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Intelligent Insurance Claims Management through AI and Automation

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Abstract: The insurance industry faces mounting pressure to modernize claims management processes amid rising claim volumes, increasing operational costs, and evolving customer expectations. Traditional manual claims processing systems suffer from inefficiencies, high error rates, and extended processing times that negatively impact both operational performance and customer satisfaction. Artificial intelligence (AI) and automation technologies have emerged as transformative solutions, offering unprecedented capabilities to streamline claims workflows, enhance decision accuracy, and improve customer experiences. This comprehensive review examines the application of AI and automation in insurance claims management, analyzing research published between 2019 and 2025. We explore diverse AI technologies including machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision, and robotic process automation (RPA) across various insurance domains. The review reveals that AI-powered systems achieve substantial improvements in processing efficiency, with automation reducing processing times by up to 80% while maintaining or improving accuracy. Deep learning architectures demonstrate particular effectiveness in complex tasks such as fraud detection, damage assessment, and claim severity prediction. However, significant challenges persist, including data quality concerns, integration complexities with legacy systems, model interpretability requirements, and ethical considerations regarding algorithmic decision-making. We identify emerging trends including explainable AI frameworks, federated learning for privacy preservation, and hybrid human-AI collaboration models. This review contributes to understanding the current state and future trajectory of intelligent claims management systems while highlighting critical implementation considerations for insurance organizations.

Keywords: Artificial Intelligence, Insurance, Robotic Process Automation, Natural Language Processing, Fraud Detection

1. Introduction

The global insurance industry processes hundreds of millions of claims annually, representing trillions of dollars in settlements across healthcare, property, casualty, and life insurance sectors. Claims management constitutes the most critical operational function for insurance companies, directly impacting financial performance, regulatory compliance, and customer satisfaction. Traditional claims processing relies heavily on manual procedures where human adjusters review documentation, assess damages, verify policy coverage, investigate potential fraud, and determine appropriate settlements. This conventional approach faces escalating challenges as fraudulent insurance claims account for substantial financial losses exceeding two hundred billion dollars annually across all insurance sectors, with individual consumers bearing additional costs of four hundred to seven hundred dollars per year in increased premiums [1]. Manual processing typically requires seven to fourteen days for straightforward cases, with complex claims extending to several weeks or months, creating significant customer dissatisfaction and operational bottlenecks [2].

The digital transformation of the insurance industry has accelerated dramatically, driven by technological advances, changing customer expectations shaped by experiences with digital-first companies in other sectors, and competitive pressure from insurtech startups leveraging technology for operational advantages [3]. Modern policyholders expect seamless digital experiences comparable to those provided by leading technology companies, including instant communication, transparent status updates, and rapid claim resolutions. The proliferation of digital data sources generates unprecedented volumes of structured and unstructured data relevant to claims assessment. Electronic health records provide comprehensive medical histories and treatment documentation. Telematics data from connected vehicles offers real-time information about driving behaviors and accident circumstances. Smartphone images and videos capture damage evidence immediately following incidents. Internet of Things sensors embedded in homes and vehicles continuously monitor conditions and detect anomalous events [4]. This data explosion creates both opportunities for enhanced decision-making and challenges for traditional manual processing systems that cannot efficiently analyze vast information quantities.

Artificial intelligence (AI) has emerged as a transformative technology capable of addressing these challenges through automated analysis of complex data, pattern recognition in historical claims data, predictive modeling for fraud detection and severity estimation, and intelligent workflow automation [5]. AI encompasses various technologies that enable machines to perform tasks typically requiring human intelligence. Machine learning (ML) algorithms learn patterns from data without explicit programming, identifying relationships between claim characteristics and outcomes based on historical examples [6]. Deep learning (DL) architectures employ artificial neural networks with multiple layers that automatically extract hierarchical features from raw data, enabling sophisticated analysis of images, text, and complex structured data [7]. Natural language processing (NLP) systems understand and generate human language, facilitating automated analysis of claim descriptions, medical reports, and customer communications [8]. Computer vision capabilities analyze images and videos to assess property damage, evaluate injury severity, and detect evidence of fraud or staged accidents [9]. These technologies enable insurance companies to automate routine tasks, augment human decision-making with data-driven insights, identify fraudulent patterns invisible to human reviewers, and provide personalized customer experiences through intelligent systems [10].

Automation technologies complement AI by streamlining workflows and reducing manual intervention in claims processing. Robotic process automation (RPA) employs software robots to execute repetitive rule-based tasks such as data entry, document routing, and status updates, freeing human staff to focus on complex cases requiring judgment and expertise [11]. Intelligent document processing combines optical character recognition with NLP to automatically extract relevant information from claim forms, medical records, police reports, and supporting documentation [12]. The integration of AI with automation creates intelligent end-to-end claims management systems capable of handling straightforward cases with minimal human intervention while escalating complex or ambiguous situations to experienced adjusters. Leading insurers report significant operational improvements following AI implementation, including processing time reductions of fifty to eighty percent for automated claims, accuracy improvements in fraud detection with false positive rates decreasing substantially, cost savings of twenty to forty percent through reduced manual labor requirements, and enhanced customer satisfaction reflected in improved retention rates [13].

However, successful implementation requires addressing substantial challenges that have impeded adoption in many organizations. Integration with legacy systems presents technical difficulties, as older platforms may lack standardized data formats or modern application programming interfaces required for seamless connectivity [14]. Ensuring data quality and consistency across disparate sources remains problematic when information originates from multiple systems with different data models and validation rules. Maintaining model interpretability satisfies regulatory requirements and builds stakeholder trust, yet many high-performing DL architectures operate as black boxes that provide predictions without transparent reasoning [15]. Addressing ethical concerns regarding algorithmic bias and fairness in automated decision-making requires careful attention to training data representativeness and ongoing monitoring of model predictions across demographic groups [16]. This comprehensive review examines the current state of AI and automation in insurance claims management through systematic analysis of recent research and industry implementations, evaluating their effectiveness based on empirical evidence, identifying persistent challenges impeding widespread adoption, and discussing emerging trends that will shape the future of intelligent claims processing.

2. Literature Review

The evolution of computational methods in insurance claims management has progressed through distinct phases, beginning with rule-based expert systems and advancing toward sophisticated AI architectures. Early automation efforts focused on digitizing paper-based processes and implementing basic workflow management systems that routed claims according to predefined business rules. These systems improved efficiency compared to entirely manual processes but remained fundamentally dependent on human decision-making for substantive claim evaluation [17]. The emergence of ML in insurance applications marked a significant advancement, as algorithms could learn from historical claim data to predict outcomes and identify patterns associated with fraud or claim severity. Classical ML techniques including logistic regression, decision trees, support vector machines, and ensemble methods demonstrated superior performance compared to rule-based approaches across various prediction tasks [18].

