JOURNAL OF INTERNATIONAL CRISIS AND RISK COMMUNICATION RESEARCH
ISSN: 2576-0017
2021, VOL 4, No S4

AI Applications in Commercial Insurance Claims Management and Fraud Detection

Lahari Pandiri[1],

1 SR Systems Test Engineer, Progressive Insurance, lahripandiri@gmail.com, ORCID ID : 0009-0001-6339-4997

Abstract

Detecting fraudulent claims in the insurance industry is of great significance and remains challenging due to the complex nature of the fraud schemes and the sophisticated way of submitting claims. Online retail insurance, which protects sellers from goods return fraudulent claims, is designed for the business scenario of e-commerce platforms. The personal personal-item share information of claimants is defined to indicate a new network between claimants to describe potential interactions. The claimants are represented by network nodes, and the network feature is the personal-item share information. Network learning that leverages the network information is developed to capture sophisticated information. The above procedures combined with a basic classifier successfully identify regular users and fraudsters, achieving a precision of over 80%.

AI applications, especially deep learning architectures for text embeddings, are presented to improve the speed and quality of fraud detection. The architectures process unstructured information and detect fraud with machine learning and statistical models. As transaction data in the finance industry have become larger and more complex given the rise of digital channels, most fraud detection systems need to evolve for efficiency in terms of speed and increasing false rejection. Unstructured information raises many challenges, and deep learning methods that outperform other machine learning and statistical models for analyzing unstructured data are developed. An end-to-end solution is presented to analyze fraud with enhancements on different levels, from embeddings to quantitative characteristics with specific enhancements for fraud prediction.

Keywords: Commercial Insurance ,Insurance Fraud Detection ,Fraud Detection ,Text Classification ,Unsupervised Learning ,Neural Networks ,Claims Processing.

1. Introduction

Insurance companies are faced with a constant flow of insurance claims that, owing to their complexity, necessitate an extraordinary volume of human and technical resources during the adjustment process. Approaches to automated claims assessment rely heavily on a few keywords, character counts, and preprocessing steps such as filtering, stemming, and sentence selection. However, in a compelling text-generating task, an approach based on transformer architecture could be developed. Other extensive data sets with their respective cleansing and data preparation architectures give insight into the possibility of a fully automated claim assessment based on BERT-like models.

Fraud in the car insurance industry significantly reduces insurers' income and risk evaluation efficiency, reducing payment efficiency for users, taxing the normal development of the industry, and more seriously reshaping a corrupt social environment. Outlier detection, graph mining, and

NLP are three fundamental techniques for fraud detection in the insurance industry. Outlier detection is the most widely used fraud detection technique. It could discover novel fraud cases by spotting abnormal cases, fully unsupervised, modeling individual characteristics behind data noise, being applicable in various industries, extensive input selection, good explainability, and output.

Fig 1: Artificial Intelligence (AI) in Insurance Industry

1.1. Background and significance

Digitalization and connectedness, the twin megatrends of the digital age, are also reshaping the insurance industry, with the core value chain changing from legacy to digital. On the one hand, large volumes of structured data and unstructured data on customer behaviour, claims, and underwriting information become increasingly accessible to insurance companies, thanks to the ubiquity of mobile internet and embedded sensors. Such data provides an unprecedented opportunity to improve operational efficiency, customer experience and subsequently profitability. On the other hand, fintech start-ups with innovative business models and nimble operations are emerging to disrupt the stable but slow-insurance market. Start-ups focus on a specific business model as they seek bank partnerships to enter the market and gain customers. Digital-only offerings allow users to interact with an app entirely online, with policies available in minutes. Big customers influence commercial insurers' claims behaviour with fraudulent ones seeking to hide and smooth forensic evidence and pressure small claims management companies to prevaricate. As a result, insurance companies view data in a new light and are on a digitalization journey, changing their operating model in a transformative way. However, the digital shift remains slow, and few companies have achieved a high level of digitalization. Many insurance companies are still in the early stages of digitalization, trying to streamline existing operating procedures to accommodate more data. To realise the objective of smarter claims management systems, insurance companies need to go far beyond automating existing claims management systems and processes. They need to refine processes with dedicated solutions informed by data and to nurture an agile culture to incorporate the new capabilities.

Equ 1: Anomaly Detection (Unsupervised)

$$\text{Loss} = \sum_{i=1}^{n} (x_i - \hat{x}_i)^2$$

- x_i: Original input features of a claim.
- $\hat{x}_i$: Reconstructed output from autoencoder.

