Streaming Loss Reserve Estimation and Emerging Risk Signal Detection: Real-Time AI Frameworks for Dynamic Insurance Risk Monitoring

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1. Introduction

The insurance industry is facing major disruption with the rapid advance of technologies and rapidly changing customer expectations. New digital-native companies are entering the market and challenging traditional business models, causing an increasing need for innovation in the industry. New data sources, often unstructured and evolving at a rapid pace, are more broadly available now compared to the past. This could be from IoT sensors, social media, digital footprints, etc. Also, significant advances have been made in the area of AI and deep learning techniques, particularly in relation to the growing usage of it in finance.

When facing disruption, risk management and the ability to adapt become more important than ever; this is even more relevant in the conservative, risk-averse, heavily regulated insurance industry. The paper demonstrates how big data technology and artificial intelligence can be used to deliver innovative solutions to longstanding problems in the insurance industry – particularly by providing insurers with real-time monitoring of their risk at an incredibly high resolution. Non-life insurance covers a wide range of risk categories across personal, commercial, and specialty lines of business. All carry their own unique challenges, and we decide to focus on the risk monitoring of a commercial insurance risk. This kind of hosting, we believe, is a common exposure area, and we believe our methods can be applied more generally to other areas. Our case study targets the risk of fire damage to properties in London that are or are likely to be hosting places of large gatherings such as theatres or concert halls. Our mathematics build and borrow from work done in other areas; we perform spatial and demographic analysis using machine learning and deep learning modeling to produce a real-time view of the evolving risk landscape.

1.1. Background and Significance

Background and significance. Many areas of our modern world rely on the insurance industry to thrive. In today's society, we can finance large construction projects, secure our wealth in the form of homes or business assets, or guarantee that our loved ones will be taken care of in our absence because of the backing of this system. However, although one of the earliest uses of modern AI can be traced to feasibility proof research done by an existential risk coverage company shortly after the coining of the term in 1955, we have made little progress in implementing this work in actual insurance practice. The data-centric practice of risk quantification that we see in the reinsurance market today makes our risk models as good as the adequacy of the data on which they are based. During the last two millennia, our societal practices associated with the pricing of risk evolved from the normal activities of merchants and money lenders to highly specialized businesses, which, despite their cold, faceless appearance, actually permit most real wealth-generating activities to proceed at full speed. However, many of the practices remain firmly rooted in the humanity of their origins. Our unaccommodating risk models do not allow us to fully take advantage of the reams of new data that are becoming available today. This is because, even today, the contingency of human trust in these practices depends more on an individual's view of their history. It has also become prohibitively complicated for a common man's cognitive resources to encompass the diversity of the variables that are integrated into the abstract concept of risk. That is, within a 10-minute computed risk framework, a person should be able to quantify the risk before deciding whether his friend jumping from a cliff on an adrenaline rush holiday was crazy and whether he should be barred from any future company event planning. To remedy this, we propose a two-phase risk quantification scheme. In the first phase, we strictly employ AI methods that will monitor the insured asset in real time, extracting a wide variety of features that encapsulate the risk of that asset. Extracted features include patterns such as exposure to storm activity and electrical use. In the second phase, the real-time data are used in models trained with real-time data alone to obtain the risk. This lets the citizen belonging to modern society continue to compare despite her cognitive limitations. Since all data that the model uses to make its decisions, input and output, are transparent to anyone, the internal AI model's quality is easy to guarantee. These ideas are not new and have been proposed before, such as working on the transparency and explainability of AI models or deploying AI algorithms as data crunchers rather than knowledge bearers. However, none of this work has been applied to insurance risk quantification, nor have they been combined as we propose here.

1.2. Research Objectives

The objective of this research is to provide an answer to the crucial new issue and long-term corporate governance challenge of how to create a tool that enables insurance companies to manage the major risk of their business—underwriting—on a real-time basis. The paper focuses on an objective function's real-time parameter estimation for the Neyman-Scott model with a random superposition of a binomial process, which is a good model for risk counting data with a large number of zeros compared with the total number of occurrences. Risk counting statistics requirements for mathematical statistics basic assumptions tend to be scandalously misunderstood. The classical risk counting models result from ad hoc evidential reasoning strings for model fitting without model definition likelihood calculation, which allows making statistical inference. The maximum likelihood estimate of the objective function gives a clear statistical model identification.

