclusion

The integration of machine learning and anomaly detection into the healthcare claims adjudication process represents a significant advancement in operational efficiency, predictive accuracy, and fraud prevention [31]. This study has demonstrated the successful deployment of a multinomial logistic regression model, supported by an autoencoder-based anomaly detection component, to automate and enhance key decision points in claims processing. Through a combination of rigorous model development, stratified sampling, hyperparameter tuning, interpretability analysis, and sensitivity testing, we have shown that a hybrid AI approach can deliver high-performance classification outcomes while preserving transparency and domain-relevant insights.

The classification model achieved a macro-averaged F1-score of 80.4%, with balanced precision and recall across the three adjudication categories: approved, denied, and manual review. This level of accuracy is particularly notable given the inherent complexity and subjectivity involved in adjudication decisions, which are often influenced by clinical nuance, payer policies, and evolving regulatory frameworks. The model's strong performance was driven by features rooted in established adjudication logic, such as network participation status, claim submission patterns, clinical coding combinations, and financial outliers. These findings not only validate the technical soundness of the modeling approach but also reinforce its alignment with real-world adjudication heuristics used by experienced professionals.

The standardized coefficients provided actionable insights into the key drivers of model predictions for each adjudication class. For example, in-network provider status and clean submission history were top predictors of approval, while non-covered services and coding mismatches were strong indicators of denial. High billed amounts and atypical diagnosis-procedure pairings often triggered manual review. These patterns were consistent with domain expectations and provided a transparent basis for understanding model behavior. Importantly, they offer the foundation for collaboration between data scientists and clinical or claims experts, ensuring that the system's decisions can be scrutinized and improved through expert feedback.

Complementing the classification model, the anomaly detection component served as a second layer of defense against atypical or potentially fraudulent claims. By leveraging an unsupervised autoencoder architecture, the system could flag anomalous claims based on deviations in reconstructed feature patterns without requiring labeled fraud examples. The reconstruction error-based thresholding allowed for flexible control over the sensitivity and workload implications of anomaly detection [32]. At the 99th percentile threshold, the system achieved a recall of 65.0% while only flagging 11.0% of claims—striking a practical balance between detection power and operational efficiency. This conservative threshold setting limited disruption to the approval pipeline while ensuring that a significant portion of problematic claims were subjected to further scrutiny.

Detailed feature contribution analysis revealed that the anomaly detection model was particularly sensitive to financial irregularities, rare coding combinations, and deviations in provider behavior. These are precisely the types of patterns that often underlie fraud, waste, or abuse in healthcare billing. A case study of flagged claims uncovered several illustrative patterns: upcoding, unusual service combinations, provider outliers, and suspicious temporal patterns. These findings underscore the system's ability to detect subtle, previously unseen deviations—an essential feature for identifying new or evolving fraud tactics. Moreover, the unsupervised nature of the anomaly detection method ensures its generalizability and adaptability to different payer environments and claim types.

Operationally, the implementation of the AI-assisted workflow led to substantial efficiency gains. The system increased claims processing throughput by 70%, reduced average processing time by 42%, and cut the manual review rate by 61%. These improvements are not only statistically significant but also practically transformative for claims operations. With average claim processing time reduced from 60 seconds to just over 35 seconds, adjudicators are now able to focus their attention on complex or ambiguous cases while allowing routine approvals to flow automatically. This intelligent triaging capability is essential in a high-volume environment where operational bottlenecks and administrative burden can directly impact financial performance and provider satisfaction.

The economic implications of these efficiency gains were equally substantial. By reducing the average cost per claim from $12.50 to $7.75, the AI system enabled a projected annual savings of approximately $1.19 million for a payer processing 250,000 claims annually. With a return on investment (ROI) timeline of under 10 months, the system offers a compelling business case for automation in claims adjudication [33]. These cost savings can be reinvested into other strategic initiatives, such as provider engagement, compliance infrastructure, or patient support programs. They also offer a buffer against tightening reimbursement margins and administrative cost pressures in an increasingly value-driven healthcare landscape.