High loss indicates potential fraud or unusual patterns.

2. Overview of Commercial Insurance

The global commercial insurance segment of the property and casualty insurance sector was valued at nearly USD 558.53 billion in 2022. The global commercial insurance segment is anticipated to grow at a compound annual growth rate (CAGR) of nearly 10.08% to USD 967.948 billion by 2030. The process of trading risk has become one of the key preconditions for social and economic development. The rapid growth of the economy has led to a rise in the types of risks, scale, and losses. Risk trading services such as reinsurance, insurance, financial derivatives, and insurance-like products have been patented in many industrialized countries. Commercial insurance is increasing in such services. Commercial insurance has different types than personal insurance, and special conditions are used for various types of businesses. Commercial insurance is a form of general insurance service which is taken to cover the risks of business, required by law or self-need, for business itself. Such risks include property damage, property loss, liability covered by law, and business interruption. As businesses are of entity and have various types, commercial insurance is composed of different types of insurance. Each business has unique conditions leading to outstanding risk factors. Therefore the conditions composed of type definition and optional terms are more complicated than those of personal insurance. In the previous phase, the development of commercial insurance was mainly limited on risk pricing. As commercial property risks are very complex, the prices of such insurances could not be reflected by relying on one or two pure premium estimation models. Meanwhile, some extra types of risks which arise from the business activities, such as business interruption and third-party liability. In addition, to enhance the competitive advantage, some new types of coverage have been designed to meet specific needs.

Fig 2: Commercial Insurance Underwriting

2.1. Types of Commercial Insurance

Commercial insurance policies are defined as the type of insurance for businesses that provides property, liability, and workers' compensation coverage. This general definition can be further broken down into five categories, including general liability, business auto, workers' compensation, and professional liability/types of errors and omissions. Commercial insurance can cover a business's assets, value lost due to a loss or liability that occurs. Typically, a commercial insurance policy includes insurance for the building and any contents within, limits on claim payments as a percentage of total values, and with a deductible. Insurance may also include provisions for income loss due to damage of the building. In the last two years, commercial policies have included additional insured that covered losses suffered by others due to the negligence of the insured, and additional building provisions against wind and hail damage.

General liability insurance covers the business as a whole and provides defense against bodily injury, property damage, personal and advertising injury, and medical charges due to accident or injury. Examples of bodily injury can include slips and falls that happen on the property while property damage claims can arise from a job site that damages someone else's property. Insurance coverage usually consists of general aggregate, per occurrence limit, and medical expense coverage with advertising limits. Business auto insurance covers liability for business-used vehicles. This refers to a company-owned fleet of vehicles or employee vehicles used for business purposes. Coverage types can include liability for damage done to others, physical damage for damage done to your vehicle, and uninsured limits. Workers' compensation is traditionally added to protect against employee injury. If an employee is injured on the job, coverage pays for medical bills and lost wages. This type of coverage can only be purchased through state-run programs. Professional liability is also referred to as errors and omissions insurance and covers professional errors, and negligence procedures, or advice given in providing services to customers. Agents can be sued if they make a faulty recommendation that leads a business down the wrong path.

2.2. Importance of Claims Management

Insurance companies want to have fair settlements of claims as early as possible, as the total claim cost borne can be significant in case of disputes. Serious attacks on insurance companies can disrupt their businesses. To detect and handle dubious claims early, insurance companies should have an efficient fraud prevention system. In order to protect from increasing fraud, health insurance companies need to have a fraud management system in place. However, this system should not be unnecessarily restrictive to avoid dropping valid claims on friendly patients. Health insurance companies also press on the importance of maintaining good relations to satisfy their owned hospitals to maintain quality services. They hope to resolve problems without escalating conflicts to expensive legal disputes that require a significant amount of time and resources. To this end, health insurance companies often compromise payments by knowledgeable claims handlers and highly intelligent people from top management teams as one-on-one agreements.

A combination fraud management system with a rules engine and advanced analytics has been frequently referred to as the best practice in the insurance domain. The rising number of claims triggers the need for automation with artificial intelligence algorithms, digital solutions, and self-learning tools. Since health insurance companies can be blatantly unfair, it is the consumer's role in achieving fuller and fairer settlements as well as mitigation in claim costs. Oftentimes the claim handling agency is unfair in turn, as a partner. Aging manual work gauges down productivity and leads to higher leakage. Potential pro bono fraud on publicly-funded health insurance systems can redirect scarce resources from genuine claimants, making things inequitable. Many reduction opportunities lie in process steps, detective methods, and positions. It is important to capitalize on invalid claims, service process improvements, and self-claim process applications. Systems cannot be run by a single algorithm only, board-level strategic options keep the process in check.