The main goal is to research the real-time identification of the insurance contracts' risk effect using the frequency measures as counts of precipitating events analyzed by the Neyman-Scott model, which will allow creating a good real-time monitoring system. The frequentist point of view will be applied, which corresponds to the practical problem of excessively high communicative costs of calling final score sessions. Therefore, an alphabet of risk events can be guessed from the raw data, which may be noisy. In this connection, two values—the probability of a risk event precipitating together with the probability of independence of risk events in a given period—can form the number of precipitating events in the pure premature speculation model.

2. Foundations of Risk Monitoring in Insurance

The concept of real-time risk monitoring is not an entirely novel one in insurance. For decades, actuaries have developed algorithms to score and price risk at the time of underwriting. However, I argue that given increased flows of dynamic, fine-grained data, and our new ability to analyze it, we can fundamentally change our approach to risk evaluation, management, and pricing. The cornerstone of my argument is that the cardinal rule of risk pricing must be more finely focused on a specific moment rather than a deferred period in time. The technological availability of clustering and risk monitoring tools today makes this possible and timely.

Insurance companies take their name from the action of ensuring things in our world. Most insurance companies usually ensure two categories of risks: property and liability. This responsibility is shouldered by expanding the arm of an insurance company called the underwriting department, enabling their clients to gain from the availability and efficient exploitation of risk data. In return, this department should collect and filter the risk information received and supply it in a form that is consumable by other business units that have the capabilities to measure and control those risks that have been accepted. However, in contrast to the developed intelligence in collecting, processing, and presenting risk data to customers, a number of insurers still rely on a subjective assessment of the data collected in order to make a sound risk analysis.

2.1. Traditional Risk Assessment Methods

Insurers must be able to estimate policyholder behavior in order to manage the associated risk. The true cost of an insurance policy can only be determined in hindsight. This often makes it difficult for actuaries to accurately determine pricing and reserving until enough data is accumulated. Because this latency negatively affects the insurer's business and its policyholder relations, traditional risk assessment methods have always been crucial for insurance. A traditional insurance model distinguishes between three types of risk: premium rate risk, insurance coverage risk, and investment risk.

Premium rate risk is the possibility that a given pricing model misrepresents the true level of claim exposures, i.e., the number of claims an insurer can expect and the size of each claim. In order to keep a solvent position in a competitive industry, an insurer must avoid underwriting adverse selection. The ability to gauge policyholder behavior helps an insurer manage concerns related to coverage risk. Such concerns include the ability of the insured to stage accidents and the fraudulent nature of a claim. Besides the protection of the insurance policy, another key function of an insurer is as a risk pool for policyholders who are subject to loss. Rapid changes in investment trends and rapid financier behavior make investment risk difficult to evaluate. To protect policyholders, actuaries must assess these several risks carefully. In the near future, traditional insurance models may face severe tests, erroneously pricing and reserving portfolios and failing to maintain the stability of capital and surplus levels.

2.2. Challenges in Traditional Risk Monitoring

Traditional risk monitoring in insurance has long been built on actuarial science, with back-testing and calculating liability and solvency in a rear-view mirror mode to ensure life insurers have the capacity to pay policyholders over the long term. In the case of requiring risk mitigation when the insurers' solvency drops to a dangerous level, it usually takes three to six months to approve, implement, and operationalize its positions. Despite the tremendous development of the financial industry and improved risk monitoring capability over the years, two critical issues remain in the life insurance field: 1) Choosing the variables such that they accurately represent the risk, and 2) These variables are often static in nature, that is, already lagging. In terms of the macroeconomic environment, most of the statistical models adopt a fixed set of macroeconomic variables to represent the trend.

However, entering the mega-data era, the abundance of financial market data implies we could build models for various innovations to process these attributes because insurance products are being continuously renewed, such as spring renewal in property insurance and deposit checking accounts in life insurance. Thus, we believe an expanded list of macroeconomic variables is worth trying. Last and most importantly, proposing models that could provide real-time decision support to identify the over-simplicity-status risk. With the above motivations, we decided to utilize artificial intelligence and big data analytic approaches together with some financial and economic knowledge to derive a robust model that can support real-time insurance solvency risk indirect monitoring for the policyholders to ensure they are protected.

