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USING MACHINE LEARNING TO OPTIMIZE LIFE INSURANCE CLAIM TRIAGE PROCESSES VIA ANOMALY DETECTION IN DATABRICKS: PRIORITIZING HIGH-RISK CLAIMS FOR HUMAN REVIEW

Nihar Malali
Senior Solutions Architect, UT Dallas

ABSTRACT
Life insurance companies and policyholders need quick claim processing to receive payment properly and reduce needless payments. Standard claim triage methods require too much time and make mistakes that worsen business expenses and delay payment to policyholders. Machine learning systems have transformed insurance functions by deploying anomaly detection systems in this field. This research studies how ML-based anomaly detection works with the Databricks data analytics platform to enhance life insurance claim handling. Insurers detect more effective fraud risks earlier when they apply ML models and advanced analytics data on claims that clearly differ from typical behavior. The discussion presents how unsupervised models like Isolation Forests, Autoencoders, and One-Class SVMs discover abnormal data points specifically in claims information sets. The discussion includes details on why Databricks fits well for large-scale ML workflows along with its benefits for processing data in real-time and deploying models. Insurers can optimize their claim processing system when they review problems first since this practice reduces costs while giving customers improved service quality. Our research proves that ML-based anomaly checking improves claim evaluation by helping insurance businesses use better data strategies to update their operations.

Keywords:
Machine Learning, Anomaly Detection, Life Insurance Claims, Claim Triage, Databricks

1. INTRODUCTION

The operations of insurance firms relying on life insurance claims management encounter significant problems which impede their processing speed. The evaluation process for insurance claims takes longer than usual because employees commit numerous human errors according to Bohnert et al. (2016). Companies that operate as benefits organizations need to thoroughly review a significant number of claim documents with medical records along with accident reports. Business success relies on fast and accurate claim examination because it enables top-class customer service and profits (Ahmad et al., 2017).

The analysis of insurance claims must happen speedily and precisely to allow threat response while upholding the proper management of genuine claims. Insurance companies benefit from correct claim identification by building financial stability alongside preserving a strong reputation. Claims evaluation starts when abnormal data becomes noticed thus leading to increased chances of fraud and payment errors which grow progressively (Grill, Pevný, & Rehak, 2017). Improved automated claim handling technology is necessary for our company to maximize daily operational achievements. The insurance sector applies machine learning technology to improve its claims assessment process for businesses. Data-based systems decrease costs through decreased personnel involvement and prevent errors to help insurance companies. A system that applies ML to claims data enables our platform to detect suspicious claim activities combined with hazardous situations in a prompt manner (Bosman et al., 2017). The technology enables staff members to spot abnormal claims early and facilitates immediate accurate claim processing of each submission.

Databricks, a unified analytics platform, plays a pivotal role in the successful implementation of these ML-driven solutions. Through Databricks software customers can help insurance companies process their large-scale data more

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effectively for improving claim management (Zaharia, 2019). Databricks features enable insurance providers to adapt their business operations successfully by directing effective claim processing through collaborative efforts.
Important barriers slow down life insurance claim processing since the procedures face problems with operational efficiency and precision requirements. Machine learning, particularly through anomaly detection, offers a promising solution to these challenges. By using Databricks insurance firms receive enhanced procedures to manage their claims data.

2. UNDERSTANDING THE NEED FOR MACHINE LEARNING IN CLAIM TRIAGE

The insurance industry has used traditional claim triage systems as its core element for years but these methods face multiple issues during implementation. The combination of human-driven manual steps together with static rules and inflexible approaches to new patterns in data creates productivity issues. Traditional systems face a major disadvantage because they cannot handle rising claim complexity as well as increased claim volume especially within health and life insurance (Carvalho, Pereira, & Cardoso, 2019). The combination of human mistakes with inconsistent choices and unmodernized procedures leads to slower operations backed by elevated operational costs (Leo, Sharma, & Maddulety, 2019).