3. Understanding AI in Insurance

To facilitate the discussion about justice issues arising from the application of AI in insurance, intention and impact need to be disentangled. It is possible for discrimination to arise either unintentionally or contrary to the intention to discriminate. Moreover, even when discrimination is benign, it may still be unjust. This literature is fundamental for the exploration of discrimination by AI in insurance pricing. Yet, public debates about AI in insurance involve broader socioeconomic concerns than discrimination. Unfair differentiation matters as it may flourish under the guardrails of non-discrimination law, especially when it becomes entrenched through cascades of algorithmic decision-making. While existing critiques applying behavioural economics on behaviour-based insurance touch upon some of these points, there is no integrated literature on unfair differentiation in the context of insurance. Many parties that would traditionally have caused an increase in premiums have found ways to mitigate risk. To create an insurable atmosphere, new clients and products require new models and longitudinal data for risk assessment. Standard models and data literatures that worked for generations no longer suffice for risk assessment and capital allocation across agents, products, and locations, especially large portfolios. Modern models for probabilities or certainty equivalence across agents and actions presently take years. Despite advances in modelling, geography and behaviour causal variables affecting fire, wind, or rain depth remain complex and elusive.

As a mitigation measure, data providers and re-insurers are developing models, global stress tests, and regulatory audits all focused on the new world. To diagnose systemic consequences, risk may be reframed as liability. Modern-operational risk allows for artifact-based classification of transparent or algorithmic risks, defining intuitively a set of expected worst case externalities. Financial regulators have recently stepped up their action against operational risk and modelling flaws. However, liability-climate risk questions are political, and hence very difficult to engage regulators. It is necessary to signal specifically and clearly the consequences for insurance portfolios so as to delineate solvability capital requirements and potential payouts.

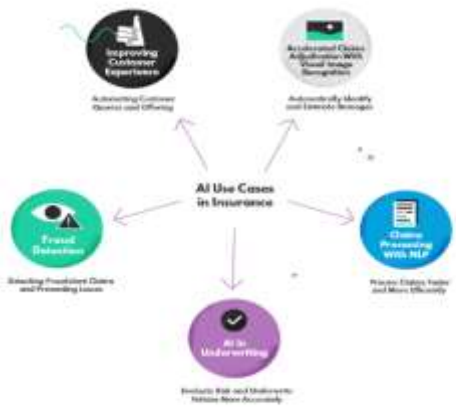

Fig 3: AI in Insurance

3.1. Definition of Artificial Intelligence

Artificial intelligence can be defined as “a machine-based system that, for explicit or implicit objectives, infers from the input it receives how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments”. From the earliest days of insurance, insurers determined the risk associated with the premium manually. AI systems can perform tasks that normally require human intelligence, albeit in a different way. There is a difference between rules-based systems, statistical models, AI models, and AI itself.

The two most useful types of advanced AI for underwriting are machine learning and natural language processing (NLP). Machine learning models build a mathematical model based on training input and corresponding outcomes. In this way, machine learning models “learn” from data and can automatically and iteratively improve their performance on a task without being explicitly programmed. The patterns that the models discover based on the data are often too complex for the human mind. For this reason, it can be very hard to explain why certain predictions are made.

Insurers could apply machine learning models to underwriting, which is the process of assessing the risk and setting the premium. In machine learning, a system learns from a corpus of data to discover a pattern. Insurers could analyse many types of consumer characteristics like age, gender, marital status, credit score, education, etc. to understand the risk that he or she will file a claim. Insurers could train a machine learning model with data on filed claims and aspects from consumers that filed a claim and those that did not. Such a learning model can identify other consumer characteristics that are likely indicative of filing claims. It may therefore be able to make price differentiation.

3.2. AI Technologies Relevant to Insurance

In the following, general AI applications are outlined per type. AI applications for underwriting submitted claims are not yet widely used. Nevertheless, there is a clear need for insurance companies to either out-of-the-box stop fraudsters or, with the help of available software, perform analysis and heuristics on large amounts of internal or external structured and unstructured data.

