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A Survey on Property Insurance Claims Using Machine Learning Models in Finance Sector

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***Abstract*—The complexity of property insurance claims and the rising number of risk factors involved in financial risk prediction are factors that have made proper early claim prediction an essential requirement among insurers. Conventional means of assessment cannot process heterogeneous data, and increases of fraud attempts and the changing conditions of the market, which demonstrates the need to use more efficient and data-focused approaches. This paper considers the property insurance terrain within the finance industry and investigates how supervised and unsupervised machine learning methodologies can be used to enhance the accuracy of claim prediction and the operational decision-making process. The survey summarizes the important considerations in claims, key important ML approaches applied in risk assessment, and issues in early prediction, such as data imbalance, scarcity of early information, and large-scale heterogeneous data. Combining the results of recent research, this paper enables systematic knowledge on the effects of ML in improving claim assessments, fraud detection, and risk modeling in property insurance. The results also bring out the existing constraints that should be overcome in order to attain credible and scalable early claim prediction.**

Keywords—Property Insurance, Finance, Insurance Claim, Artificial Intelligence (AI), Machine Learning (ML), Banking.

I. Introduction

Financial analysis is a critical element in evaluating the health, stability, property and future prospects of any organization, particularly in the life insurance sector, which operates under complex regulatory, market, and risk management conditions [1]. The insurance system is one of the key elements of the financial system of a country. Insurance companies, being institutions of public trust, play a vital role as financial intermediaries [2]. They enable processes of converting savings into investments both tangible and financial ones. Housing finance plays a significant role in housing delivery, and without financing, housing delivery may not occur. The importance of housing finance is evident in both the demand and supply sides of the housing delivery chain. Households and investors rely heavily on financing to decide on housing tenure and investment strategies[3]. Similarly, housing developers who are in the business of supplying houses are also reliant on financing in various forms to develop the mass housing projects required to deal with the enormous housing deficit confronting many regions.

The insurance industry is a powerful sector of financial operations in the world [4]. Insurance companies offer insurance for property and health, industrial equipment of all kinds, vehicles and freight, passenger travel and flight safety, space launches, manned space flights, financial transactions, and much more. On the other hand, an insurance firm faces the risk of paying out large sums of money if its clients apply for insurance claims all at once. Insurance firms use proven methodologies to assess their risks and to price insurance policies for different insurance situations [5]. When deciding whether to insure their property, the insured must determine whether they are satisfied with the property insurance offered by the firm and the price of that insurance [6]. The simplest way to decide whether to insure a property is to compare the expected cash benefits with the price of the policy. However, in addition to the monetary value, the property may have an additional utility for the individual, which cannot always be expressed in terms of a simple monetary equivalent.

The Property and casualty insurance domain has recently adopted Artificial Intelligence is in these carriers are due to changes from traditional Mainframe applications which are using in decades [7]. In the earliest days, artificial intelligence (AI) was thought of as a dead-end technology and was seen as an invention that would never be adopted or used to its highest potential. These innovative technologies have brought digital development to all insurance carriers. Today, Artificial Intelligence technologies are rapidly reshaping the way business operates across industries [8]. Artificial Intelligence in insurance is helping property and casualty insurers keep up with customer demands, operating the requirements of agents or customers and competitors. The insurance sectors are leveraging the new emerging technologies of Artificial Intelligence (AI) [9], Machine Learning (ML), and Natural Language Processing (NLP), which help to manage the customer experience in all insurance fraud [10]. AI applications involve ML and predictive analysis, which aim to handle large amounts of claims settlements and policy enrollment. People would fail to mention any of the business needs of an insurance company that could not be handled with AI, be it the process of underwriting, risk assortment, new product development, pricing strategies, consumer services, or claims settlements.

A. Structure of the Paper

The paper is structured as follows: Section II describes the Landscape of finance sector in property insurance. Section III describes machine learning systems and methods of early finance prediction. Section IV talks about the major issues about early insurance claim prediction. Section V is a review of the relevant literature and Section VI is the conclusion and future directions.