2.1 Common Causes of Claim Processing Inefficiencies

Traditional claim triage systems encounter various performance-limiting factors during operations. The insurance industry encounters substantial financial damage from fraudulent claims because they total billions annually. The implementation of modern detection systems becomes essential due to their inability to speed up or minimize human errors when dealing with fraud (Uddin, Khan, Hossain, & Moni, 2019). Data entry or processing mistakes create delayed claim settlements that result in dissatisfied policyholders who also force insurance providers to spend more resources to manage operations. The workflow suffers from delays because such policies contain unclear areas which demand manual expert evaluation to determine eligibility criteria (Bohnert, Gatzert, & Kolb, 2016).

2.2 Benefits of Machine Learning in Automated Claim Prioritization

The application of machine learning (ML) technology serves as an innovative solution which brings automated claim triage to insurance companies for greatly improved and expedited decision-making effectiveness. Through ML algorithms insurers can process huge data collections to recognize warning patterns of errors and fraud that lead to claim prioritization decisions (Baltrusaitis, Ahuja, & Morency, 2019). The automated triaging system shortens claim processing duration and eliminates human errors due to its capability to produce objective and unbiased decisions (Belkin, Hsu, Ma, & Mandal, 2019). Continuous improvement becomes possible through ML-driven systems because they gain accuracy by using new data which enables them to adapt to fresh fraud methods and claim industry patterns.
The implementation of this technology provides organizations with important savings opportunities. The elimination of human involvement in claim processing leads insurance companies to reduce their operational costs and improve customer satisfaction through rapid claim resolution (Asri, Mousannif, & Moatassime, 2019). Through machine learning algorithms insurers obtain improved risk management capabilities which enable them to forecast claims that need extensive examination or processing better.

Key Points	Impact/Outcome
ML technology automates claim triage, improving decision-making effectiveness and expediting claim processing.	Faster and more efficient claim processing
ML algorithms help insurers process large data sets to identify patterns of errors and fraud, aiding in claim prioritization.	Improved fraud detection and more accurate claim prioritization.
The automated triaging system reduces claim processing time and eliminates human errors, providing unbiased decisions.	Reduced human error, leading to more objective and timely decisions.
Continuous improvement is possible with ML systems	Ongoing enhancement of system accuracy and fraud

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that adapt to new data, enhancing accuracy and adjusting to emerging fraud methods.	detection capabilities.
The implementation of ML leads to significant savings by reducing human involvement, lowering operational costs, and improving customer satisfaction.	Cost savings and improved customer experience through faster claim resolutions.
ML improves risk management, helping insurers better forecast claims that require extensive examination.	More effective risk management and targeted claim scrutiny.

Table 1: Benefits of Machine Learning in Automated Claim Prioritization

2.3 Case Studies of ML Applications in Insurance Fraud Detection

The use of machine learning has achieved positive outcomes in insurance fraud detection according to various documented cases. Researchers at Araya et al. (2017) established an ensemble learning method to analyze building energy consumption claims resulting in fraud detection discoveries of abnormal activities. Maxwell, Warner, and Fang (2018) examined machine learning applications in remote sensing where satellite imagery is classified through data analysis in order to detect insurance fraud based on geographical and behavioral information patterns. The enumerated examples demonstrate that ML technology serves to automate fraud detection while improving claim accuracy which demonstrates its potential to improve insurance claim triage system reliability and performance.

Machine learning changes insurance operations through advanced processing and triage of claims within the industry. Technology advances with machine learning enable insurance operators to obtain more efficient operations and extended scalability which result in reduced prices through automated claim assessment and fraud discovery and diminished manual mistakes (Grill, Pevný, & Rehak, 2017). Insurers must implement these technologies as a strategic requirement to compete within their data-intensive industry.

3. ANOMALY DETECTION IN INSURANCE CLAIMS

Insurance anomaly detection entails the method of identifying claims which significantly deviate from standard patterns in order to detect potential fraudulent conduct or mistakes and irregularities. Insurers need to detect anomalies promptly because irregular activities which include insurance fraud and system errors together with uncommon risky claims expose them to financial risks. Anomaly detection bases its principle on irregularities acting as "outliers" while showing substantial differences compared to most claims (Ahmad, Lavin, Purdy, & Agha, 2017).

3.1 Types of Anomalies in Insurance Claims

Insurance claim anomalies fit into three general groups which include fraudulent claims and two other categories.