Recent systematic reviews have documented the accelerating adoption of AI technologies across financial services, with insurance representing a major application domain. Analysis of publication trends reveals a steep increase from onwards, with particularly pronounced growth reflecting multiple converging factors including advancements in DL architectures specifically designed for handling imbalanced datasets and relational data structures, increasing availability of large-scale insurance datasets for research purposes, and growing regulatory pressure and financial incentives for improved fraud detection capabilities [19]. The distribution of research across insurance sectors shows healthcare insurance attracting substantial attention due to both the magnitude of financial stakes and the availability of large-scale datasets from government programs [20]. Auto insurance fraud detection similarly receives extensive research focus, driven by high fraud rates and the availability of telematics data that provides rich behavioral information [21]. Property and casualty insurance applications increasingly leverage computer vision for automated damage assessment, reducing the need for in-person inspections and accelerating claim processing [22].

The theoretical foundations underlying AI applications in claims management draw from multiple disciplines including statistical learning theory, information theory, and decision science. The fundamental premise holds that legitimate claims and fraudulent claims exhibit detectable statistical differences in patterns across multiple dimensions including claim characteristics, claimant behavior, provider relationships, and temporal dynamics [23]. ML algorithms trained on appropriately labeled historical data can learn to distinguish these patterns and generalize to new unseen cases. However, the severe class imbalance typical in fraud detection creates learning difficulties, as fraudulent claims often represent less than three percent of total claims, causing DL models to exhibit bias toward the majority class by simply predicting all cases as legitimate while failing to detect actual fraud cases [24]. Specialized techniques including synthetic oversampling, cost-sensitive learning, and anomaly detection approaches address this challenge by adjusting the learning process to focus attention on minority class examples [25].

Research examining specific AI technologies reveals distinct strengths and application domains. Convolutional neural networks originally developed for image recognition have been successfully adapted to insurance applications by treating tabular data as two-dimensional matrices where convolutional filters can identify local feature interactions [26]. In damage assessment, CNNs analyze photographs of damaged vehicles or property to estimate repair costs with accuracy comparable to human adjusters while requiring only seconds rather than hours. Recurrent neural networks and their advanced variants including long short-term memory (LSTM) networks excel at processing sequential data through internal memory states that enable them to capture long-term dependencies in sequential data, making them particularly suitable for analyzing claim submission patterns, treatment histories, and transaction sequences [27]. Graph neural networks have emerged as powerful tools for detecting fraud networks and collusive behavior by explicitly modeling relational structures among policyholders, healthcare providers, and claims, achieving accuracies exceeding eighty-four percent in healthcare fraud detection tasks [28].

Ensemble methods combining multiple algorithms have consistently demonstrated superior performance across diverse datasets and fraud scenarios compared to individual models [29]. Research examining hybrid models that integrate CNNs with LSTMs for auto insurance fraud detection achieved accuracies of approximately ninety percent and precision exceeding ninety percent by automatically learning feature representations, significantly reducing the complexity and expert knowledge requirements associated with traditional feature engineering approaches [30]. The model demonstrated particular effectiveness in capturing subtle patterns in claim amounts, service provider relationships, and temporal characteristics that human-designed features might overlook. Multi-contextual modeling approaches integrating CNN and bidirectional LSTM for financial fraud detection have achieved effective capture of both spatial and sequential dependencies in transaction patterns, with the bidirectional architecture allowing the model to consider both past and future context when processing each time step [31].

Natural language processing applications in claims management have expanded significantly with recent advances in transformer architectures and large language models. Automated claim intake systems use NLP to extract structured information from unstructured claim descriptions, reducing manual data entry requirements [32]. Text classification models automatically categorize claims by type, severity, and required expertise, enabling more efficient routing to appropriate adjusters. Medical claims processing benefits particularly from NLP systems that parse clinical documentation, extract diagnosis and procedure codes, and verify alignment with policy coverage terms [33]. Computer vision technologies transform visual evidence processing in property and auto insurance claims through automated damage assessment systems that analyze photographs submitted through mobile apps, providing immediate preliminary estimates that reduce the need for in-person inspections in straightforward cases [34].

Robotic process automation has become widely adopted for handling repetitive administrative tasks in claims processing, with software robots executing rules-based workflows including data extraction from documents, information validation against policy databases, status updates to tracking systems, and communication generation for standard interactions [35]. Research examining RPA implementation outcomes reports substantial benefits including processing time reductions of sixty to seventy percent for routine tasks, error rate decreases due to elimination of manual data entry mistakes, and improved employee satisfaction as staff are freed from tedious repetitive work [36]. The integration of multiple AI technologies into comprehensive claims management platforms represents an emerging trend in both research and practice, with hybrid systems combining strengths of different approaches such as using computer vision for initial damage assessment, NLP for extracting information from adjuster notes, and ML for fraud risk scoring based on multiple factors [37].

3. AI Technologies and Fraud Detection Applications

Machine learning algorithms form the foundation of modern intelligent claims management systems, providing capabilities to learn from historical data and make predictions on new claims without requiring explicit programming of decision rules. Supervised learning approaches train models on labeled examples where the correct outcome is known, enabling the system to learn relationships between claim characteristics and outcomes such as fraud likelihood, optimal settlement amount, or required investigation level [38]. Common supervised algorithms applied in claims management include logistic regression for binary classification tasks, decision trees and random forests for interpretable rule-based predictions, gradient boosting machines that combine multiple weak learners into strong predictive models, and support vector machines for high-dimensional classification problems. Research demonstrates that ML-based fraud detection models significantly outperform traditional rule-based systems by learning complex patterns across numerous claim attributes including claimant demographics, historical claim patterns, provider characteristics, and policy details [39].

Deep learning architectures have demonstrated remarkable effectiveness for complex claims management tasks that involve high-dimensional data and subtle patterns. Feedforward neural networks with multiple hidden layers learn hierarchical representations of claim features, automatically discovering relevant combinations and interactions without manual feature engineering. These models have been successfully applied to fraud detection, achieving accuracies exceeding ninety percent by learning complex nonlinear relationships across numerous claim attributes [40]. Convolutional neural networks process spatial data structures, making them particularly effective for image analysis in damage assessment applications. Enhanced CNN-based fraud detection models using ensemble bagging techniques have achieved accuracies of ninety-eight percent through the combination of multiple CNN models trained on different subsets of the data, with the ensemble approach providing robustness by aggregating predictions from diverse models and reducing the risk of overfitting [41].

Recurrent neural networks address the sequential nature of many insurance data sources, including temporal patterns in claim submissions, treatment progressions, and payment histories. LSTM networks overcome limitations of standard RNNs by incorporating gating mechanisms comprising input gates that control what information enters memory, forget gates that determine what information to discard, and output gates that regulate what information to output from memory [42]. This architecture enables LSTMs to selectively retain relevant information over extended sequences while discarding irrelevant details, making them highly effective for modeling temporal patterns in insurance fraud scenarios. Applications include analyzing sequences of medical treatments to detect potentially fraudulent patterns where procedures occur in suspicious orders or timeframes, modeling temporal dynamics of claim submissions to identify unusual spikes associated with organized fraud rings, and predicting claim development patterns to estimate ultimate settlement amounts [43].