Be it data on submitted claims, which are suspicious or exceptional in another aspect, or risk characteristics concerning either claimants or claim adjusters, to systematically reason against. Machine learning models per internal problem vary per subform of insurance desired output in both character and complexity. Criminal groups which focus on commercial scams come up with new subforms faster than models can anticipate on readily available data. The last phase of the chain covering the claimed damages marks a hiatus in the reasoning and analysis with employed AI models. First-order social stops in money laundering channels are covered, checking whether procedure and output are in line with internal guidelines and in addition or alternatively legal ones, are outside the AI domain. Dominant emphasis is presently on the legality aspect of procedures instead of considering any social role along the other two axes of being in line with the 'spirit' of the law or going the extra mile to fulfil a social role. The 5W+H methodology aids in simply summarizing the available reasoning and rules. The focus could shift from merely legality towards deemed moral behaviour. A parallel can be drawn with supervisory techniques in financial markets and reporting discrepancies on the three axes to regulatory supervising agencies. Finally, explicit semi-decentralized framing appears to be a trap too. Overlaps within, across and beyond are not or too simply taken into account with metrics such as automatically or random checks. Questions pertain either to the social vs moral role of the procedures or to the social role of the audit. Such designs vs objectives would be better off reconsidered with all naive temptations in mind earlier in the process chain and broader than merely in a supervisory agency context.

Equ 2: Named Entity Recognition (NLP on Claims Text)

$$P(y \mid x) = \frac{1}{Z(x)} \exp\left(\sum_{t=1}^{T} \sum_{k} \lambda_k f_k(y_{t-1}, y_t, x, t)\right)$$

- x: Input text.
- y: Sequence of labels (e.g., "Claimant Name",
- f_k: Feature functions.
- λ_k: Weights.

4. AI Applications in Claims Management

The insurance industry has greatly benefitted from AI applications in claims management processes. AI can automate claim registration, reducing the time and effort for stakeholders. Natural language processing can extract information from structured and unstructured data, making it easier to parse data to classify and assess the viability of claims. AI can also improve collaboration between insurers and insured parties through chatbots. AI-supported decision-making can help insurers detect claim inconsistencies, reveal fraudulent actor behaviour patterns, and improve assessment of claims and fraud risks. Most large (re)insurers have AI applications in claims management.

Fraud detection is an important task in insurance claims management and a significant problem faced by insurance organisations today. In extreme cases, fraudulent behaviour, such as arson, leads to moral hazard, which drives up claims and makes insurances unviable. However, fraud is almost impossible to detect with an absolute guarantee. Therefore, evaluating the credibility of claims is currently an alternative approach to assessing fraud potential. Such credible claim evaluations typically consider a claim's diagnosticity and the claim's plausibility in relation to a central scenario. Currently, insurers rely on a combination of historical data, rules, and cues for fraud detection, which requires large numbers of trained experts with specific insight into the types of fraud relevant to their domain. To address this, various deep learning techniques, such as recurrent neural networks, have been studied. This is a promising field for insurance organisations, but early implementation was limited to basic text classification methods.

Claims management is an area that greatly benefits from exploration by analysts, and fraud detection can take many forms. Currently, clear exploration of the opportunities and limits of neural networks is absent in practice. To contribute to knowledge in this respect, the following business question has been formulated: Which representations of recent claims text provide optimal fraud detection performance when relying solely on a few expert labels? This question gives insurance organisations an opportunity to evaluate recent text representations and neural network architectures.

Fig 4: AI Applications in Claims Management

4.1. Automation of Claims Processing

Within the framework of a holistic analysis of the applications of AI systems in insurance, the focus here is not on the co-founding but on the idiosyncratic applications of AI in commercial insurance. AI systems in commercial insurance are applied in the underwriting, claims process, and active fraud detection. Each of these key areas is analyzed with regard to specific applications of AI systems. The focus is not on the revenue and market volumes of the applications but on the detailed description and analysis of the technology and the models behind them. A related inspection of the regulation of these applications additionally reveals their significance for consumer protection.

Key processes in the insurance business are the underwriting of new policies and the processing of claims. Insurers evaluate risks based on behavioural and demographic characteristics of the individual and geographical risk factors. Based on this data, an estimation of the expected return and expected costs is made. To assess risks, on the one hand, expert knowledge enters a mathematical pricing model. On the other hand, consumer characteristics are directly or indirectly measured to feed the model. Since the turn of the millennium, data processing has changed rapidly and dramatically. Individual characteristics are processed more automatically in more time-efficient and unsupervised predictive models. Expert knowledge is increasingly replaced by AI-based underwriting systems.

