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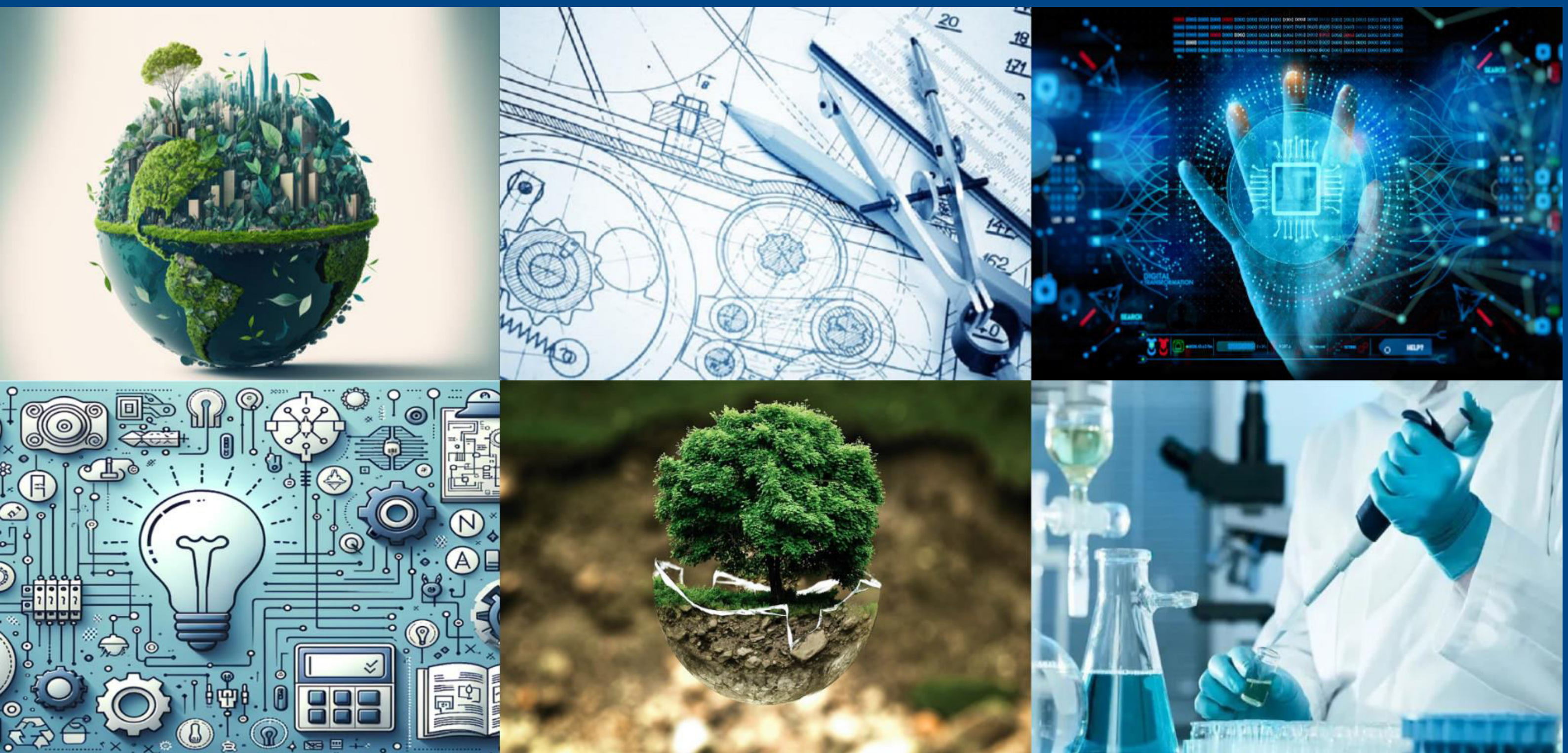

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Improving Insurance Fraud Detection through Machine Learning and AI Technique

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ABSTRACT: Artificial intelligence (AI) and machine learning (ML) technologies are fundamentally transforming insurance fraud detection. This study evaluates various AI and ML models to determine their effectiveness in enhancing fraud detection, improving operational efficiency, and boosting customer satisfaction within the insurance sector. By integrating advanced AI and ML techniques, insurers can achieve more accurate fraud detection, reduce false positives, and optimize operational workflows.