3. AI and Machine Learning in Insurance

Within core insurance operations, AI and machine learning not only can cut costs significantly while boosting efficiency but also can vastly improve service delivery and address some customer pain points. Robotic process automation can perform highly repetitive tasks and free employees for tasks requiring human judgment. In one case, AI proved capable of identifying a significant percentage of claims requiring no further review, allowing the company to apply its resources to the remaining disputed claims.

Machine learning in service centers can assist with customer inquiries and complaints, while chatbots can help speed up the customer experience and cut costs.

Furthermore, machine learning can fine-tune underwriting and pricing. As data become more precise and predictive about risk, AI can potentially help generate bindable quotes for a large percentage of business customers' commercial insurance needs in less than two minutes. Also, simpler products enable much improved customer service and satisfaction. Policyholders can get on-demand, per-mile car insurance through a mobile app that estimates daily driven miles and schedules time to go on and off. In the case of health insurance, some companies offer simple, low-cost, and highly transparent health insurance products to address areas of need in a system that may be under duress. Overall, broadening the customer base with less complicated products can also bring in many customers who were underinsured or uninsured, bringing needed simplicity and predictability into their lives.

3.1. Overview of AI and Machine Learning Technologies

Artificial intelligence (AI) and especially machine learning systems (ML) have made remarkable progress in the last few years, and real opportunities exist to apply machine learning to gain a whole new level of insight. Machine learning models are particularly good at experiencing complex underlying patterns within high-dimensional data sources. This can be both structured, such as tabular data, and unstructured data, such as images and sounds. Through the use of machine learning, we can create models that are tuned to real-world applications and thus provide insight that is rooted in these use cases. The types of models that are typically applied to real-world businesses are similar to those taught as part of machine learning instruction. These include supervised learning methods such as classification or regression and unsupervised learning methods including clustering. Information garnered from these models can be presented in a visually meaningful way, allowing human intervention in the decision-making process, further enhancing their value. Choosing the most appropriate model to use is both an art and a science. Different algorithms are more appropriate for different problems as they have various pros and cons, which can make applications arduous but rewarding.

3.2. Applications in Insurance Industry

The AI deployment in the industry brings the potential of upgrading the workforce and establishing new business opportunities by creating new competitive advantages. More insights from IoT, auto claims, remote sites, and mobile assistants lead to better claims service and loss prevention, which mitigates risk and offers appropriate risk premiums to the insured companies. What is required to make this possible is merely realistic scenarios verifying the benefits of AI solutions and compliance with current regulations. Several countries are preparing to establish national AI strategies to address the regulatory requirements, mainly in financial institutions, to realize the benefits for the economy.

There are various applications of artificial intelligence in the insurance industry in recent times. Some of these are the following: AI has significant potential in the insurance industry to improve pricing models, claim fraud detection, customer service, loss control, automate the subrogation process, and reduce expense ratios and loss reserve assessments. In fact, many insurance companies are using sophisticated technologies to solve their regular problems. Offering personalized insurance policies according to one's perception, behavior, and intention is key to successful pricing. With the aid of AI discipline and trained algorithms, insurance agents could now create their own personal brand and win the loyalty of the customer. We also observe a cutting-edge IoT concept that lets customers proactively manage risk.

4. Real-Time Risk Monitoring with AI

The insurance industry is turning its strategic focus towards live risk monitoring. In contrast with the traditional system of providing a service and then analyzing the data for more efficient improvements, the new approach to keep control of a risk directly is to constantly look into the risk over its life. This relationship will remain however long the product is alive and might only end when the service part of the product comes into play. The insurance industry might just be the best positioned for proposing these new offerings as it is reinstating the human relationship inside the industrial processes.

The reliance of property insurance on remote inspections performed with sensory enriching reports is being challenged by the development of drone technologies. Provided the transformation of the data into something actionable is quick and rich, it might just succeed. Property insurance companies are in a good position to add a few introductory charges and perform small on-demand air screenings around the claimant's environment. This is an extremely powerful way of reinstating an agent and seeing the context in which this specific loss has occurred and dismiss or fast track the claim. In a world where drone prices are dropping significantly, this new offering should be a no-brainer. In land transportation, the quality of the driving and the convictions are essential to understand the level of insurance risk. In health underwriting, social circles and health issues define the final level of health risk. In business underwriting, the way the bookkeeping records are kept is also much more informative than the assumed risk. All these actions would likely have minor or no impact on these potential clients as this behavior covers very much the day-to-day life. After all, anyone might unnoticeably be sharing the requested rather than imagined risk reduction goal.