Within the area of underwriting, statistical risk estimation is made more flexible and much more powerful in terms of prediction. The automation of the data-driven identification of information gradients between accessible data and the risk probability means the majority of increment performance improvements. In contrast to traditional processing, many more data providers are employed without even a model architecture specifying the required input data. In a bidirectional flow of information between input and output, several ghettos of valid reasonings exist, even though the usage of marketing data and the advantage of fair consumer treatment may be questionable. Most commercial-grade AI systems are insusceptible to agent-level interpretability. Hence, the insurance sector might face reputational risk as it expands the use of opaque ML predictors.

4.2. AI in Customer Service

In the competition to offer increasingly effective personalized services and grind out cost savings, the adoption of AI in the service industries is running rampant. The successful deployment of AI in service contexts has significant structural ramifications for customer service, marketing communication, the design of communication channels, and everything in between. In all of these contexts, gaining the cooperation of and working alongside customers is essential to ensure the smooth design-in and deployment of AI. The adoption of AI in the service industries has been rapid, enabling a new economy in which services are more personalized, intuitive, and less error-prone. However, the impact of AI on communication has been neglected. AI allows companies to better tailor their service processes to individual customers. AI is a crucial opportunity to increase the precision of marketing communication messages directed at prospective customers, tailoring messages to the needs, preferences, and capabilities of target audiences. AI-Powered service engagement has fundamental structural effects on customer-company interactions. Who is in control of the interaction? Who initiates the interaction? What are the expectations as to the interaction? What communication channels are used? What is the scope and direction of the interaction? AI is a great opportunity for companies to better tailor their marketing communication and advertising messages to individual customers. Two AI processes enable this: AI can sift through large amounts of both structured and unstructured data to discover connections and trends that would not come to a human analyst’s mind. AI can use these insights to predict the preferences and behaviour of individual customers. There are two important traditional applications of AI in marketing communication and several applications that are relatively novel. In many advanced economies around the world, the adoption of AI has rapidly spread in recent years, especially in the service industry's front office consumer-facing contexts. Companies aim to use AI to enhance the customer experience, as evidenced by their growth strategies. AI is often defined as 'the science of making machines do things that would require intelligence if done by men'. More formally, AI can be described as 'a machine-based system that infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions'. Among the many application areas for AI, natural language processing has received a great deal of interest. AI can capture, analyze, and interpret voluminous unstructured textual data. Using NLP, customer service can be automated to some degree. Additionally, AI can discover patterns among many variables, assisting in the onboarding of new customers, performing risk assessments, and predicting payment problems. AI-based analytical and statistical solutions are also offered as a service.

5. AI in Fraud Detection

Insurance fraud, which involves dishonest statements made with the intent of duping an insurer, is one of the oldest forms of financial crime. It is also one of the most costly white-collar crimes, resulting in trillions of dollars lost worldwide each year. Insurers, and particularly property and casualty insurers, are under constant pressure to make good on legitimate claims while denying fraudulent ones. With the rapid growth of the insurance market, insurance fraud is becoming an increasingly serious problem. To counter fraudsters, insurance companies generally employ fraud detection agencies to review suspicious cases manually. However, as the number of insurance applications increases, the backlog of suspicious applications accumulates quickly, which results in greater chances that fraudsters escape punishment.

Experts in finance and law enforcement use complicated algorithms or rules to identify patterns in fraud cases. Despite the success of this approach, knowledge concerning fraud patterns is rare and specific to certain types of fraud. Additionally, traditional techniques may not be applicable to new and evolved fraud scenarios that conflict with pre-existing patterns. With the explosion of big data, researchers have turned to more efficient and effective supervised learning methods based on historical fraud cases. However, in many practical situations, historical cases are inaccessible or undetectable, which results in a need for unsupervised or semi-supervised methods that can detect fraud patterns without any prior guidance. In particular, newly emerging techniques that micro-cast fraud detection as a graph learning problem are proposed. With these techniques, systems can be designed to generalize suspicious accounts or groups from raw data across various domains and scenarios, such as money laundering in banking, phishing websites in cybersecurity, and fraudulent claims in insurance.