- Claimants deliberately file false reports that constitute fraudulent claims. Insurance claim fraud takes multiple forms such as exaggerating claim values and creating fake incidents and lying about nonexistent damage (Bosman et al., 2017). False claims represent the biggest problem for insurance organizations because they lead to important financial setbacks for the company.
- Unintentional mistakes that happen because of human or technical errors result in Erroneous Entries. Even though such errors were unintentional they have the capability to destroy the claims processing. The claims categorization or data errors can result in incorrect payouts because of what Garrido, Genest and Schulz (2016) describe.
- Genuine insurance claims that fall into the category of exceptional situations because of their infrequent and special nature get identified as system anomalies. Traditional detection systems detect those valid claims based on their extraordinary nature but not their validity (Araya et al., 2017). Finding appropriate solutions for these cases helps prevent the denial of valid claims by mistake.

3.2 Traditional Rule-Based Systems vs. Machine Learning-Driven Approaches

The detection of anomalies through traditional rule-based systems depends on predetermined threshold conditions together with pre-established rules. The framework exists of rules that specialists create from available historical information. The system sets specific thresholds so that high-value claims automatically activate warning systems. These systems manage to identify established fraud patterns but they generally encounter difficulties when handling

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emerging or altering fraud patterns. The systems tend to generate many incorrect alerts that require extensive probing (Leo, Sharma, & Maddulety, 2019).

The mechanisms of anomaly detection in machine learning differ from traditional processes since they deploy algorithms to discover data patterns which grants improved detection abilities for novel anomalies. The complex data patterns found by ML models work automatically while recognizing feature interrelations without manual rules (Liu & Lang, 2019). ML-driven approaches provide maximum flexibility because they detect newly emerging insurance claim fraud patterns while identifying other anomalous activities through their adaptable nature.

3.3 Key Machine Learning Algorithms for Anomaly Detection

The detection of anomalies in insurance claims becomes successful through various machine learning models which include:

- The unsupervised method of Isolation Forest identifies outliers as it isolates cases instead of creating profiles for normal instances. Random selection of features follows random splitting of data points to achieve its functionality. Anomalies stand apart from typical data points because their numbers remain low and distinctive from the main population (Liu & Lang, 2019). This method operates excellently when processing large data collections, which makes it perfect for insurance applications containing numerous variables.
- The neural network system called Autoencoders teaches itself to reduce data while restoring original forms. The training process uses normal data samples then the reconstruction phase identifies anomalies through measurement of reconstruction error. A high reconstruction error in a claim point suggests an anomaly according to Baltrusaitis, Ahuja, and Morency (2019). Autoencoders exhibit strong capability to find fraud and errors in complex claims data distributions.
- The detection of anomalies relies on One-Class SVM as an unsupervised Support Vector Machine approach. The method identifies a boundary plane which optimally distinguishes normal data points from anomalies. The One-Class SVM strikes its peak when dealing with limited or absent labelled data because it excels at teaching itself to separate normal patterns from anomalous ones (Sayad, Mousannif, & Al Moatassime, 2019).
- In K-Means clustering outliers appear through data point segregation into clusters based on their closeness. Anomalies detect themselves through measuring distances between points and clustering centers. Claims with positions outside the cluster center receive anomaly status. The method effectively detects isolated cases which deviate from recognized patterns according to Maxwell, Warner, and Fang (2018).

Insurers need anomaly detection technologies to identify improper as well as rare insurance claims alongside cases of fraud. Insurance companies continue using traditional rule-based systems but these are being superseded by machine learning algorithms because they provide better accuracy and flexibility. Among the most successful ML algorithms for anomaly detection stand Four approaches which include Isolation Forests, Autoencoders, One-Class SVM and K-Means Clustering because they excel in different data and anomaly types. The advanced techniques enable insurers to better detect fraudulent claims while lowering false positives among claims and boosting their overall operational effectiveness (Zaharia, 2019).