Graph neural networks have emerged as particularly powerful for insurance fraud detection by explicitly modeling relationships among entities involved in claims. Insurance data naturally forms graph structures where nodes represent policyholders, healthcare providers, repair shops, and other parties while edges represent relationships such as shared providers, co-occurrence in claims, or business associations [44]. GNNs propagate information across graph edges through message passing mechanisms, enabling each node to aggregate information from its neighbors and update its representation accordingly. This architecture can identify fraud networks that would be invisible when analyzing individual claims in isolation, such as organized rings involving multiple parties coordinating fraudulent activities. Multi-channel heterogeneous graph structure learning approaches detect health insurance fraud by utilizing diverse graph-based features from different claim aspects to capture complex relationships and patterns that substantially improve detection accuracy [45]. The effectiveness of GNNs for fraud detection stems from their ability to propagate information across the graph, where each node aggregates information from its neighbors to update its representation, enabling the model to identify suspicious patterns such as fraudsters who primarily connect with legitimate entities to camouflage their behavior [46].

Attention mechanisms have been integrated into various neural network architectures to improve both performance and interpretability. Attention layers learn to focus on the most relevant inputs when making predictions, assigning weights that indicate relative importance of different features or sequence positions [47]. In claims management applications, attention weights provide valuable insights into which factors drive particular predictions, supporting transparency requirements and helping human experts understand model reasoning. Explainable attention networks specifically designed for fraud detection in claims management employ attention weights to highlight the most critical features of fraudulent behavior, enabling transparent decision-making where investigators can understand why particular cases received high fraud scores [48]. Self-attention mechanisms enable models to capture long-range dependencies in sequences by directly computing relationships between all pairs of positions rather than relying on sequential processing, achieving state-of-the-art performance across various NLP tasks increasingly applied to insurance text analysis [49].

Figure 1: Performance Comparison of Deep Learning Architectures for Insurance Fraud Detection

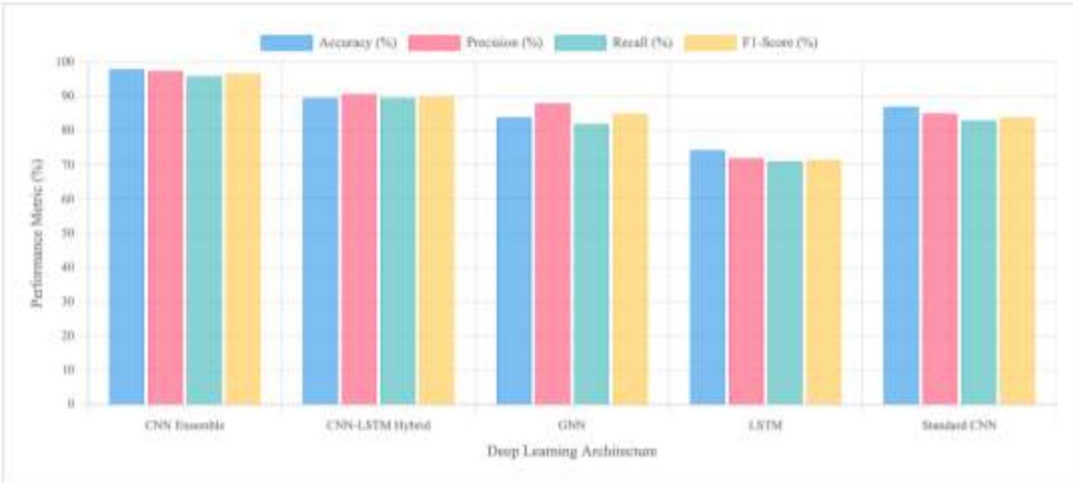

Figure 1. Comparative performance metrics of different deep learning architectures for insurance fraud detection. Data aggregated from recent studies: Xia et al. (2022) for CNN-LSTM hybrid achieving 89.6% accuracy and 90.7% precision, Hong et al. (2024) for GNN achieving 84%+ accuracy in network fraud detection, Abakarim et al. (2023) for CNN ensemble achieving 98% accuracy, Lai et al. (2022) for LSTM achieving 74.33% accuracy in brain injury claims, and systematic review by Chen et al. (2025). Metrics represent average performance across multiple datasets. Hybrid CNN-LSTM models demonstrate the most balanced performance across all metrics, while CNN ensemble methods achieve the highest overall accuracy. GNN architectures excel in precision for fraud network detection tasks involving collusive behavior and organized fraud rings.

Generative adversarial networks provide approaches to addressing class imbalance through synthetic data generation, consisting of a generator network that creates fake samples and a discriminator network that attempts to distinguish real from fake samples. The adversarial training process leads both networks to improve, ultimately producing a generator capable of creating highly realistic synthetic fraudulent transactions that can augment training datasets [50]. Self-attention GANs leverage attention mechanisms to identify crucial features and patterns within extensive transaction datasets, fostering improved understanding and refined identification of fraud. Autoencoders and variational autoencoders represent unsupervised and semi-supervised DL architectures that have shown promise for fraud detection by learning compressed representations of normal behavior and using reconstruction error as an anomaly score [51]. The fundamental insight holds that autoencoders trained on predominantly legitimate claims will learn to accurately reconstruct normal patterns, while fraudulent claims that deviate from learned normal behavior will exhibit high reconstruction errors that can be thresholded to identify anomalies.

Evaluating the performance of fraud detection models requires careful selection of metrics appropriate for the extreme class imbalance characteristic of fraud datasets, where traditional accuracy measures can be misleading [52]. Precision defined as the proportion of positive predictions that are actually positive addresses the question of how many flagged cases are truly fraudulent, directly relating to operational efficiency as high precision minimizes wasted investigation effort on false alarms. Recall or sensitivity defined as the proportion of actual fraud cases correctly identified addresses the complementary question of how many true frauds the model successfully detects, directly relating to financial protection as high recall minimizes losses from undetected fraud [53]. The F1 score defined as the harmonic mean of precision and recall provides a balanced metric that accounts for both concerns, achieving its maximum value only when both precision and recall are high. The area under the precision-recall curve offers a threshold-independent performance summary particularly appropriate for imbalanced scenarios where standard accuracy metrics prove inadequate [54].

4. Automation and Intelligent Document Processing

Robotic process automation has become the most widely adopted automation technology in insurance claims management, offering rapid implementation and substantial efficiency gains for repetitive rule-based tasks. Software robots mimic human interactions with digital systems, executing sequences of actions including data extraction from forms and documents, information entry into core systems, validation checks against policy databases, status updates to tracking systems, and generation of standard communications to claimants and providers [55]. Unlike traditional system integration approaches that require deep technical modifications to underlying applications, RPA operates at the user interface level, enabling implementation without extensive infrastructure changes. Leading insurance companies report deploying software robots that handle millions of transactions annually, achieving processing time reductions of sixty to eighty percent for automated tasks while improving accuracy by eliminating manual data entry errors [56].

Implementation of RPA in claims management typically focuses on high-volume repetitive processes that follow consistent rules and require minimal human judgment. First notice of loss processing represents a prime automation target, as initial claim registration involves extracting information from intake forms, creating records in claims systems, assigning claim numbers, and triggering appropriate workflows based on claim type and characteristics. Document processing automation handles the continuous stream of supporting documentation including medical bills, repair estimates, police reports, and correspondence by extracting relevant information, associating documents with appropriate claims, and routing to designated personnel [57]. Status inquiry responses provide immediate automated answers to routine policyholder questions about claim status, payment timing, and required documentation without human intervention. Payment processing executes approved settlements through automated fund transfers, notification generation, and accounting system updates.