We introduce a device-sharing network among claimants and develop an automated solution for fraud detection based on graph learning algorithms, separating fraudsters from regular customers and uncovering groups of organized fraudsters. This solution applied at achieves more than 80 precision while covering 44 more suspicious accounts compared with a previously deployed rule-based classifier after human expert investigations. Our approach can easily generalize to other types of insurance.

Fig 5: AI in Fraud Detection

5.1. Identifying Fraudulent Claims

Fraud causes substantial costs and losses for companies and clients in the finance and insurance industries. It has been estimated that roughly 10 percent of the insurance industry's incurred losses stem from fraudulent claims. Hence fraud detection is a key function in these industries and core to the claims management process. The rise of digitization in finance and insurance has led to big data sets, which can be exploited for fraud detection. In this paper, we propose architectures for text embeddings via deep learning that help improve the detection of fraudulent claims. Analyzing fraud with statistical and machine learning methods poses special challenges. Transaction data and claims data are often available only in an unstructured format. Fraud data are highly unbalanced, meaning that the number of fraudulent cases is very small compared to non-fraudulent ones. Claims do not have a fixed length because the number of items in an invoice varies. Deep learning outperforms other machine learning methods for analyzing unstructured data comprising text. We develop deep learning architectures tailored to claims data to handle these challenges. Our analysis is based on doctor's bills, which consist of unstructured text. Such bills usually have the properties of text data, and some variables are coded with many thousands of categories. We test our methods on a data set from a health insurance company, and our empirical results show that these outperforms state-of-the-art methods in predicting fraudulent claims.

Fraudulent claim detection is one of the greatest challenges the insurance industry faces. receives thousands of potentially fraudulent claims daily. Such abuse of the insurance policy could lead to heavy financial losses. To detect and prevent fraudulent claims, we developed a data-driven procedure to identify organized fraudsters, a major contribution to financial losses, by learning network information.

5.2. Machine Learning Algorithms in Fraud Detection The use of machine learning algorithms for the detection of fraud in healthcare claims has gained a lot of attention in the recent past, as it is imperative for health insurance companies to keep up with claims processing. Therefore, there is a need for automated systems that can assist in the easy and seamless identification of anomalies that suggest fraudulent claims in a semi-automated manner. The research work attempted to improve upon the accuracy and precision of the identified anomalies as well as the claims classified as normal. This was done by suggesting alternative modeling techniques such as Decision Tree Classifier and Random Forest, as well as new data preprocessing techniques capable of normalizing numerical values and reducing anomalies along with improving on the chosen set of features. A model was implemented in Python to initially assess the accuracy and precision of the available methodology and then the suggested possible enhancements. Initial experimentation and modeling made use of only the available dataset that was gathered with the assumption that some existing knowledge about the problem domain and data can assist in shaping the enhancements. The final model was the reality of the suggested methodologies that could further discover additional improvements.

The intention is to create a model capable of providing an explanation into the reason for the choice of features and the possibility of improving the existing model accuracies of the identification undertaken. The features used in the suggested ensemble model are insights into the pattern of claim abnormalities that can guide the design of insurance policies and implementations of fraud detection models in the early stages. In the first section, a base model was created using the data preprocessing methodology and modeling of known modeling techniques that was to be improved upon in the later sections with a suggestion of various enhancements to the existing model.

Equ 3: Customer Claim Segmentation

$$\min_{C} \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2$$

- C_i: Cluster i.
- μ_i: Mean of cluster i.
- x: Claim feature vector.

6. Conclusion

Numerous applications show that AI can improve performance, reduce costs, mitigate risks, and improve product service in the insurance industry. However, the technology is still developing, and companies are struggling to harness the potential of AI-driven applications across company, customer, and product perspectives and attention to the need for integration. AI and big data analytics will be essential for property-casualty (P&C) insurers in the coming years. AI introduces high hopes, disruption, and significant challenges for the incumbent insurance business model and value chain. AI will augment the development and pricing of property-casualty products, automate and improve risk assessment, and accelerate product service delivery. AI data analytics will help mitigate risk, enrich customer touchpoints, decrease costs, prevent fraud, and conquer digital channels in P&C underwriting. At the same time, AI represents significant challenges to developing new data-sourcing business models, managing digital demands of small businesses, and wealth concentration amongst high-income individuals. Challenges for implementation are affected by a considerable gap between the fast innovation cycle in AI and the slow fare rule development of regulatory and self-regulatory practices. AI in Commercial Insurance is less intense as compared to life insurers. However, it is generally accepted that it will grow as AI tools or services become available to insurers without cutting-edge innovation resources and knowledge.