Generative AI, for instance, provides powerful tools for simulating and identifying fraudulent activities, improving accuracy while minimizing traditional false positive rates. Optimization of ML models enhance their performance, leading to better fraud detection and greater operational efficiency. Semi-supervised learning frameworks offer a cost-effective approach to leveraging both labelled and unlabelled data, balancing accuracy with labelling expenses. Additionally, AI-driven claims processing streamlines workflows, reduces processing times, and enhances customer service.

Overall, these advancements lead to significant cost savings and operational improvements for insurers, highlighting the transformative impact of AI and ML technologies in the insurance industry.

KEYWORDS: Artificial Intelligence, Insurance, Fraud, Machine Learning

I. INTRODUCTION

Insurance fraud represents a formidable challenge for the insurance industry, leading to considerable financial losses and inflated premiums for legitimate policyholders. As fraudulent schemes become increasingly sophisticated, traditional fraud detection methods, which rely heavily on rule-based systems and manual reviews, have struggled to keep pace. These conventional approaches often suffer from high false positive rates, inefficiencies in processing, and a limited ability to adapt to evolving fraud tactics.

Traditional fraud detection techniques are often characterized by their reliance on predefined criteria and static rules that can quickly become outdated. Rule-based systems, while providing a foundation for fraud detection, lack the flexibility to address the nuances of more complex fraud schemes. Manual reviews, although thorough, are resource-intensive and susceptible to human error, leading to delays and inconsistencies in identifying fraudulent claims.

The advent of artificial intelligence (AI) and machine learning (ML) technologies offers a promising alternative to these traditional methods. AI and ML provide advanced analytical tools capable of learning from vast amounts of data, adapting to new patterns, and improving over time. This study delves into the application of various ML models to enhance fraud detection capabilities and overcome the limitations of traditional approaches.

The focus of this research includes several prominent ML models, such as Isolation Forest, weighted logistic regression, Random Forest Classifier, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and XGBoost. Each of these models has distinct advantages that contribute to improved fraud detection. Isolation Forest excels in identifying anomalies by isolating outliers in high-dimensional datasets, while weighted logistic regression effectively manages imbalanced data by adjusting class importance. Random Forest Classifier, with its ensemble of decision trees, enhances predictive accuracy, and SVM is renowned for its classification capabilities. KNN offers simplicity and efficiency in pattern recognition, and XGBoost utilizes gradient boosting to achieve high model performance.

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In addition to these models, the study incorporates a semi-supervised, cost-sensitive learning framework. This framework integrates both labelled and unlabelled data, addressing the challenge of obtaining extensive labelled datasets, which are often costly and labour-intensive. By including a cost-sensitive component, the framework aims to optimize the balance between detection accuracy and operational costs, such as those associated with data labelling and customer service.

The integration of AI and ML models within this advanced framework seeks to improve the precision of fraud detection, reduce false positives, and enhance overall operational efficiency. False positives not only result in unnecessary investigations but also contribute to increased operational costs and customer dissatisfaction. By leveraging these advanced technologies, insurers can achieve more accurate fraud detection, streamline their operations, and enhance the customer experience.

This introduction sets the stage for a comprehensive exploration of how AI and ML technologies are reshaping the landscape of insurance fraud detection, offering new solutions to long-standing challenges in the industry.

II. OBJECTIVES

The primary objectives of this study are designed to explore and enhance the capabilities of insurance fraud detection through advanced artificial intelligence (AI) and machine learning (ML) techniques. Each objective is aimed at addressing specific challenges and opportunities within the industry to improve fraud detection, operational efficiency, and customer satisfaction.