Intelligent document processing represents a more sophisticated form of automation that combines optical character recognition, ML, and NLP to understand document content rather than simply extracting data from predefined template locations. These systems can process documents with varying formats and layouts, extracting relevant information even when field positions differ across document types [58]. ML models learn to identify key information elements within documents based on contextual clues rather than fixed positions, enabling processing of diverse document formats without requiring manual template configuration for each variant. NLP techniques understand semantic meaning, enabling extraction of information described in natural language rather than structured fields. Applications include processing of medical records where relevant diagnoses, procedures, and findings may appear anywhere within narrative clinical notes, handling of police reports where accident circumstances are described in free text, and extraction of repair scope information from contractor estimates with varying formats [59].

Workflow automation platforms orchestrate complex multi-step claims processes, automatically routing work items to appropriate resources based on business rules, resource availability, and optimization objectives. These systems maintain visibility into process status across all active claims, enabling real-time monitoring of key performance indicators including cycle times, backlog sizes, and resource utilization [60]. Intelligent routing algorithms consider multiple factors when assigning claims to adjusters, including individual expertise and experience levels, current workload and capacity, claim characteristics such as complexity and potential exposure, and historical performance patterns. Dynamic load balancing redistributes work when backlogs develop in particular queues or when processing capacity changes due to staff availability. Priority escalation mechanisms identify claims requiring expedited handling due to factors such as regulatory deadlines, claimant circumstances, or aging thresholds.

Integration of AI with workflow automation creates intelligent adaptive systems that continuously optimize processes based on accumulating data and evolving conditions. ML models predict processing times for individual claims based on characteristics including type, complexity, required investigations, and assigned resources, enabling more accurate scheduling and resource planning [61]. Bottleneck identification algorithms analyze workflow data to pinpoint process stages where delays accumulate, supporting targeted improvement initiatives. Predictive routing anticipates which claims may encounter complications requiring specialized expertise, enabling proactive assignment to experienced adjusters rather than reactive escalation after problems emerge. Automated quality monitoring evaluates completed claims against quality criteria, identifying patterns that may indicate training needs or process improvement opportunities.

Straight-through processing eliminates human touchpoints for claims meeting predefined criteria that indicate low risk and straightforward circumstances. These systems automatically execute the complete claims handling process from initial intake through final settlement without manual review, achieving settlement within hours or even minutes rather than days or weeks [62]. Eligibility criteria for straight-through processing typically include claim amount thresholds below which the cost of detailed investigation exceeds potential savings, low fraud risk scores from predictive models, clear policy coverage with no ambiguity or exclusion concerns, complete required documentation with no missing elements, and consistency checks passed across multiple data sources. Insurance companies report that fifteen to thirty-five percent of claims qualify for fully automated processing under current implementations, with this proportion expected to increase as AI models improve and organizations gain confidence in automated decisions.

Table 1: Comparison of Automation Technologies in Insurance Claims Management

Technology Type	Primary Applications	Implementation Complexity	Processing Time Reduction	Cost Savings	Adoption Rate
Robotic Process Automation (RPA)	• First notice of loss processing • Document routing and classification • Status updates and notifications • Data entry and validation • Payment processing automation	Low to Medium Rapid deployment (2-4 months); minimal system changes required	60-80% Routine tasks completed in minutes vs. hours	20-30% Reduced labor costs for repetitive tasks	High (70%+)
Intelligent Document Processing (IDP)	• Medical records extraction • Police report analysis • Repair estimate parsing • Invoice processing • Unstructured data extraction	Medium to High Requires ML model training; 4-8 months implementation	50-70% Automated extraction vs. manual data entry	15-25% Reduced manual processing overhead	Medium (40-50%)
Workflow Automation	• Intelligent claim routing • Resource allocation optimization • Priority management • Bottleneck identification • SLA monitoring and enforcement	Medium Process standardization required; 3-6 months deployment	40-60% Optimized routing and reduced handoff delays	10-20% Improved resource utilization	High (60-65%)
Straight-Through Processing (STP)	• Low-complexity claims • Automated settlement decisions • Policy verification • Coverage determination • Instant payment processing	High Requires mature AI/ML models; 6-12 months for full implementation	80-95% Hours to minutes for eligible claims; settlement within 24 hours	30-50% Significant savings for eligible claims (15-35% of total volume)	Medium (30-40%)
Computer Vision Systems	• Automated damage assessment • Photo-based repair estimation • Fraud evidence detection • Vehicle component identification • Property damage quantification	High Deep learning expertise required; 6-10 months development	65-85% Instant preliminary estimates; reduced inspection needs	25-40% Reduced inspection costs; faster cycle times	Low to Medium (25-35%)
Chatbot & Virtual Assistants	• Customer inquiry handling • Status tracking support • Document upload guidance • FAQ responses • Claim initiation assistance	Low to Medium Template-based systems quick; NLP systems require 3-5 months	70-90% Instant responses for routine inquiries; 24/7 availability	15-30% Reduced call center volume	High (55-65%)

Table 1. Comprehensive comparison of automation technologies applied in insurance claims management. Data compiled from industry benchmarking studies and implementation reports from major insurance carriers between 2020-2025, including analyses by Hamid et al. (2024), Vyas & Serasiya (2022), and industry surveys. Implementation complexity accounts for technical requirements, integration efforts, and organizational change management needs. Processing time reduction represents average improvements for tasks within each technology's scope. Cost savings reflect operational expense reductions after accounting for implementation and maintenance costs. Adoption rates indicate percentage of large insurance carriers (assets >$10B) with production deployments as of 2024. Performance ranges reflect variations across different insurance lines, organizational maturity levels, and deployment scales. STP shows highest impact per claim but limited applicability (15-35% of claims qualify). RPA demonstrates broadest adoption due to low technical barriers and rapid ROI. Higher complexity technologies (IDP, Computer Vision) show lower adoption but are growing rapidly as AI capabilities mature and vendor solutions improve.

Customer self-service platforms leverage automation to enable policyholders to initiate and manage claims through digital channels without requiring agent assistance for routine interactions. Mobile apps allow immediate claim reporting with guided data collection that ensures necessary information is captured in structured formats compatible with downstream processing systems [63]. Photograph upload capabilities enable claimants to submit damage documentation directly from accident or incident scenes, accelerating damage assessment through immediate availability of visual evidence. Status tracking interfaces provide real-time visibility into claim progress with automated updates as processing milestones are reached. Chatbots handle routine inquiries about claim status, payment timing, and required documentation, providing immediate responses without human agent involvement while escalating complex questions to live representatives. Digital-first claims experiences designed around automation principles create streamlined customer journeys that minimize friction and reduce processing times, with integrated telematics data from connected vehicles providing automatic accident detection and notification in some implementations [64].