4. IMPLEMENTING ML-BASED ANOMALY DETECTION IN DATABRICKS

The cloud-based software system Databricks serves as a title for operating large-scale data analytics together with machine learning capabilities. The system uses Apache Spark to deliver big data functionality combined with real-time data processing in addition to ML development collaboration features. Through Databricks organizations optimize their data workflows starting with ingestion and ending with model deployment which makes the platform suitable for performing anomaly detection using ML (Zaharia, 2019).

4.1 Data Ingestion And Preprocessing In Databricks

Successful data intake operations directly impact an anomaly detection system. Databricks permits users to extract data from various sources which encompass AWS S3, Azure Blob, databases and real-time streaming through Kafka and Event Hubs. Data preprocessions starts by handling absent data points followed by feature normalization and

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outlier removal processes on numerical characteristics. Homomorphic encryption offers secure data protection through privacy-preserving operations that preserve data integrity (Alabdulatif et al., 2017).

4.2 Feature Engineering For Anomaly Detection Models

A complete feature engineering methodology plays a crucial role in separating standard operational patterns from abnormal events. Data preprocessing follows three steps which include time-series decomposition, statistical aggregations and embedding-based transformations. The accuracy of anomaly detection gets boosted through ensemble learning systems that unite several unique feature interpretive methods (Araya et al., 2017). The addition of spatial-temporal features serves to enhance sensor network detection and specifies the exact location of anomalies (Bosman et al., 2017).

4.3 Model Selection and Hyperparameter Tuning

Success in anomaly detection requires the selection of appropriate ML models. Common choices include:

- **Isolation Forests:** Well-suited for high-dimensional anomaly detection.
- A neural network architecture known as Autoencoders consists of model types which learn normal data distributions.
- **One-Class SVM:** Effective for binary anomaly classification.

Within Databricks users conduct hyperparameter optimization by applying grid search along with Bayesian optimization alongside automated ML ecosytem known as AutoML. A successful anomaly detection system requires an equilibrium between bias and variance because weakness in either front weakens detection sensitivity (Belkin et al., 2019).

4.4 Training and Validation of ML Models for Claim Triage

The training process requires organizations to feed their selected yet labelled datasets to models. The objective of anomaly detection models in claim triage systems is to identify both insurance data inconsistencies and cases of fraudulent claims. The generalization of analysis results is achieved through k-fold validation and other cross-validation techniques (Garrido et al., 2016). The XAI methods of explainable artificial intelligence help solve interpretability issues which allow finance and insurance industries to move forward under regulatory oversight (Carvalho et al., 2019).

4.5 Deployment of ML Models within Databricks for Real-Time Claim Assessment

The deployed models operate through Databricks by using MLflow which provides an integrated system for tracking and versioning different models. The assessment of incident claims operates through API interfaces and streaming automation which handle claims the moment they arrive. The implementation of adaptive anomaly detection strategies enables the refinement of alerts in a dynamic manner according to (Grill et al., 2017).

The implementation of Databricks enables organizations to boost their anomaly detection systems for delivering precise and scalable ML solutions in claim triage while fighting fraud.

5. PRIORITIZING HIGH-RISK CLAIMS FOR HUMAN REVIEW

The current insurance claims processing evolution demands the use of machine learning (ML) in anomaly detection as a way to enhance operational efficiency. Human experts must continue to oversee claim triage operations because their involvement upholds accuracy and fairness and ensures compliance (Murdoch et al., 2019). Operation efficiency maximization and error reduction happen when automation works in harmony with human review analysis.

5.1 The Importance of Human Oversight in Claim Triage

The ability of ML models to identify patterns and outliers exists within claims data although they will always miss some elements. The interpretation of complex cases requiring delicate assessment needs human decision makers to deal with situations that include both ambiguous fraudulent claims and abnormal legitimate claims (Carvalho et al., 2019). The absence of human oversight enables insurers to make incorrect assessments both in fraud detection and eligibility review of claims through solely automated processes.

5.2 Establishing Thresholds for Flagging Anomalies

The effective operation of anomaly detection systems heavily depends on correct threshold selection which directs human inspectors toward relevant claims for examination. Setting inadequate threshold values produces excessive

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wrong positive findings thus increasing labor requirements yet high threshold levels permit undetected fraudulent claims (Grill et al., 2017). An analysis of historical insurance claims allows insurers to determine the best detection accuracy thresholds without creating unnecessary review fatigue for employees.