First, the study aims to evaluate the impact of generative AI technologies, particularly large language models (LLMs), on detecting and managing fraudulent activities within the insurance sector. Generative AI, known for its advanced capabilities in natural language processing and data synthesis, offers a novel approach to fraud detection. By leveraging LLMs, insurers can simulate complex fraud scenarios and generate synthetic data to train detection models more effectively. This approach not only enhances the ability to recognize new and evolving fraud schemes but also improves the accuracy of detection by analysing vast amounts of unstructured data, such as claim descriptions and communication logs. Evaluating the effectiveness of these technologies involves assessing how well they can identify subtle patterns and anomalies that traditional methods might miss, and how they contribute to overall fraud management strategies.

Second, the study seeks to analyse the effectiveness of various machine learning models in identifying fraudulent claims. This includes a comprehensive evaluation of models such as Isolation Forest, weighted logistic regression, Random Forest Classifier, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and XGBoost. Each of these models has distinct strengths and weaknesses in handling fraud detection tasks. For instance, Isolation Forest is particularly effective at detecting anomalies in high-dimensional data, while Random Forest and XGBoost are known for their robust performance in classification tasks. By comparing these models, the study aims to identify which algorithms offer the best performance in terms of precision, recall, and overall fraud detection accuracy. This objective also involves optimizing these models to reduce false positives and improve the efficiency of the detection process.

The third objective is focused on implementing a semi-supervised learning framework to balance fraud detection accuracy with data labelling costs. Traditional supervised learning methods rely heavily on large amounts of labelled data, which can be costly and time-consuming to obtain. Semi-supervised learning, which integrates both labelled and unlabelled data, provides a cost-effective alternative by leveraging the vast amounts of unlabelled data that are often readily available. This approach aims to enhance the detection capabilities of fraud detection systems while managing the expenses associated with data labelling. The study will develop and apply this framework to evaluate its effectiveness in improving detection performance and reducing operational costs.

Fourth, the study explores methods to optimize the cost-benefit ratio of advanced fraud detection technologies. Implementing AI and ML solutions involves significant investment in terms of technology, resources, and training. Therefore, it is crucial to develop strategies that balance the costs associated with these technologies against the benefits they provide. This includes evaluating the return on investment (ROI) for different AI and ML models, understanding the financial implications of their implementation, and identifying ways to maximize their effectiveness while minimizing costs. The goal is to ensure that the adoption of advanced technologies leads to tangible improvements in fraud detection and overall operational efficiency.

Additionally, the study aims to enhance detection accuracy, reduce false positives, and streamline claims processing using AI-driven solutions. Improved detection accuracy is essential for identifying fraudulent activities with greater precision, while reducing false positives helps in minimizing the impact on legitimate policyholders. Streamlining claims processing through automation and AI technologies can lead to faster processing times and more efficient workflows, ultimately benefiting both insurers and their customers.

Improving customer experience is also a key objective of the study. By leveraging AI technologies to enhance the accuracy and efficiency of fraud detection, insurers can offer a more seamless and satisfactory experience to their customers. This includes reducing delays in claims processing, providing timely and accurate information, and minimizing the inconvenience caused by false positives. The study will assess how AI-driven solutions can contribute to a better customer experience and overall satisfaction.

The development of advanced fraud detection strategies is another important objective. As fraud schemes continue to evolve, it is crucial for insurers to stay ahead by developing and implementing innovative strategies that leverage AI insights. This involves identifying emerging fraud patterns, testing new detection methods, and continuously adapting strategies to address new challenges in the fraud landscape.

Measuring the financial impact of AI technologies is also a significant objective. The study aims to quantify the reductions in fraud-related losses resulting from the implementation of AI and ML models and assess the overall return on investment. This includes analysing cost savings, improvements in fraud detection accuracy, and the financial benefits derived from enhanced operational efficiency.

Enhancing risk assessment capabilities is another critical goal. AI technologies can improve risk assessment in insurance underwriting, particularly for complex products like life and disability insurance. By integrating AI with existing risk assessment processes, insurers can develop more accurate risk models, leading to better-informed underwriting decisions and improved financial outcomes.