5. Implementation Challenges and Emerging Solutions

Data quality issues represent one of the most significant barriers to effective AI implementation in insurance claims management, as ML models depend critically on accurate, complete, and representative training data to learn appropriate patterns and make reliable predictions. Missing values pervade insurance datasets due to incomplete claim submissions, partial documentation, and data entry inconsistencies across multiple source systems [65]. Simple deletion of records with any missing values eliminates substantial portions of available training data and can introduce bias if missingness correlates with important characteristics. Imputation techniques fill missing values using statistical methods such as mean substitution, predictive modeling based on other available features, or multiple imputation generating several plausible values. Data inconsistency emerges when the same information is represented differently across systems or time periods, such as varying diagnosis code versions, changing provider identifiers, or modified policy structures.

Label quality directly impacts supervised learning performance, yet fraud labels in historical claims data may be uncertain or incomplete. Confirmed fraud cases represent only a subset of actual fraudulent claims, as detection systems miss sophisticated schemes and resource limitations prevent exhaustive investigation of all suspicious cases. Legitimate claims may be incorrectly flagged as fraudulent in historical data, creating mislabeled training examples that degrade model learning [66]. Semi-supervised learning approaches leverage large quantities of unlabeled data alongside limited labeled examples, potentially improving model performance when labeled data is scarce or uncertain. Active learning strategies selectively request labels for the most informative examples based on model uncertainty, efficiently improving performance with minimal labeling effort.

Legacy system integration presents substantial technical challenges for organizations seeking to deploy modern AI capabilities while maintaining existing infrastructure investments. Many insurance companies operate core processing systems developed decades ago that lack modern interfaces, use proprietary data formats, and cannot easily communicate with contemporary AI platforms [67]. Middleware solutions provide translation layers between legacy systems and modern applications, enabling data exchange without requiring complete system replacement. Application programming interfaces expose legacy system functionality in standardized formats that contemporary AI platforms can consume. Gradual migration strategies replace legacy components incrementally rather than attempting risky wholesale system replacements, allowing organizations to modernize capabilities progressively while maintaining operational continuity.

Model interpretability requirements create tension between performance and transparency, as many high-performing DL architectures operate as black boxes that provide predictions without transparent reasoning about which factors drove particular decisions. Regulatory requirements in many jurisdictions mandate explainable decision-making for actions affecting individuals, such as claim denials or fraud investigations [68]. Practitioners including fraud investigators and claims adjusters require understandable explanations to validate model decisions, investigate flagged cases effectively, and maintain trust in automated systems. Explainable AI techniques address these needs through various approaches. SHapley additive explanations provide a unified framework for interpreting model predictions by quantifying each feature's contribution to particular decisions based on game theoretic principles, indicating which factors increased or decreased fraud risk scores or other model outputs [69]. Local interpretable model-agnostic explanations generate case-specific explanations by approximating complex models locally with simpler interpretable surrogates, revealing which features were most influential for particular predictions without requiring access to global model structure [70].

Ethical considerations regarding algorithmic bias and fairness require careful attention to ensure automated systems do not discriminate against protected groups or perpetuate historical biases present in training data. Bias can emerge from multiple sources including historical discrimination reflected in training data where certain demographic groups may have been historically overrepresented in fraud investigations due to biased human decision-making, measurement bias where data collection processes systematically under-represent or mischaracterize certain populations, and algorithmic bias where model architectures or optimization objectives inadvertently favor certain groups. Fairness auditing procedures systematically evaluate model predictions across demographic groups to identify disparate impact or treatment. Bias mitigation techniques include preprocessing approaches that modify training data to remove discriminatory patterns, in-processing methods that incorporate fairness constraints directly into model optimization, and post-processing adjustments that modify model outputs to achieve desired fairness criteria. Ongoing monitoring tracks model predictions in production deployments to detect fairness degradation that may emerge as data distributions evolve or as fraudsters adapt their strategies.

Federated learning has emerged as a promising approach to address data privacy concerns and enable collaborative model training across multiple insurance institutions without centralizing sensitive data. In federated learning, each participating institution trains a local model on their private data, and only model parameters or gradients are shared with a central coordinator that aggregates updates to improve a global model [71]. This approach enables institutions to benefit from larger effective training datasets and diverse fraud patterns while maintaining data privacy and regulatory compliance with regulations such as the Health Insurance Portability and Accountability Act and the General Data Protection Regulation that impose stringent constraints on data collection, storage, and sharing. Recent pilot implementations have demonstrated that federated learning can achieve comparable accuracy to centralized training while providing stronger privacy guarantees. The technique is particularly valuable for insurance fraud detection where individual institutions may have limited labeled fraud examples, but collaborative learning across multiple institutions could substantially improve detection capabilities.