4.1. Concepts and Definitions

An algorithm takes a set of insurance policies and instantaneously predicts the potential claims for the individual policies. By chaining this risk assessment function with the premium and term, we obtain the expected loss for each policy in the portfolio. The marginal contribution of a group of policies can be calculated with a conditional generator model to aggregate potential correlation effects. A real-time risk monitoring model integrates the scores into the three-dimensional features of time, region, and risk exposure for the risk managers or business operators to monitor and manage the portfolio. Next, we discuss each of these components in more detail. The process of setting risk and pricing is highly linked; therefore, we will talk about risk assessment and pricing in one section first. However, they are fundamentally two different problems; therefore, we split out the following section to solve the monitoring and management of portfolio risks. Lastly, we discuss some of the correlation effects in risk aggregation of the potential claims. Overall, the relevant machine learning techniques are summarized, both explaining how machine learning is viewed in insurance.

4.2. Key Components and Technologies

The implementation of real-time risk monitoring will generally involve several technical components. The major technical components include data collection and pre-processing, learning predictive models with relevant features, creating interfaces that allow relevant queries, and operationalizing the predictive models in a reliable manner. Although each company’s specific implementation details might depend on several factors such as size, data infrastructure, culture, and the number and types of products, the key pieces of this architecture can apply to all companies.

The collection of vast amounts and expanse of data is a key initial step for creating predictive models. The data collected may come from sensors or wearables, internal company databases, internet-enabled services, microeconomic and macroeconomic indicators, and others. Pre-processing may involve several important steps, such as normalization, data imputation, identifying relevant variables for incorporation into the models, discretization, time-series alignment, and possibly feature reduction. The data collected is often in a raw form with observable errors and is in formats that may not readily interface with machine learning packages. For the design of real-time monitoring, exact pre-processing steps are problem-dependent, company-dependent, and product-dependent, and may not always be simple. The decision of whether to use all the data or only a subset of the data also depends on company-specific conditions, such as the granularity of the data model, the model transparency desired, the comfort level of the underwriters and regulators, and the siloed nature of insurance companies' data structure. For the data from external sources, decisions are also needed on whether obtaining the data involves additional costs.

5. Machine Learning Techniques for Continuous Risk Assessment

Modern risk adjustment methods compare characteristics of an enrolled population to a model or base of predicted enrollees that has a similar distribution of characteristics. Oftentimes, these models are machine learning models issued well before the actual coverage period. The models were trained and tuned on the past and not necessarily optimized for a future insurance coverage period at the time of deployment. Assuming that the model delivered the best results when it was trained may lead to severe miscalibrations and larger residual variance if not used properly. Also, there are a lot of systematic changes, like the many and currently incompletely understood interaction dynamics of premium development and incentivization for individual mandates, risk corridors, guaranty funds, etc., but also underpricing pressure, political decisions in nationalizing losses to providers, or the concentration of profitable products in profitable markets, that cause daily risks to change over time. The difficulty with handling continuous real-time information of changing risk typically stems from the limitation of non-adaptive thresholds, simple one-off predictions, and the absence of random outcome testing to assess the real-life ability to predict the most relevant end-of-period outcome, i.e., received medical services per period and per person.

For the active feedback loops and contributions to scarcity dynamics in a supposedly stable pooled entity balancing two main business functions (actuarial soundness with a frank charge and the cross-subsidization between different subclasses vs. affordable, sustainable coverage in a regular market situation), it is necessary to allow the base case to automatically adjust to the new period type and to trigger publicly acknowledged monitoring and active intervention in the right price-making entities, just as much as in participating organizations when and where necessary. In order to come to an applicable, machine learning derived solution that can cope with these issues as before, the previously described analytical lacunas are addressed on an additional level of complexity: we develop a machine learning framework like automatic difficulty annotation, sequence splitting, continuous real-time performance metrics, and evaluation including into existing insurance practices of price-making monitoring and prospective corrective and risk-correctional algorithms. Moreover, the decision model this complex sophistication is embedded in will first check the learnability condition for continuously adjusting machine learning models and then apply models where and when necessary. This decision will then be linked with existing front-end consumer guidance algorithms that are at the moment mainly but not entirely based on the current period versus model, the plan's historical growth pattern, and the relation between community rating area and network pricing.