Regulatory compliance is an essential aspect of implementing AI-driven fraud detection systems. The study will ensure that the technologies used adhere to industry regulations and standards, including data protection and privacy laws. This involves identifying relevant regulations, integrating compliance measures into AI systems, and conducting regular audits to ensure ongoing adherence.

Promoting AI integration across various insurance functions is another key objective. Beyond fraud detection, AI can offer benefits in marketing, underwriting, claims management, and customer support. The study will explore how AI applications can be integrated across these functions to maximize their benefits and enhance overall business operations.

Addressing implementation challenges is also a critical focus. Integrating AI technologies can present various challenges, including technical, organizational, and resource-related issues. The study will identify these challenges, develop solutions to overcome them, and monitor the effectiveness of these solutions to ensure successful implementation.

Lastly, the study emphasizes the importance of developing AI training and support programs. Effective use of AI tools and models requires adequate training and support for insurance professionals. The study will assess training needs, develop customized programs, and establish support mechanisms to ensure that staff are equipped to leverage AI technologies effectively.

Overall, these objectives collectively aim to advance the field of insurance fraud detection by leveraging AI and ML technologies to improve accuracy, efficiency, and customer satisfaction while managing costs and ensuring regulatory compliance.

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III. METHODOLOGY

The methodology of this study is designed to systematically evaluate and compare the effectiveness of various artificial intelligence (AI) and machine learning (ML) technologies in enhancing fraud detection within the insurance industry. This approach involves multiple stages, each crucial for understanding and optimizing these advanced technologies' impact on fraud detection and management.

To begin with, the study undertakes a comprehensive literature review to evaluate the role of generative AI in fraud detection. This review focuses on collating and analyzing existing research on generative AI technologies, particularly large language models (LLMs). These models are assessed for their capabilities in generating synthetic data and simulating complex fraud scenarios. The aim is to identify how generative AI can be leveraged to improve the accuracy and efficiency of fraud detection processes. The review also considers how these models compare to traditional methods in terms of performance and cost-effectiveness. To provide a robust comparison, benchmarking is performed, where AI-driven systems are measured against conventional fraud detection approaches. Key performance indicators (KPIs) such as detection accuracy, false positive rates, and cost-efficiency are used to assess the relative benefits of generative AI.

In analysing machine learning models, the study involves collecting relevant datasets that contain information about insurance claims and fraud. The datasets are used to train various machine learning models, including Isolation Forest, weighted logistic regression, Random Forest Classifier, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and XGBoost. Each model's performance is evaluated using metrics such as precision, recall, F1-score, and AUC-ROC. These metrics help determine how well each model identifies fraudulent claims and how effectively it minimizes false positives. The analysis includes a comparison of these models to understand their strengths and weaknesses in the context of insurance fraud detection.

The implementation of a semi-supervised learning framework is another critical aspect of the methodology. This involves designing a system that integrates both labelled and unlabelled data to enhance fraud detection. The framework aims to balance the trade-off between detection accuracy and the costs associated with labelling data. By incorporating cost-sensitive components, the study seeks to develop a cost-effective approach to fraud detection that maintains high accuracy. The effectiveness of this framework is tested through various validation methods to ensure its robustness and reliability.

Optimizing the cost-benefit ratio of advanced fraud detection technologies is also a key objective. To achieve this, the study compares the current costs of fraud detection methods with those associated with implementing AI technologies. This comparison helps identify the financial benefits of adopting AI-driven solutions and develop strategies to balance costs and benefits effectively. The focus is on maximizing the return on investment while ensuring that the advanced technologies deliver substantial improvements in fraud detection.

Model refinement is an ongoing process aimed at enhancing detection accuracy and reducing false positives. This involves fine-tuning the machine learning models based on initial performance evaluations. Techniques such as cross-validation and error analysis are employed to assess and address sources of inaccuracies. By iterating on the model parameters and incorporating feedback from performance evaluations, the study seeks to improve the overall effectiveness of the fraud detection models.