5.3 Integrating ML Predictions with Human Decision-Making Workflows

The integration of ML prediction systems with current claims processing systems must happen smoothly to optimize operational efficiency. A review structure featuring different levels can be deployed as an effective solution.

- Claims belonging to the low-risk category go through automatic processing with no need for manual supervision.
- Medium-risk claims stand for a dual evaluation by AI systems before an escalation to a human reviewer occurs.
- A human reviewer examines claims which present high-risk classification.

Modern workflows designed in this way direct human expertise to critical points which results in improved efficiency alongside perfect accuracy (Araya et al., 2017).

5.4 Optimizing the Balance Between Automation and Manual Review

The proper combination of automated processes and human monitoring operations strengthens claim truthfulness and provides cost efficiency. Data extraction along with preliminary fraud detection operates through ML models so human experts can take charge of evaluating complex situations which demand judgment together with experience (Belkin et al., 2019). A feedback process linking ML systems with human evaluators enables progressive improvement of predictive accuracy as manual oversight needs to decrease.

5.5 Reducing False Positives and Improving Claim Accuracy

When high-risk claims get falsely identified as such it causes resource exhaustion followed by delayed claim payment processing. Polytechnic institutions reduce false positive errors through ensemble learning approaches together with sophisticated anomaly detection systems (Bosman et al., 2017). XAI explainable AI techniques demonstrate the logic of ML decision processes to enhance claims adjuster understanding of case flagging reasons thus improving human adjustment quality (Carvalho et al., 2019).

Insurance companies that merge anomaly detection based on ML technology with human judgment expertise will enhance both claims resolution speed and customer satisfaction and minimize false insurance claims. Insurers can achieve the required results through threshold refinement alongside hybrid review approaches which should be enhanced using human feedback for ML algorithm optimization.

6. BENEFITS AND CHALLENGES OF ML-DRIVEN CLAIM PROCESSING

Through machine learning techniques the insurance sector experiences optimization of claim operations coupled with fraud reduction while obtaining operational speed increases. The benefits ML offers insurers need to be addressed by insurers to maintain transparent and fair and effective implementations.

6.1 Advantages

The implementation of ML-driven claim processing enabled insurance entities to accomplish claim assessments with greater speed. The traditional method of claims processing takes a long time because it requires scanners of documents which then need to be manually verified. Through automation, ML can verify documents and classify claims, which shortens the processing duration (Ahmad et al., 2017). The real-time analysis from AI tools determines high-risk claims but simultaneously provides fast approval for straightforward claims to enhance customer satisfaction (Carvalho, Pereira, & Cardoso, 2019).

Fraud detection along with prevention operations heavily depend on ML technology. The analysis of extensive databases through ML models detects fraudulent patterns which reduces annual insurance loss from fraudulent claims. To detect fraudulent behavior at an early stage insurers use anomaly detection and predictive modeling approaches which decrease their financial losses (Bosman et al., 2017). ML algorithms analyze present claims data along with past insurance claims for detecting anomalies which leads to identifying fraudulent cases that require investigation (Grill, Pevný, & Rehak, 2017).

The use of this solution brings better operational efficiency to the system. The automation of claims assessment through ML technology helps insurers direct their staff toward more valuable responsibilities after minimizing

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human involvement in routine work processes. Claims adjusters work on complex cases needing human assessment while avoiding time-consumption on ordinary claim evaluations (Asri, Mousannif, & Al Moatassime, 2019).

Insurers achieve financial savings because of the automation which ML provides. Faster production speeds when combined with reduced fraud occurrences cut down both legal and administrative costs. Insurance companies achieve operational excellence through their ability to distribute resources effectively while limiting unwarranted payout expenses thanks to automated workflow systems and diminished fraudulent claim numbers (Leo, Sharma, & Maddulety, 2019).