5.1. Supervised Learning for Risk Prediction

Let's assume that the insurance company operates in a geography where vice, fraud, and money laundering are societal issues, and they want to take strict actions on these events. Also, premiums and claim reserves are invested in other financial instruments, and the earnings of insurance companies are driven by the difference between incoming premiums and payment of claims. Large claims can directly impact the financial balance of an insurance company. So, a substantial part of the insurance operational cycle is to take strict actions and to separate them from genuine losses. The first step in implementing an AI module for real-time risk monitoring is to identify the features that help to separate such losses. These could include known details of the customers, such as age, profession, or nationality, or other discovered attributes, such as the particular insurance area, gross or net premium, or the payment status. Fraudulent claims often correlate with what appears to be desperation on the customer side or luxury on the insured's part. The dependent classes of the model are the loss entries. There could be logistic regression that gives probabilities in percentage or a decision tree, which is useful for a two-direction separation.

5.2. Unsupervised Learning for Anomaly Detection

This chapter describes the general framework and architectural settings for AI-driven platforms for real-time risk monitoring in insurance. It defines the main elements of such platforms and precisely delineates the functions and responsibilities between human operators and the system or its components. Furthermore, it investigates opportunities to implement automation of decision-making, remediation, and even recommendation generation, focusing on the use of linguistic formalization and explainable models. The most commonly used approach to anomaly detection is unsupervised and focuses on defining which points in the data are outliers, i.e., points that differ from the majority usually because their feature values appear infrequently. Recurring examples are: (a) clustering-based techniques usually consisting of allocating records into different groups based on their encoded features, each of them representing an alleged homogeneous family of records and utilizing distance metrics to detect the ones with dissimilar characteristics, and (b) trained models using the reconstruction error to identify input data points lying in an improbable region of the space. Other, less used anomaly modeling, probably more aligned with the type of applications insurance risks pose, are those related to point-based statistics such as density thresholds, local distance metrics, enhanced features for shrinkage, clipping, data parsimony, and nearest prototype proximity joining.

In the context of real-time risk monitoring, anomaly detection aims to assure that the input data sampled at regular intervals only varies within a predictable, predefined range. Periodic assessment against defined anomaly thresholds might generate alerts that hint operators to abnormal data behavior and that the company's measurement or classification processes need revision. In the context of robotics, it is known as a detection technique induced by domain shift where the difference in meaning of some attributes of the training data distribution and the test data used in production is signified, commonly resulting in a deteriorated generalization. In this work, we are interested in the training of two types of anomaly detection models using unsupervised learning algorithms able to spot record-level deviations related to measures of solvency, i.e., computed using the best estimate assumptions of market-consistent valuations, i.e., an actuarial measure including financial assets and contingent liabilities, and specific accounting standards.

6. Policy Adjustment in Response to Real-Time Risk Assessment

A challenge with frequently updated risk monitoring is the increasing risk of policy adjustment. In insurance, this means that contracts may need to be adjusted repeatedly in the course of a policy period. Such micro-adaptations have the potential to make the contract difficult to interpret, and the policy administration costly. This is particularly the case for products sold through direct channels at low industrial premium levels. Risk sharing through various structures, such as profit participation or stop-loss arrangements, is one way of coping with contract adjustments. The price of regular risk monitoring is then a potentially lower profit capture. Other approaches involve more severe restrictions of policy developments and policyholder refunds if undertakings benefit more than is contractually due to them. Advantages of these latter approaches would be a better consumer understanding of the product, potentially lower back office costs, and a stronger alignment of risk monitoring with other life insurance objectives. Maintaining insurability is an important aspect of insurance regulation, and contracts should avoid "self-fulfilling prophecies" which increase insurers' incentives for terminating or adapting contracts. In real life, very few adaptation contracts are implemented, which suggests that the willingness of consumers to comply with frequent changes of insurance terms and conditions is restricted. Even if a statistical relationship between changes in health care behavior and high internal credit ratings can be attributed to moral hazard problems, health insurers have to take care not to create an adverse selection cycle with all its negative impacts on medical care quality and the insurance market as a whole.