Streamlining claims processing is another area of focus. The study identifies inefficiencies in current claims processing workflows and explores how AI can automate and optimize these tasks. By integrating AI tools to handle repetitive and data-intensive tasks, the study aims to reduce processing times and improve accuracy. The impact of these improvements on operational efficiency is measured through performance metrics and process evaluations.

Enhancing customer experience is also a critical objective. The study collects feedback from policyholders regarding their experiences with claims processing and service quality. AI tools are implemented to address common issues and provide timely and accurate information. The effectiveness of these tools is evaluated by analyzing changes in customer satisfaction and service delivery metrics.

Developing advanced fraud detection strategies involves analyzing emerging fraud patterns and using AI to develop innovative detection techniques. The study examines how AI can identify new types of fraud and adapt to evolving tactics. New strategies are implemented and tested to assess their effectiveness in addressing complex fraud schemes.

The financial impact of AI technologies is measured by quantifying reductions in fraud-related losses and assessing the return on investment. By analyzing the financial benefits of improved fraud detection and comparing them with the costs of implementing AI solutions, the study provides insights into the economic advantages of adopting these technologies.

Enhancing risk assessment capabilities is another important objective. The study integrates AI with existing risk assessment processes to improve the evaluation of complex insurance products. New AI-enhanced models are developed and validated to better assess risk and predict potential fraud.

Regulatory compliance is ensured by mapping relevant regulations and integrating compliance requirements into AI systems. Regular audits are conducted to verify that the AI-driven solutions adhere to industry standards and data protection laws.

Promoting AI integration across insurance functions involves analyzing the benefits of AI applications in various areas such as marketing, underwriting, and support. Pilot programs are implemented to test AI solutions in different functions, and successful applications are scaled organization wide.

Identifying and addressing implementation challenges is crucial for the successful adoption of AI technologies. The study involves stakeholder interviews to identify potential challenges and develops solutions to overcome them. Continuous improvement is monitored to ensure that the solutions remain effective and relevant.

Training and support programs for AI tools are developed based on a needs assessment. Customized training programs are designed to help insurance professionals effectively use AI tools, and support mechanisms are established to provide ongoing assistance.

Finally, AI performance is monitored and evaluated through the development of defined metrics and continuous monitoring systems. Periodic reviews are conducted to assess the effectiveness of AI-driven fraud detection solutions and make necessary adjustments to improve performance.

IV. CASE STUDIES

Case Study 1: Generative AI for Fraud Detection

In the first case study, an insurance company grappling with significant financial losses due to fraud explores the application of generative AI to bolster its fraud detection capabilities. The primary objective of this case study is to assess the effectiveness and cost-efficiency of generative AI technologies in detecting fraudulent activities. The methodology begins with a thorough literature review to understand existing research on generative AI and its applications in fraud detection. This review helps identify relevant generative AI tools, such as large language models (LLMs), which can generate synthetic data and simulate various fraud scenarios.

Following the literature review, the study involves selecting appropriate generative AI tools and preparing data for integration. This process includes curating datasets that reflect real-world fraud patterns and ensuring that the data used for training the generative models is comprehensive and representative. The integration phase involves incorporating generative AI models into the company's existing fraud detection infrastructure. This integration aims to enhance the detection capabilities by providing a more nuanced analysis of potential fraud scenarios.

A critical component of the methodology is conducting a cost-benefit analysis. This analysis compares the costs associated with implementing generative AI technologies against the financial benefits realized through improved fraud detection. Key performance indicators such as detection accuracy, false positive rates, and operational efficiency are used to evaluate the effectiveness of the generative AI models.

The outcomes of this case study reveal a significant improvement in fraud detection accuracy, with a notable reduction in false positives. The generative AI models contribute to a more accurate identification of fraudulent claims by simulating and analysing complex fraud patterns that traditional methods might miss. Additionally, the cost-benefit analysis indicates a positive return on investment, as the enhanced detection capabilities lead to substantial savings by reducing fraudulent payouts and improving operational efficiency. Overall, the integration of generative AI in fraud detection proves to be a cost-effective and impactful solution for the insurance company.