II. Property Insurance Landscape in the Finance Sector

Property insurance, as a type of insurance in general, plays an important, multilateral role in economic turnover. It not only acts as an important element of the functioning of the entire financial system of the state, ensuring the continuity of social production, depending on unfavorable phenomena and events, but also guarantees social protection of the population and stabilizes the process of investment in the economy [11]. If, however, an unfavorable event occurs, and damage to the property of the owner (user) is caused, often the injured party to restore its former economic situation decides to apply to the court with a statement of claim to the guilty party with a claim to compensate for the caused losses.

A. Role and Structure of Property Insurance

Insurance of property is an important tool for safeguarding individuals and companies against losses of money in case of destruction of buildings, assets, or belongings. It offers an organized system where policyholders pay their premiums as they seek cover against any of the specified risks [12] which can be fire, theft, natural calamities and other unpredictable issues. Property insurance usually has certain specified limits of coverage, exclusions, deductibles and conditions that rely on assessing and compensating claims. The property insurance is secure because it can diversify the risk spread among numerous policyholders, provides recovery following a loss, and prepares households and businesses to be resilient in the long term.

1) Importance in Financial Risk Management

Financial risk management has mostly focused on controlling and ensuring regulatory compliance, rather than improving performance. Risk management, on the other hand, frequently leads to improved financial performance since regulatory compliance and risk control allow the firm to save money. Banks [13] goes on to say that by controlling risks, managers may raise the value of the company by assuring its continuous profitability. To minimize financial losses [14] and bankruptcy, proper risk management is critical in the everyday operations of any insurance company. Risk is the possibility that an event will occur and adversely affect the achievement of objectives, create financial loss, and arise from uncertainties of given situations plus certainties of exposing oneself to such situations

2) Types of Property Insurance Coverage

The insurance premiums paid by a commercial firm for insurance coverage under TRIA today is much lower than it would be without the free up-front reinsurance provided by the government program. An important policy question that has been debated in the past few years is whether the federal government should continue to provide this type of free reinsurance or whether the market [15] should provide all or part of this reinsurance.

3) Claim Lifecycle and Industry Practices

The claim lifecycle includes a process of reporting the loss up to the final settlement stages, which comprise assessment, verification, and payout. Insurers go through policy conditions, examine paperwork work and assess the outcomes of risks in determining the claim outcome. Excesses (deductibles) to be paid by the insured when a claim is made, as well as exclusions and conditions [16], play a key role in determining how much compensation is provided. Such practices also make sure that there is fair processing, misuse is avoided as well and consistency in insurance activities.

B. Key Factors Influencing Property Insurance Claims

Various factors, such as environmental risks, such as storms, customer behavior and reporting patterns, financial or regulatory environment, which impact the cost and processing of claims, determine property insurance claims [17]. All these factors contribute to claim frequency, severity and efficiency of settlement, and therefore aid in risk assessment as well as efficient loss management by the insurers.

- **Environmental Risk Factors:** sustainable weather is vital to the future well-being of humankind, economic growth and continued financial protection make it difficult to cope with the long-term damage caused by climate change. Climate change negatively influences the cost and supply of insurance and pressures the organizations and citizens[18]. The insurers, regulators and insurance sector are working collaboratively to build a deeper view of physical and business risks.
- **Customer and Behavioral Factors:** Behavioral finance encompasses a set of discoveries regarding simplified methods of comprehending the world (the so-called heuristics), as well as the errors individuals make in the assessment and decision-making processes. Participants in financial markets[19], including the insurance market, are susceptible to these biases and heuristics. Economic frameworks that are elaborated in the field of behavioral finance do not just concentrate on prediction but primarily on explaining particular behaviors.
- **Financial, Regulatory, and Market Conditions:** The property insurance claims are greatly affected by the financial, regulatory and market conditions. The severity of claims and the amount of the settlements depend on such factors as inflation, repairs, reinsurance rates, and the regulations establish fair practices and proper solvency to pay the claims. Premium and underwriter stability along with the general claims results are also formed by economic changes and market cycles. These conditions combined define the level of efficiency and consistency with which insurers can work out and pay out claims on property [20] insurance.