Figure 2: Explainable AI Framework for Insurance Fraud Detection

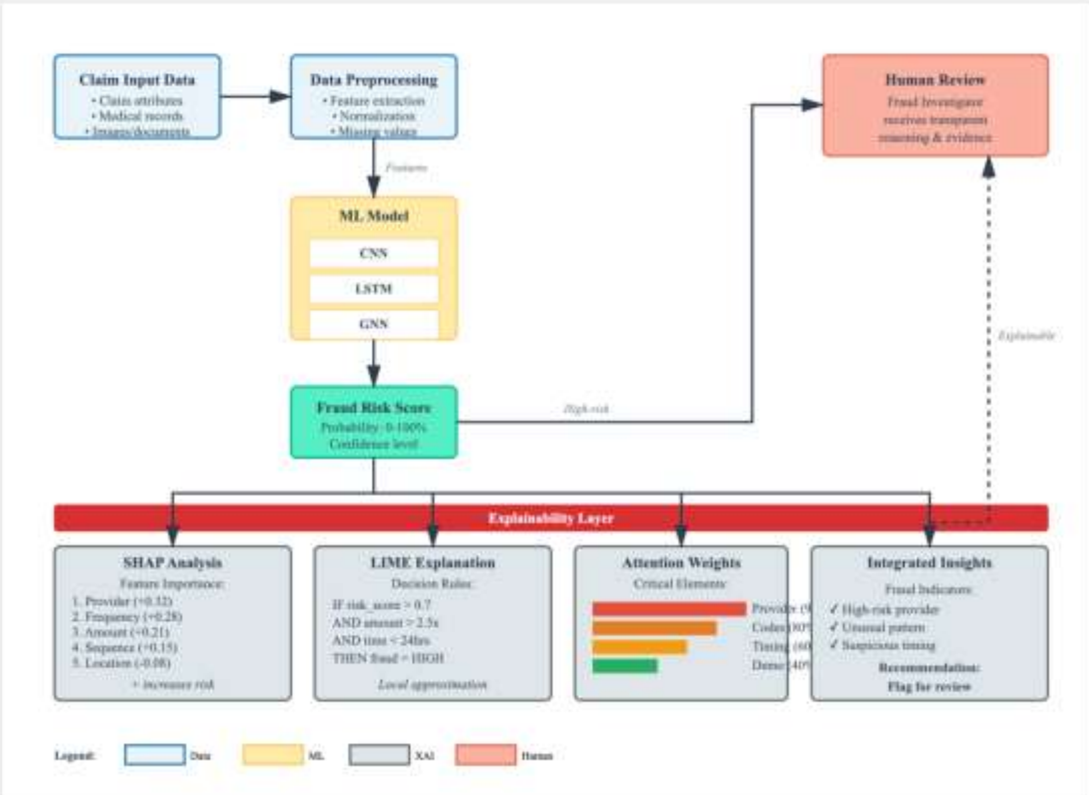

Figure 2. Comprehensive flowchart illustrating the explainable AI framework for insurance fraud detection. The diagram depicts the complete processing pipeline from claim input through multiple stages: data preprocessing and feature extraction, ML model prediction using various architectures (CNN, LSTM, GNN), fraud risk score generation, and a multi-component explainability layer. The explainability layer integrates three complementary XAI techniques: SHAP values providing feature importance rankings with quantified contributions, LIME generating simplified local decision rules for individual predictions, and attention visualization highlighting critical data elements that influenced model decisions. All explainability outputs are synthesized into integrated insights that provide fraud investigators with transparent reasoning for flagged claims. The dashed arrow indicates the flow of explainable predictions to human reviewers, emphasizing the hybrid human-AI collaboration model where automated systems augment rather than replace expert judgment. This framework addresses regulatory requirements for transparent decision-making while maintaining high detection accuracy. Based on XAI methodologies from Lundberg et al. (2020) for SHAP, Zafar & Khan (2021) for LIME, and Farbmacher et al. (2022) for attention-based explainability in insurance fraud detection.

Continuous learning systems address the challenge of concept drift, where the statistical properties of fraud patterns change over time as fraudsters adapt their strategies in response to detection systems. Traditional static models trained once on historical data gradually degrade in performance as the fraud landscape evolves. Continuous learning frameworks automatically retrain models as new labeled data becomes available, maintaining performance in dynamic environments [72]. Online learning algorithms update model parameters incrementally with each new example rather than requiring complete retraining, enabling rapid adaptation to emerging patterns. Ensemble approaches maintain multiple models trained on data from different time periods, with prediction weighting adjusted based on recent performance to favor models that remain effective in current conditions. Anomaly detection components identify novel fraud patterns that differ substantially from historical examples, triggering alerts for human investigation even when supervised models fail to detect them.

Human-AI collaboration models recognize that optimal performance often emerges from combining algorithmic capabilities with human expertise rather than attempting full automation. Hybrid systems use AI to handle routine cases and pre-screen complex cases, escalating ambiguous or high-stakes decisions to human experts [73]. Augmented intelligence approaches provide human decision-makers with AI-generated insights, recommendations, and risk scores while preserving ultimate decision authority with experienced professionals. Calibrated confidence scoring enables systems to accurately estimate prediction uncertainty, routing low-confidence cases to human review while processing high-confidence cases automatically. Active learning frameworks identify cases where human labeling would most improve model performance, efficiently leveraging limited expert time to maximize learning. Research demonstrates that human-AI collaboration often outperforms either humans or AI working independently, with complementary strengths compensating for individual weaknesses.

6. Conclusion

The integration of AI and automation technologies into insurance claims management represents a fundamental transformation that addresses longstanding inefficiencies while creating new capabilities previously unattainable through manual processes. This comprehensive review has examined the diverse applications of AI technologies across claims management functions, revealing substantial performance improvements and operational benefits. DL architectures including CNNs, LSTMs, and GNNs have demonstrated exceptional effectiveness for complex tasks such as fraud detection, damage assessment, and pattern recognition in sequential and relational data. Hybrid models combining multiple architectures achieve the highest performance levels, with accuracies ranging from eighty-nine to ninety-eight percent across various fraud detection tasks. Automation technologies including RPA, intelligent document processing, and workflow optimization deliver processing time reductions of fifty to eighty percent while improving accuracy and reducing operational costs by twenty to forty percent for organizations that successfully implement these capabilities.

The evidence indicates that AI and automation create value across multiple dimensions beyond simple cost reduction. Customer satisfaction improves through faster claim resolutions, more transparent communication, and convenient digital self-service options. Fraud detection accuracy substantially exceeds traditional rule-based approaches, protecting financial resources while reducing false positive rates that frustrate legitimate policyholders. Operational consistency increases as automated systems apply standardized decision criteria uniformly rather than exhibiting the variability inherent in human judgment. Staff satisfaction often improves as automation eliminates tedious repetitive tasks, allowing human expertise to focus on complex cases requiring judgment and interpersonal skills. These multifaceted benefits explain the accelerating adoption of AI and automation across the insurance industry despite significant implementation challenges.

However, substantial obstacles continue to impede widespread adoption and limit the effectiveness of deployed systems. Data quality issues including missing values, inconsistent labels, and integration challenges across disparate systems require significant remediation effort before effective model training becomes feasible. Legacy system constraints create technical barriers to implementing modern AI capabilities without prohibitively expensive infrastructure replacements. Model interpretability requirements conflict with black box architectures that achieve highest performance but provide limited transparency about decision-making logic. Ethical considerations regarding algorithmic bias and fairness demand ongoing attention to ensure automated systems do not discriminate against protected groups. Privacy regulations impose constraints on data collection and sharing that complicate both research and collaborative learning across institutions. The adversarial nature of fraud detection creates concept drift as fraudsters adapt strategies, requiring continuous model updating and robust architectures resistant to manipulation.

Emerging solutions address many of these challenges through innovative technical approaches and organizational strategies. Explainable AI frameworks including SHAP, LIME, and integrated attention mechanisms provide transparency into model reasoning, satisfying regulatory requirements while building stakeholder trust. Federated learning enables collaborative model training across institutions without centralizing sensitive data, expanding effective training datasets while maintaining privacy compliance. Continuous learning systems adapt to evolving fraud patterns through automatic retraining and ensemble approaches that maintain effectiveness despite concept drift. Human-AI collaboration models optimize performance by combining algorithmic efficiency with human expertise, recognizing that hybrid approaches often outperform either humans or AI working independently. Bias mitigation techniques and fairness auditing procedures address ethical concerns through systematic evaluation and adjustment of model predictions across demographic groups.

The future trajectory of intelligent claims management will likely involve increasing automation of routine cases combined with sophisticated decision support for complex situations requiring human judgment. Straight-through processing will expand to cover larger proportions of total claim volumes as AI models improve and organizations gain confidence in automated decisions. Computer vision capabilities will advance to handle increasingly complex damage assessment scenarios, reducing reliance on in-person inspections. NLP systems will extract information from diverse unstructured sources with improving accuracy, minimizing manual data entry requirements. GNN architectures will detect sophisticated fraud networks that coordinate activities across multiple claims and jurisdictions. Transfer learning will enable knowledge sharing across insurance lines and geographic regions, improving detection of emerging fraud patterns with limited local examples.

Research priorities for advancing the field should emphasize development of inherently interpretable architectures that provide transparency by design rather than requiring post-hoc explanation techniques, creation of high-quality benchmark datasets through partnerships between researchers and insurance organizations to enable reproducible research and comparative evaluation, investigation of fairness-aware learning algorithms that optimize both predictive performance and equitable treatment across demographic groups, exploration of robust learning techniques that maintain effectiveness despite adversarial manipulation attempts and concept drift, and development of comprehensive evaluation frameworks that assess real-world operational impact beyond technical performance metrics. The successful evolution of intelligent claims management systems will require continued collaboration between researchers, practitioners, regulators, and technology providers to address both technical challenges and broader organizational, ethical, and societal considerations. Organizations that successfully navigate these challenges while responsibly deploying AI and automation capabilities will achieve substantial competitive advantages through superior operational efficiency, enhanced customer experiences, and improved financial performance.