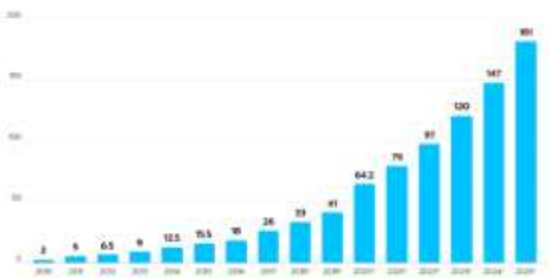

Fig : Streamlining insurance claim management with AI

6.1. Emerging Technologies

The two of the two areas examined for implementation of AI technologies for claims management are clarifying the claim process for policyholders and on-line theft claims. Regarding the latter area, two commercial projects were outlined, involving off-line task allocation and personalization of alerts. Personalization efforts were based on claims data linking external parameters and policyholder internal characteristics, and thereby providing a starting point for estimating the best point of personal communications. Attachments based on these estimates are altered using generative AI to comply with context and risk for each type of communication and policyholder. The results of the four projects covered suggest many unexplored opportunities for other large and medium-sized insurers to adopt similar technologies in these two areas. The three AI projects examined in the area of fraud detection all involve a detection model predicting the likelihood of fraud of more recent claims using the information on all claims in the history of the insurer. In the first project, the standard decomposition of the latter model into a base and an anomaly model was adopted. Here, the internal variables for which the standard decomposition no longer holds were also addressed in a similar manner. Since generally only aggregated external variables are available, a simpler, one-step model, which could handle external behavior, was developed.

Empirical tests revealed the explained variance of the latter model to be almost certainly higher than that of the standard decomposition. However, the performance of the former model is further improved using wider coverage of aggregated external variables. AI services aided by extensive external variables were able to predict future claim rates accurately and directly at the level of internal variables.

Lastly, even large insurers might have too few claims for training a robust communication prediction model in the area of claims management. Nevertheless, publicly available recent, rare event prediction methods were presented that estimate the likelihood of an event for data from any size company. These can thereby serve as very effective benchmarks. This ability was illustrated in the insurance domain using property restoration as an example, using data for which little information was available for training. In a project in the context of societal and economic finances, a new use case combining lots of data spills from social media with the lack of own data was proposed for accurate detection of frauds as they develop. AI use cases in the areas of on-line theft detection and prevention or supported business models in insurance were examined using an approach. The four AI projects discussed suggest many other unexplored areas for AI in insurance be addressed for large and medium-sized insurers worldwide.

7. References

[1] Ganti, V. K. A. T. (2019). Data Engineering Frameworks for Optimizing Community Health Surveillance Systems. Global Journal of Medical Case Reports, 1, 1255.

[2] Maguluri, K. K., & Ganti, V. K. A. T. (2019). Predictive Analytics in Biologics: Improving Production Outcomes Using Big Data.

[3] Polineni, T. N. S., & Ganti, V. K. A. T. (2019). Revolutionizing Patient Care and Digital Infrastructure: Integrating Cloud Computing and Advanced Data Engineering for Industry Innovation. World, 1, 1252.

[4] Chava, K., Chakilam, C., Suura, S. R., & Recharla, M. (2021). Advancing Healthcare Innovation in 2021: Integrating AI, Digital Health Technologies, and Precision Medicine for Improved Patient Outcomes. Global Journal of Medical Case Reports, 1(1), 29–41. Retrieved from https://www.scipublications.com/journal/index.php/gjmcr/article/view/1294

[5] Nuka, S. T., Annapareddy, V. N., Koppolu, H. K. R., & Kannan, S. (2021). Advancements in Smart Medical and Industrial Devices: Enhancing Efficiency and Connectivity with High-Speed Telecom Networks. Open Journal of Medical Sciences, 1(1), 55–72. Retrieved from https://www.scipublications.com/journal/index.php/ojms/article/view/1295

[6] Adusupalli, B., Singireddy, S., Sriram, H. K., Kaulwar, P. K., & Malempati, M. (2021). Revolutionizing Risk Assessment and Financial Ecosystems with Smart

Automation, Secure Digital Solutions, and Advanced Analytical Frameworks. Universal Journal of Finance and Economics, 1(1), 101–122. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1297