6.1. Dynamic Policy Adaptation Strategies

In this section, we present some dynamic policy adaptation strategies that can be implemented using risk and premium estimates, along with the client's marginal impact. Policy adaptation should be seen as a global decision with potentially complex implications in terms of claims. Therefore, to avoid gaming at the claim submission, this is a strategy with a dynamic nature. The use of indicators relative to business relationships and the utilization of long-term reward objectives, rather than short-term ones, should ensure that fairness is realized. It should be used in consultation and planning time use and not in emergencies. Such a strategy may also replace the vast majority of traditional policy selection methodologies. Such a set of strategies can also be seen as inputs to meta-features that have an impact on the claim's evolution in an attention-based predictive model on claims.

6.2. Case Studies and Success Stories

This section discusses success stories and use cases of solutions for the insurance industry. These products have been implemented by insurance companies with great success. The Insurance Industry Framework includes software modules for Claims Event Monitoring, Claims Visibility, and Policy Monitoring in the area of risk monitoring.

The first use case is a solution implemented at a large European bank that also offers a wide variety of insurance products, including property and motor insurance. One of the most successful products is smartphone insurance. From a business and risk monitoring perspective, it was important for the bank to be able to understand the key aspects of the risk landscape to which they are exposed in these connected products in real time. Therefore, the bank decided to implement the Claims Event Monitoring. They used an insurance solution to set up a sandbox environment of products, to capture and identify the relevant data, and to analyze the relevant key performance indicators or to build predictive models on these new products to be able to assess the connected products from a business and risk perspective. The event-driven claims service has been designed to be the default operation platform for a majority of direct-to-customer insurance portfolios in Europe, serving 20 million policyholders, supported by a partner network in 23 countries. It covers all the touchpoints needed after an accident, covering motor and mobility, and maintaining the NPS targets.

7. Ethical and Regulatory Considerations in AI-Driven Risk Monitoring

7.1. Introduction The use of AI for risk monitoring in the insurance industry needs to take into consideration the existing ethical principles and regulations of insurance. Not doing so risks creating models and systems that perform well in critical but narrow technical senses and yet are rejected by increasing parts of society or render their owners unable to commercially exploit them for technological progress, profitability, and job creation. This chapter first presents the traditional concerns and regulations of the insurance industry with a focus on the ethical aspects of pricing and rating according to the industry's communal principles, including access to insurance and fairness. We use these principles and regulations as benchmarks to identify potential pitfalls when designing AI for real-time risk monitoring in insurance. This does not preclude that further principles could be proposed and implemented, such as new legislation, but reliance on and building upon an existing body of knowledge of over 300 years is inherently conservative and pragmatic.

7.2. Principles of Risk in Insurance The principle of good faith is a long-established ethical duty in the law of insurance. Although varying between jurisdictions, the principle generally requires the parties negotiating a contract to provide all the material facts about which they know and are judged. This disclosure is the cornerstone on which the entire foundation of insurance rests. Indeed, it is stated that if "it is the amount of information about the risks which is held by the educated insurer that determines the flat fee charged for the elimination of risk (discernment), then apart from taxation, no higher ethical recognition should be given to the elimination of risk through insurance."

7.1. Data Privacy and Security

One of the greatest challenges that the insurance industry will face in implementing real-time monitoring is managing data privacy and security risks. More data collection does not always engender better insight, and in some cases, data privacy laws may provide obstacles to collecting the data necessary to track the health and behavior of policyholders. Finally, the consequences of data theft become greater the more that sensitive data is aggregated, while the risk of attacks will increase as AI-dependent systems become consumers of, and dependent on, ever more real-time location-control data.

Privacy laws are designed to protect a portion of the population from the misuse of their health records and the resulting harmful effects. It is important to achieve a balance in terms of how much we increase access to this information—particularly current locations, which have many health-revealing associations—and the potential harmful consequences of data misuse, and to implement controls that reinforce trust between insurer and consumer. From a purely financial perspective, investment in data security

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is an overhead cost based on an understanding of the costs associated with a security breach. Insured losses arising from a data breach are generally capped, either directly or as a percentage of total assets. However, this does not take into account the fraud that can occur or the longer-term damage to an insurance company's brand. Security breaches are typically made to a limited number of records—comparatively the size of a claim handling operation using Social Security numbers. A large security breach coinciding with other catastrophic events could cause an insurance company's claims handling operations to reach close to maximum capacity, which could be significantly greater than the firm's digital capacity, news of which would quickly spread. Thus, whether or not a firm operates in the insurance industry, the security breach actually incurs extra costs beyond the immediate expenses associated with a security breach. The insurance company's operation breaches digital capacity and puts pressure on the claims personnel, which could cause reputational harm and payer relationship challenges. Not to mention, that as AI becomes more and more dependent on real-time data, the potential targets for ransomware will simply increase, further exposing all businesses to potential risk.