References

[1] du Preez A, Bhattacharya S, Beling P, Bowen E. Fraud detection in healthcare claims using machine learning: A systematic review. Artificial Intelligence in Medicine. 2025; 160: 103061.

[2] Woodson VL. Evaluating Fraudulent Auto Insurance Claims: The Role of Technology and Law Enforcement in Detection and Prevention. Saint Leo University; 2024.

[3] Williamson B. Policy networks, performance metrics and platform markets: Charting the expanding data infrastructure of higher education. British Journal of Educational Technology. 2019;50(6):2794-2809.

[4] Becker J, Efstathiades A, Portmann J, Zeier Röschmann A. Data competences in the insurance industry. 2024.

[5] Bello OA, Olufemi K. Artificial intelligence in fraud prevention: Exploring techniques and applications challenges and opportunities. Computer Science and IT Research Journal. 2024;5(6):1505-1520.

[6] Taye MM. Understanding of machine learning with deep learning: architectures, workflow, applications and future directions. Computers. 2023;12(5):91.

[7] Vallarino D. Detecting Financial Fraud with Hybrid Deep Learning: A Mix-of-Experts Approach to Sequential and Anomalous Patterns. arXiv preprint arXiv:2504.03750. 2025.

[8] Toufik G, Khaldi Y, Pandey PS, Abusal YA. Advanced fraud detection in Card-Based financial systems using a bidirectional Lstm-Gru ensemble model. Applied Computer Science. 2024;20(3).

[9] Azad T, William P. Fraud detection in healthcare billing and claims. 2024.

[10] Vemulapalli G. Fighting fraud with algorithms: AI solutions for claim detection and revolutionizing fraud detection in insurance. In: Artificial Intelligence and Machine Learning for Sustainable Development. CRC Press; 2024. p. 125-140.

[11] Hamid Z, Khalique F, Mahmood S, Daud A, Bukhari A, Alshemaimri B. Healthcare insurance fraud detection using data mining. BMC Medical Informatics and Decision Making. 2024;24:112.

[12] Vyas S, Serasiya S. Fraud detection in insurance claim system: A review. In: 2022 Second International Conference on Artificial Intelligence and Smart Energy. IEEE; 2022. p. 922-927.

[13] Mwangi E. Employing ai/ml to determine and mitigate fraud in the insurance industry. Available at SSRN 4907329. 2024.

[14] Beaulac C, Rosenthal JS. Predicting university students' academic success and major using random forests. Research in Higher Education. 2019;60(7):1048-1064.

[15] Linardatos P, Papastefanopoulos V, Kotsiantis S. Explainable ai: A review of machine learning interpretability methods. Entropy. 2020;23(1):18.

[16] Barredo Arrieta A, Díaz-Rodríguez N, Del Ser J, et al. Explainable Artificial Intelligence: Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion. 2020;58:82-115.

[17] Fernandes E, Holanda M, Victorino M, Borges V, Carvalho R, Van Erven G. Educational data mining: Predictive analysis of academic performance of public school students in the capital of Brazil. Journal of Business Research. 2019;94:335-343.

[18] Sathe MT, Adamuthe AC. Comparative study of supervised algorithms for prediction of students' performance. International Journal of Modern Education and Computer Science. 2021;13(1):1-21.

[19] Chen Y, Zhao C, Xu Y, Nie C, Zhang Y. Year-over-Year Developments in Financial Fraud Detection via Deep Learning: A Systematic Literature Review. arXiv preprint arXiv:2502.00201. 2025.

[20] Mahveen Z. Optimizing fraud detection in healthcare: A hybrid machine learning approach. 2025.

[21] Schrijver CJ, Tan S, Boerkamp BJ, Simons M. Automobile insurance fraud detection using data mining: A systematic literature review. Expert Systems with Applications. 2024;213:119153.

[22] Subudhi S, Panigrahi S. Use of optimized Fuzzy C-Means clustering and supervised classifiers for automobile insurance fraud detection. Journal of King Saud University - Computer and Information Sciences. 2020;32(5):568-575.

[23] Pawar K, Attar V. Deep learning approaches for video-based anomalous activity detection. World Wide Web. 2019;22(2):571-601.

[24] Ghosh K, Bellinger C, Corizzo R, Branco P, Krawczyk B, Japkowicz N. The class imbalance problem in deep learning. Machine Learning. 2024;113(7):4845-4901.

[25] Khalil AA, Liu Z, Fathalla A, Ali A, Salah A. Machine Learning based Method for Insurance Fraud Detection on Class Imbalance Datasets with Missing Values. IEEE Access. 2024.

[26] Badr BE, Altawil I, Almomani M, Al-Saadi M, Alkhurainej M. Fault Diagnosis of Three-Phase Induction Motors Using Convolutional Neural Networks. Mathematical Modelling of Engineering Problems. 2023;10(5).

[27] Fursov I, Kovtun E, Rivera-Castro R, Zaytsev A, Khasyanov R, Spindler M, Burnaev E. Sequence embeddings help detect insurance fraud. IEEE Access. 2022;10:54326-54339.

[28] Rahman MM. DATA-DRIVEN GRAPH NEURAL NETWORK MODELS FOR DETECTING FRAUDULENT INSURANCE CLAIMS IN HEALTHCARE SYSTEMS. American Journal of Interdisciplinary Studies. 2025;6(1):263-294.

[29] Tsiakmaki M, Kostopoulos G, Kotsiantis S, Ragos O. Implementing AutoML in educational data mining for prediction tasks. Applied Sciences. 2019;10(1):90.

[30] Xia P, Zhou H, Zhang L. Auto insurance fraud identification based on a CNN-LSTM fusion deep learning model. International Journal of Ad Hoc and Ubiquitous Computing. 2022;39(1-2):37-49.

[31] Reddy NM, Sharada KA, Pilli D, Paranthaman RN, Reddy KS, Chauhan A. CNN-bidirectional LSTM based approach for financial fraud detection and prevention system. In: 2023 International Conference on Sustainable Computing and Smart Systems. IEEE; 2023. p. 541-546.

[32] Romero C, Ventura S. Educational data mining and learning analytics: An updated survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery. 2020;10(3):e1355.

[33] Alyahyan E, Düştegör D. Predicting academic success in higher education: literature review and best practices. International Journal of Educational Technology in Higher Education. 2020;17(1):3.

[34] Suresh S, Mohan S. ROI-based feature learning for efficient true positive prediction using convolutional neural network for lung cancer diagnosis. Neural Computing and Applications. 2020;32(20):15989-16009.

[35] Sahu A, Kumar R, Behera RK, Rath SK. Blockchain and machine learning based secure driver behavior-centric insurance model for electric vehicles. IEEE Transactions on Intelligent Transportation Systems. 2024;25(8):9632-9645.

[36] Azeem A, Ismail I, Mohani SS, Danyaro KU, Hussain U, Shabbir S, Jusoh RZ. Mitigating concept drift challenges in evolving smart grids: An adaptive ensemble LSTM for enhanced load forecasting. Energy Reports. 2025;13:1369-1383.