[7] Gadi, A. L., Kannan, S., Nandan, B. P., Komaragiri, V. B., & Singireddy, S. (2021). Advanced Computational Technologies in Vehicle Production, Digital Connectivity, and Sustainable Transportation: Innovations in Intelligent Systems, Eco-Friendly Manufacturing, and Financial Optimization. Universal Journal of Finance and Economics, 1(1), 87–100. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1296

[8] Singireddy, J., Dodda, A., Burugulla, J. K. R., Paleti, S., & Challa, K. (2021). Innovative Financial Technologies: Strengthening Compliance, Secure Transactions, and Intelligent Advisory Systems Through AI-Driven Automation and Scalable Data Architectures. Universal Journal of Finance and Economics, 1(1), 123–143. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1298

[9] Anil Lokesh Gadi. (2021). The Future of Automotive Mobility: Integrating Cloud-Based Connected Services for Sustainable and Autonomous Transportation. International Journal on Recent and Innovation Trends in Computing and Communication, 9(12), 179–187. Retrieved from https://ijritcc.org/index.php/ijritcc/article/view/11557

[10] Balaji Adusupalli. (2021). Multi-Agent Advisory Networks: Redefining Insurance Consulting with Collaborative Agentic AI Systems. Journal of International Crisis and Risk Communication Research , 45–67. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2969

[11] Pallav Kumar Kaulwar. (2021). From Code to Counsel: Deep Learning and Data Engineering Synergy for Intelligent Tax Strategy Generation. Journal of International Crisis and Risk Communication Research , 1–20. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2967

[12] Somepalli, S., & Siramgari, D. (2020). Unveiling the Power of Granular Data: Enhancing Holistic Analysis in Utility Management. Zenodo. https://doi.org/10.5281/ZENODO.14436211

[13] Ganesan, P. (2021). Leveraging NLP and AI for Advanced Chatbot Automation in Mobile and Web Applications. European Journal of Advances in Engineering and Technology, 8(3), 80-83.

[14] Somepalli, S. (2019). Navigating the Cloudscape: Tailoring SaaS, IaaS, and PaaS Solutions to Optimize Water, Electricity, and Gas Utility Operations. Zenodo. https://doi.org/10.5281/ZENODO.14933534

[15] Ganesan, P. (2021). Cloud Migration Techniques for Enhancing Critical Public Services: Mobile Cloud-Based Big Healthcare Data Processing in Smart Cities. Journal of Scientific and Engineering Research, 8(8), 236-244.

[16] Somepalli, S. (2021). Dynamic Pricing and its Impact on the Utility Industry: Adoption and Benefits. Zenodo. https://doi.org/10.5281/ZENODO.14933981

[17] Ganesan, P. (2020). Balancing Ethics in AI: Overcoming Bias, Enhancing Transparency, and Ensuring Accountability. North American Journal of Engineering Research, 1(1).

[18] Satyaveda Somepalli. (2020). Modernizing Utility Metering Infrastructure: Exploring Cost-Effective Solutions for Enhanced Efficiency. European Journal of Advances in Engineering and Technology. https://doi.org/10.5281/ZENODO.13837482

[19] Ganesan, P. (2020). PUBLIC CLOUD IN MULTI-CLOUD STRATEGIES INTEGRATION AND MANAGEMENT.

[20] Chinta, P. C. R., & Katnapally, N. (2021). Neural Network-Based Risk Assessment for Cybersecurity in Big Data-Oriented ERP Infrastructures. Neural Network-Based Risk Assessment for Cybersecurity in Big Data-Oriented ERP Infrastructures.

[21] Katnapally, N., Chinta, P. C. R., Routhu, K. K., Velaga, V., Bodepudi, V., & Karaka, L. M. (2021). Leveraging Big Data Analytics and Machine Learning Techniques for Sentiment Analysis of Amazon Product Reviews in Business Insights. American Journal of Computing and Engineering, 4(2), 35-51.

[22] Routhu, K., Bodepudi, V., Jha, K. M., & Chinta, P. C. R. (2020). A Deep Learning Architectures for Enhancing Cyber Security Protocols in Big Data Integrated ERP Systems. Available at SSRN 5102662.

[23] Karaka, L. M. (2021). Optimising Product Enhancements Strategic Approaches to Managing Complexity. Available at SSRN 5147875.

[24] Katnapally, N., Murthy, L., & Sakuru, M. (2021). Automating Cyber Threat Response Using Agentic AI and Reinforcement Learning Techniques. J. Electrical Systems, 17(4), 138-148.