Case Study 2: Optimization of Machine Learning Models

The second case study focuses on optimizing various machine learning (ML) models to enhance fraud detection. The insurance company aims to improve the performance of several ML models, including Isolation Forest, weighted logistic regression, Random Forest Classifier, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and XGBoost. The objective is to compare these models and identify strategies for enhancing their effectiveness in detecting fraudulent claims.

The methodology begins with the collection of relevant datasets that contain information on insurance claims and associated fraud indicators. These datasets are used to train the selected ML models, ensuring that each model is exposed to a diverse range of fraud scenarios. Model training involves fine-tuning hyperparameters and adjusting algorithms to improve performance.

Performance evaluation is a key aspect of this case study. Metrics such as precision, recall, F1-score, and AUC-ROC are used to assess the effectiveness of each ML model in identifying fraudulent claims. The study also involves optimizing the models by employing techniques such as feature selection, parameter tuning, and cross-validation to enhance their performance.

The results of the case study demonstrate notable improvements in model performance. Each ML model shows enhanced accuracy in detecting fraudulent claims, with reduced false positive rates compared to baseline models. The optimization process reveals that models such as Random Forest Classifier and XGBoost provide superior performance, offering a balance between high detection accuracy and manageable false positive rates. The study concludes that optimizing ML models through advanced techniques significantly enhances fraud detection capabilities, making them valuable tools for the insurance company.

Case Study 3: Semi-Supervised Learning Framework

In the third case study, an insurance company adopts a semi-supervised learning framework to address the challenge of balancing detection accuracy with the costs associated with data labelling. The primary objective is to implement and evaluate a framework that integrates both labelled and unlabelled data to improve fraud detection while managing labelling expenses.

The methodology involves designing a semi-supervised learning system that leverages a combination of labelled data, which is often expensive to obtain, and unlabelled data, which is more readily available. The design of the framework includes selecting appropriate algorithms and models that can effectively utilize both types of data. Cost analysis is conducted to evaluate the financial implications of data labelling and to develop strategies for optimizing the use of labelled and unlabelled data.

Testing the effectiveness of the semi-supervised learning framework involves applying the system to real-world fraud detection scenarios and comparing its performance against traditional supervised learning methods. Metrics such as detection accuracy, false positive rates, and cost-efficiency are used to assess the framework's impact.

The outcomes of this case study show that the semi-supervised learning framework significantly improves detection accuracy while effectively managing data labelling costs. The integration of unlabelled data enhances the model's ability to identify fraudulent activities, even with limited labelled examples. The study demonstrates that the framework provides a cost-effective solution for enhancing fraud detection capabilities, offering a valuable approach for insurers seeking to balance accuracy with operational expenses.

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Case Study 4: AI-Driven Claims Processing

The fourth case study explores the integration of AI-driven solutions to streamline claims processing and enhance customer experience. The insurance company aims to investigate how AI applications can automate and optimize claims processing workflows, reducing processing times and improving service quality.

The methodology begins with process mapping to identify inefficiencies and bottlenecks in the current claims processing system. This analysis helps pinpoint areas where AI can be integrated to automate repetitive tasks, such as data entry and document analysis. AI tools are then selected and integrated into the existing system, focusing on automating workflows and improving accuracy.

Performance measurement involves evaluating the impact of AI integration on processing times, accuracy, and overall efficiency. Customer feedback is also collected to assess changes in service quality and satisfaction. The study examines how AI-driven solutions address common issues in claims processing and enhance the overall customer experience.

The results of this case study indicate that AI-driven claims processing leads to significant improvements in operational efficiency. Processing times are reduced, accuracy is increased, and customer satisfaction is enhanced. The integration of AI tools proves to be an asset for the insurance company, providing a more streamlined and effective approach to managing claims and improving service quality.

V. CONCLUSION

In conclusion, this study underscores the profound impact that artificial intelligence (AI) and machine learning (ML) technologies have on revolutionizing the insurance industry, particularly in the realm of fraud detection and management. The findings reveal that integrating advanced AI and ML models not only enhances the accuracy and efficiency of fraud detection but also significantly improves operational processes and customer experiences.