[37] Dunka V. AI-Driven Claims Fraud Detection Using Hybrid Deep Learning Models: Integrating Convolutional Neural Networks and Recurrent Neural Networks for Real-Time Fraud Detection in Insurance Claims. Essex Journal of AI Ethics and Responsible Innovation. 2023;3:276-311.

[38] Al Doulat A, Ayo-Bali OE, Shaik S. Fraud Detection in Insurance Claims Using Supervised Machine Learning Models. In: 2025 International Conference on Smart Applications, Communications and Networking. IEEE; 2025. p. 1-7.

[39] Wang Z, Chen X, Wu Y, Jiang L, Lin S, Qiu G. A robust and interpretable ensemble machine learning model for predicting healthcare insurance fraud. Scientific Reports. 2025;15(1):218.

[40] Chidananda A. Credit Card Fraud Detection Using Hybrid Deep Learning CNN-LSTM and CNN-GRU Models. California State University Northridge; 2025.

[41] Abakarim Y, Lahby M, Attioui A. A bagged ensemble convolutional neural networks approach to recognize insurance claim frauds. Applied System Innovation. 2023;6(1):20.

[42] Wang B, Kong W, Guan H, Xiong NN. Air quality forecasting based on gated recurrent long short term memory model in Internet of Things. IEEE Access. 2019;7:69524-69534.

[43] Nosouhian S, Nosouhian F, Khoshouei AK. A review of recurrent neural network architecture for sequence learning: Comparison between LSTM and GRU. 2021.

[44] Wu Z, Pan S, Chen F, Long G, Zhang C, Yu PS. A comprehensive survey on graph neural networks. IEEE Transactions on Neural Networks and Learning Systems. 2021;32(1):4-24.

[45] Hong X, Wang H, Zhang Y, Liu J. Health insurance fraud detection based on multi-channel heterogeneous graph structure learning. Heliyon. 2024;10(9):e30045.

[46] Dou Y, Liu Z, Sun L, Deng Y, Peng H, Yu PS. Enhancing graph neural network-based fraud detectors against camouflaged fraudsters. In: Proceedings of the 29th ACM International Conference on Information & Knowledge Management. 2020. p. 315-324.

[47] Li A, Xiao F, Zhang C, Fan C. Attention-based interpretable neural network for building cooling load prediction. Applied Energy. 2021;299:117238.

[48] Farbmacher H, Ihle P, Schubert I, Winter J. Explainable attention network for fraud detection in claims management. Health Economics. 2022;31(12):2599-2615.

[49] Hospedales T, Antoniou A, Micaelli P, Storkey A. Meta-learning in neural networks: A survey. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2022;44(9):5149-5169.

[50] Ali-Gombe A, Elyan E. MFC-GAN: Class-imbalanced dataset classification using multiple fake class generative adversarial network. Neurocomputing. 2019;361:212-221.

[51] Berahmand K, Daneshfar F, Salehi ES, Li Y, Xu Y. Autoencoders and their applications in machine learning: a survey. Artificial Intelligence Review. 2024;57(2):28.

[52] Powers DM. Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. arXiv preprint arXiv:2010.16061. 2020.

[53] Beneish MD, Vorst P. The cost of fraud prediction errors. The Accounting Review. 2022;97(6):91-121.

[54] Sofaer HR, Hoeting JA, Jarnevich CS. The area under the precision-recall curve as a performance metric for rare binary events. Methods in Ecology and Evolution. 2019;10(4):565-577.

[55] Liu Y, Ao X, Qin Z, Chi J, Feng J, Yang H, He Q. Pick and choose: A GNN-based imbalanced learning approach for fraud detection. In: Proceedings of the Web Conference 2021. 2021. p. 3168-3177.

[56] Steffens, T. (2020). Attribution of Advanced Persistent Threats: How to Identify the Actors Behind Cyber-Espionage. Springer Nature.

[57] Ijiga OM, Idoko IP, Ebiega GI, Olajide FI, Olatunde TI, Ukaegbu C. Harnessing adversarial machine learning for advanced threat detection: AI-driven strategies in cybersecurity risk assessment and fraud prevention. J Sci Technol. 2024;11:001-024.

[58] Chen S, Guo W. Auto-encoders in deep learning—a review with new perspectives. Mathematics. 2023;11(8):1777.

[59] Gonzales A, Guruswamy G, Smith SR. Synthetic data in health care: A narrative review. PLOS Digital Health. 2023;2(1):e0000082.

[60] Iman M, Arabnia HR, Rasheed K. A review of deep transfer learning and recent advancements. Technologies. 2023;11(2):40.

[61] Chauhan V, Yadav J. Bibliometric review of telematics-based automobile insurance: Mapping the landscape of research and knowledge. Accident Analysis & Prevention. 2024;196:107428.

[62] Monchka BA, Leung CK, Nickel NC, Lix LM. The effect of disease co-occurrence measurement on multimorbidity networks: a population-based study. BMC Medical Research Methodology. 2022;22(1):165.

[63] Hotz A, Sprecher E, Bastianelli L, Rodean J, Stringfellow I, Barkoudah E, et al. Categorization of a universal coding system to distinguish use of durable medical equipment and supplies in pediatric patients. JAMA Network Open. 2023;6(10):e2339449.

[64] Chan GK, Cummins MR, Taylor CS, Rambur B, Auerbach DI, Meadows-Oliver M, et al. An overview and policy implications of national nurse identifier systems: A call for unity and integration. Nursing Outlook. 2023;71(2):101892.

[65] Nesvijevskaia A, Ouillade S, Guilmin P, Zucker JD. The accuracy versus interpretability trade-off in fraud detection model. Data & Policy. 2021;3:e12.

[66] Foody GM. Challenges in the real world use of classification accuracy metrics: From recall and precision to the Matthews correlation coefficient. PloS One. 2023;18(10):e0291908.

[67] Richardson E, Trevizani R, Greenbaum J, Carter H, Nielsen M, Peters B. The ROC-AUC accurately assesses imbalanced datasets. Available at SSRN 4655233. 2023.

[68] Gunning, D., & Aha, D. (2019). DARPA's explainable artificial intelligence (XAI) program. AI magazine, 40(2), 44-58.

[69] Lundberg SM, Erion G, Chen H, et al. From local explanations to global understanding with explainable AI for trees. Nature Machine Intelligence. 2020;2(1):56-67.

[70] Zafar MR, Khan N. Deterministic local interpretable model-agnostic explanations for stable explainability. Machine Learning and Knowledge Extraction. 2021;3(3):525-541.

[71] Dong P, Quan Z, Edwards B, Wang SH, Feng R, Wang T, et al. Privacy-Enhancing Collaborative Information Sharing through Federated Learning—A Case of the Insurance Industry. arXiv preprint arXiv:2402.14983. 2024.

[72] Mienye ID, Swart TG, Obaido G. Recurrent neural networks: A comprehensive review of architectures, variants, and applications. Information. 2024;15(9):517.

[73] Heald JB, Wolpert DM, Lengyel M. The computational and neural bases of context-dependent learning. Annual Review of Neuroscience. 2023;46(1):233-258.