6.2 Challenges

Multiple challenges emerged with ML-based claim processing because of data quality issues and inadequate data availability rates. ML models achieve reliable predictions when they operate with extensive collections of precise and top-quality data. Claim approvals together with fraud detection may experience errors when data sets show inconsistency or biased patterns (Alabdulatif et al., 2017). Insurers need to implement mechanisms to safeguard customer privacy under regulations such as GDPR and HIPAA throughout the handling of sensitive customer information.

The use of AI for decision-making creates substantial ethical dilemmas for insurance organizations. When ML models rely on historical data for learning purposes they might reproduce the biases which already exist within previous claims assessments. The lack of proper monitoring creates a risk of unfair claim denials that primarily impact specific customer groups (Murdoch et al., 2019). For purposes of maintaining both customer trust and meeting regulatory requirements insurers need transparent AI decision systems as well as effective explanations for model predictions.

ML models need active ongoing surveillance along with regular maintenance procedures to stay powerful. Insurance designs transform because of changes in fraud patterns together with emerging laws and customer conduct alterations. The failure to perform regular updates on ML models will cause them to fall behind resulting in incorrect claim decisions and higher numbers of false positives (Liu & Lang, 2019). Insurers need to keep investing in model evaluation and retraining operations to sustain their performance and reliability levels.

The implementation of ML-driven claim processing yields multiple advantages that consist of accelerated settlement procedures together with reduced fraudulent claims and economical operational advantages. To achieve fair and effective implementation successful resolution of data quality problems and ethical considerations and continual model upgrade requirements are mandatory. Insurance organizations succeeding with ML will require automated processing and human supervision to extract its full capabilities from the technology.

7. FUTURE PROSPECTS AND CONCLUSION

The insurance industry experiences rapid change because Artificial Intelligence (AI) processing integrates with insurance claims and improves with the evolution of anomaly detection algorithms and platform capabilities of Databricks in data analytics.

7.1 Emerging Trends in AI and Insurance Claims Processing

The insurance industry continues to recognize Artificial Intelligence as an essential tool because it allows organizations to enhance their claims processing operations. Machine learning models including anomaly detection algorithms both develop toward increased operational efficiency and enhanced reduction of insurance claim fraud. The systems train to analyze massive data datasets in order to detect claim irregularities that demand further review (Ahmad et al., 2017). Advanced artificial intelligence approaches with deep learning capability are expected to optimize both speed and accuracy of fraud detection which provides insurers a forward-looking approach to risk management according to Liu and Lang (2019). Predictive analytics which uses AI allows insurance firms to make future claim volume forecasts and risk assessments and policy customization that improves customer satisfaction (Asri et al., 2019).

7.2 Potential Improvements in Anomaly Detection Techniques

Insurance fraud prevention heavily depends on anomaly detection as its fundamental principle. The current techniques require enhancement to achieve higher accuracy rates while reducing the number of incorrect detection results. The combination of several analytical models through ensemble learning frameworks represents an effective

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solution for improving traditional single-model decision-making according to Araya et al. (2017). Nature-based encryption methods like homomorphic encryption enable insurers to detect anomalies within protected patient information (Alabdulatif et al., 2017). The advancement of technology will probably lead to better security features and transparent accurate anomaly detection capabilities in upcoming systems.

7.3 The Evolving Role of Databricks in Insurance Analytics

The technology company Databricks functions as a key driver toward insurance analytics transformation as a market-leading data engineering cloud provider. Databricks offers insurers comprehensive big data and analytic integration that helps them operate data on a large scale. Databricks enables insurance firms to analyze real-time data entries instantly which transforms insurance risk evaluation and claims processing (Zaharia, 2019). Databricks has established itself as a fundamental technology solution which enables fast decision-making for insurance companies that want to access AI-based insights.

7.4 Summary of Key Findings and Final Thoughts

A transformation of the insurance industry is ready to happen because AI connects optimized anomaly detection systems with Databricks platform solutions. Insurers can boost operational outcomes through advanced technology capabilities that keep security standards and let them fight fraud and customize services and provide instantaneous data access. The insurance claims processing space will develop into a technologically-advanced and data-oriented and customer-focused system that brings valuable benefits to insurers and policyholders. The upcoming few years represent a vital time to completely harness the emerging technologies that will transform the insurance field.

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