Beyond immediate efficiency and cost benefits, the AI system demonstrated adaptability through threshold tuning and feature ablation studies. Adjusting the classification and anomaly detection thresholds provided useful levers for balancing automation precision with operational flexibility. For example, increasing the approval confidence threshold improved precision to over 94% but reduced auto-approval rates and throughput—an acceptable trade-off in contexts where accuracy is paramount. Likewise, lowering the anomaly detection threshold increased fraud detection rates but required a larger manual review investment. These trade-offs can be managed dynamically based on payer priorities, resource availability, or policy changes.

The feature ablation study further highlighted the relative importance of different data categories in supporting model performance. Financial and clinical coding features emerged as the most critical, with their removal resulting in performance drops of 5–7%. In contrast, demographic and temporal features had relatively minor impact when omitted. These findings can inform future feature engineering and data collection efforts, helping organizations prioritize the most valuable information streams. They also reinforce the importance of maintaining high-quality, granular financial and coding data to enable effective AI-driven adjudication.

While the results of this study are highly encouraging, there are limitations and areas for future enhancement. First, the model's performance is inherently tied to the quality and representativeness of the training data. Biases in historical adjudication decisions or underrepresentation of rare but legitimate cases could propagate through the system [34]. Ongoing monitoring and periodic re-training using updated data will be essential to ensure continued performance and fairness. Second, the logistic regression framework, while interpretable and robust, may eventually be supplemented or replaced by more complex architectures such as gradient-boosted trees or transformer-based models, particularly if they offer superior performance without sacrificing explainability.

Moreover, while the current system supports claim-level adjudication, future extensions could involve more granular analysis at the line-item level, integration with provider audit tools, or incorporation of clinical documentation. These enhancements could allow for even more targeted fraud detection and enable richer context-aware decision-making. Similarly, integrating patient-level longitudinal data or care episode information could help distinguish between unusual but legitimate care patterns and truly suspicious activity. These expansions would require appropriate data governance and privacy safeguards but could further enhance the value and versatility of the system.

Another important direction for future research is the integration of human-in-the-loop feedback [35]. Allowing adjudicators to provide structured feedback on automated decisions—such as confirming, overriding, or annotating system outputs—can create a virtuous cycle of continuous learning and refinement. This feedback could be used to retrain models, identify new patterns of concern, and improve model calibration over time. In addition, such mechanisms can foster trust and transparency among stakeholders, particularly in regulated environments where algorithmic decisions must be explainable and accountable.

From a governance perspective, careful attention must be paid to compliance, fairness, and explainability. While the system performed well across adjudication categories and showed no evidence of systemic bias, formal fairness audits should be conducted to assess disparate impacts across provider types, patient demographics, or geographic regions. Similarly, explainability tools and documentation should be made available to auditors, regulators, and appeals processes to ensure transparency and accountability. The system's reliance on interpretable coefficients and traceable reconstruction errors offers a solid foundation for such efforts, but ongoing vigilance will be needed as models evolve.

Finally, stakeholder engagement remains a key enabler of long-term success [36]. The implementation of AI in claims adjudication affects not only data scientists and operations staff but also clinicians, compliance officers, provider relations teams, and executives. Successful adoption will require collaborative governance structures, shared performance dashboards, and clear communication about how the system works and why decisions are made. Training and change management efforts must be integrated into deployment plans to ensure that users understand and trust the system. Over time, these efforts can foster a culture of innovation and evidence-based decision-making across the organization.

In conclusion, the AI-assisted claims adjudication system presented in this study offers a compelling example of how machine learning and anomaly detection can be combined to deliver high-impact, interpretable, and scalable solutions in healthcare operations. With strong classification accuracy, efficient fraud detection, substantial cost savings, and clear alignment with domain logic, the system demonstrates the feasibility and value of AI-driven adjudication. While further work is needed to ensure fairness, adaptability, and continuous improvement, this approach sets a new standard for intelligent automation in healthcare finance. As payers seek to modernize their infrastructure and deliver more efficient, accurate, and trustworthy services, systems like the one described here will play a central role in shaping the future of claims processing. [37]

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