The deployment of cutting-edge AI technologies, including generative AI and machine learning models, has proven to be transformative. Generative AI, for instance, enables insurers to simulate a wide array of fraudulent scenarios, thereby improving the detection of sophisticated fraud patterns that traditional methods might miss. This results in more accurate fraud detection and a reduction in false positives, ultimately leading to substantial cost savings and enhanced operational efficiency. Additionally, the application of various ML models, such as Isolation Forest, Random Forest Classifier, and XGBoost, has shown marked improvements in identifying fraudulent claims. These models, when optimized, offer superior performance and accuracy, further bolstering an insurer's ability to combat fraud effectively.

The study also highlights the effectiveness of implementing a semi-supervised learning framework. This approach balances the need for high detection accuracy with the cost of data labelling, demonstrating that integrating both labelled and unlabelled data can significantly enhance fraud detection capabilities while managing operational expenses. This framework represents a practical solution for insurers looking to maximize the value of their data while controlling costs.

Furthermore, the exploration of AI-driven claims processing has illustrated how automation and advanced analytics can streamline claims workflows, reduce processing times, and improve overall service quality. By automating repetitive tasks and optimizing processes, insurers can provide faster and more accurate claims resolutions, leading to heightened customer satisfaction.

Overall, embracing AI and ML technologies equips insurers with powerful tools to navigate the complexities of modern fraud schemes, safeguard their financial interests, and uphold the integrity of the insurance industry. The integration of these technologies not only enhances fraud detection and operational efficiency but also fosters a better customer experience, reflecting a significant step forward in the evolution of insurance practices. The study affirms that leveraging AI and ML is essential for insurers aiming to stay competitive and effective in an increasingly challenging landscape.

REFERENCES

[1] K. Nian, H. Zhang, A. Tayal, T. Coleman, and Y. Li, "Auto insurance fraud detection using unsupervised spectral ranking for anomaly," Journal of Finance and Data Science, vol. 2, no. 1, pp. 58-75, 2016.

[2] S. K. Kim, J. Kim, and Y. Kim, "A comparative study of machine learning techniques for auto insurance fraud detection," in Proc. IEEE Int. Conf. Data Mining, pp. 123-130, 2018.

[3] Y. Zhang, H. Zhu, and Y. Liu, "A hybrid approach for insurance fraud detection based on text mining and machine learning," in Proc. IEEE Int. Conf. Systems, Man, and Cybernetics, pp. 3683-3688, 2019.

[4] J. Chen and H. Xie, "A feature selection method based on principal component analysis for auto insurance fraud detection," in Proc. IEEE Int. Conf. Computer Science and Software Engineering, pp. 234-241, 2016.

[5] Y. Wang and W. Xu, "Leveraging deep learning with LDA-based text analytics to detect automobile insurance fraud," Decision Support Systems, vol. 105, pp. 87-95, 2018.

[6] Y. Sahin, S. Bulkan, and E. Duman, "A cost-sensitive decision tree approach for fraud detection," Expert Systems with Applications, vol. 40, no. 15, pp. 5916-5923, 2013.

[7] S. N. Akbari and M. SargolzaeiJavan, "A new user-based model for credit card fraud detection," Int. J. Computer Applications, vol. 4, no. 3, pp. 029-033, 2017.

[8] S. Subudhi and S. Panigrahi, "Use of optimized Fuzzy C-Means clustering and supervised classifiers for automobile insurance fraud detection," Department of Computer Science and Engineering IT, Veer Surendra Sai University of Technology, Burla, Odisha 768018, India, 2017.

[9] S. T. Balasundaram, M. Ravichandran, and S. Thamarai Selvi, "Insurance fraud detection using genetic algorithm and support vector machines," in Proc. IEEE Int. Conf. Information Communication and Embedded Systems, pp. 1-6, 2016.

[10] M. Hanafy and R. Ming, "Machine learning approaches for auto insurance big data," Risks, vol. 9, no. 2, pp. 42, 2021.