7.2. Fairness and Bias in AI Algorithms

There have been a number of ongoing concerns over inherent biases in the training data and the AI algorithms used to make decisions in many fields. Even with relatively simple methods like decision tree classification, they can still be biased based on where the decision tree places the splits based on predictors. To illustrate this, consider insurance applications. If the response variable is expected actual claims proxied by commercial and personal auto insurance premiums in a given zip code, and the predictor variables are average annual auto mileage, driving record, age, the number of young drivers, and the average education level. The average household income in each zip code is not directly used as a predictor but is very highly correlated with the education level along with being itself a primary factor associated with every other predictor variable. A decision tree will then place the appropriate splits based upon the average education level instead of the many demographic proxies utilized for this calculation.

8. Conclusion and Future Directions

In this paper, we proposed a real-time risk monitoring system for the insurance sector using advanced artificial intelligence techniques. Additionally, using the proposed system, insurance users can obtain insights and receive in-depth knowledge for preventive safety in their daily lives, and insurance companies can obtain data extensively and instantly about the actual status of the customers' lives and risk evaluations. Non-life insurance companies are concretely able to make insurance ratings and service development using life log data. This analysis is meaningful in that it is more detailed than traditional insurance ratings. In the future, by expanding the data collection measures at the device level, it is thought that additional efficient results and diverse risk evaluation could be available. In the case of the environment applied with real-time analysis, it is hard to access more advanced and diverse data. We plan to consider household or vehicle data from diverse sensors or additional human wearable devices to improve users' quality of life beyond conventional extensions though widely used throughout the region. Especially, we are thinking of applying machine/deep learning on real-time analysis by additionally attaching human wearable devices generating each risk information. We are expecting to achieve a more highly active detection and high-likelihood pattern extraction.

8.1. Summary of Key Findings

In the quest to reduce risk exposure, gain competitive advantages, and foster closer customer engagement, AI is increasingly deployed by insurers to support real-time risk management. To invest in economic capital or assess underwriting and pricing actions, the challenge is to quickly recognize and then optimize risk. In response, the practice presented here is developed, offering IoT-to-decision support in one continuous system. Results demonstrate that this approach effectively responds to the data volume and variety challenges posed by myriad and complex business activities, illustrated here with farm-scale crop insurance. An anonymized national crop modeling database comprising 13 billion phenological points was used for crop yield forecasting and, from this, forward premium risk assessment. The distributed architecture has proven optimal for real-time data processing and for rolling crop risk monitoring, meaning that this prototype has real business potential for required confidence in near-term yield expectations.

The paper presents a distributed business application and real-time risk monitoring of a key natural catastrophe risk for insurers: the agricultural sector. The core business activity is to monitor and assess the risk of future agricultural crop yield because this forms the basis of decisions affecting underwriting and loss estimation. The solution's nutrient value for this sector is to provide a framework for associating a real-time farm signal source with dedicated machine learning algorithms for detecting flex-risk early and taking action. The AI function also provides a unique enabler for the design and execution of future composite insurance types. The business application is continually monitored due to external data sources or internal algorithm changes, which will itself need the design of experiments.

8.2. Potential Areas for Future Research

The theory of real-time risk monitoring has been developed as a promising system for rapid responses to changes in the values of monitoring indices. In practice, such rapid responses could apply limitations, such as an overpayment limit for a reinsurer's premium on an individual treaty. While it is said that excessive overpayment must be stopped by reinsurers, there are no formal standards for when to stop because too steep a reduction distorts the reinsurer's function of paying for catastrophic losses. The use of the proposed real-time monitoring system could make potential scorers aware of little-known predictive factors and prevent excessive discounts. We plan to expand our use of real-time risk monitoring in the future to include human expertise and common sense. Currently, such non-predictive knowledge is not included in the models used for real-time risk monitoring. People have a soft skill that is difficult to formalize, but which significantly influences decision-making and results. We intend to use machine learning techniques to exploit the knowledge of actuaries and other insurance professionals and incorporate these into real-time risk monitoring by making user intervention.