Table I presents a cursory outline of the key components of property insurance and their effects in the financial sector. It points out that insurance helps to achieve economic stability, offers structured risk coverage, efficient claim settlement, and is susceptible to environmental, behavioral, and economic conditions. In general, Table I summarizes the way in which property insurance enhances financial security and better management of risks.

TABLE I. The Summary of Property Insurance Landscape in the Finance Sector

Topic	Focus Area	Key Description	Impact on Finance Sector	Key Outcome
Property Insurance Landscape	Economic Role	Supports financial stability, protects assets, and maintains continuity in economic activities.	Strengthens national financial systems and investment stability.	Ensures long-term economic resilience.

Role & Structure of Property Insurance	Coverage & Framework	Provides protection against risks through limits, exclusions, deductibles, and conditions.	Helps businesses and households recover quickly after losses.	Promotes financial security and risk sharing.
Importance in Financial Risk Management	Risk Control	Manages financial losses, improves performance, and ensures compliance through effective risk strategies.	Enhances insurer profitability and operational stability.	Reduces bankruptcy and loss exposure.
Types of Property Insurance Coverage	TRIA & Commercial Coverage	TRIA reduces premiums through federal reinsurance; markets debate future support models.	Influences pricing, market stability, and coverage availability.	Ensures affordability of high-risk insurance.
Claim Lifecycle & Practices	Processing Steps	Covers reporting, verification, and settlement; deductibles, exclusions, and conditions shape payouts.	Improves claim fairness, reduces fraud, and increases efficiency.	Ensures consistent and accurate settlements.
Key Factors Influencing Claims	Environmental, Behavioural, Economic	Claims driven by climate risks, customer behaviour, and financial/regulatory conditions.	Impacts claim costs, frequency, and insurer planning.	Helps insurers predict and manage risk better.

III. ML Approaches and Models in Property Insurance Claims

Machine learning methods have taken center stage in enhancing accuracy, efficiency, and decision-making in predicting property insurance claims. Supervised or unsupervised methods of learning are both commonly used to either classify claims during the early stages of claims or estimate its severity and identify any hidden latent patterns of claims, identify an anomaly, or categorize claim patterns where there is no labeled data [21] Utilizing these methods, the enigmas of insurers are able to manage high amounts of information and minimize the extent of manual labor, as well as optimize the quality of claim assessment practices. All in all, the use of ML-based solutions provides a better, data-driven approach to the property insurance claims understanding and prediction.

A. Machine Learning Approaches and Models

Supervised and Unsupervised are two major techniques of machine learning. The concept of supervised learning is based on the useful information of the labeled data [22]. The most popular activity in supervised learning (and most popular in IDS) is classification, as illustrated in Figure 1, but manual labeling of data is very costly and time-consuming. This results in the shortage of enough labeled data as the primary limitation to supervised learning [23]. Quite on the contrary, unsupervised learning uses valuable feature information on unlabeled data, and it becomes much easier to get training data.

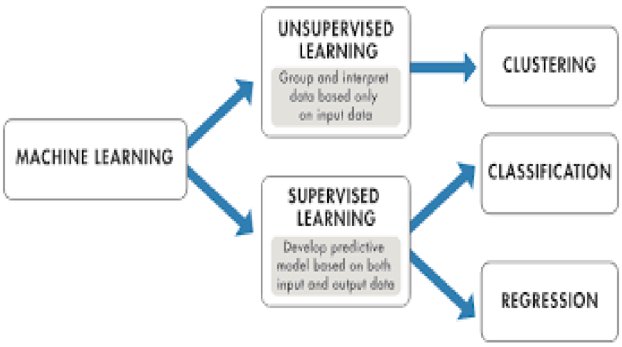

Fig. 1. Machine Learning Approaches for Property Insurance Claims

B. Supervised Learning

Supervised learning assumes the training of a data sample extracted out of data source with the correct classification already known to find the underlying patterns and relationships [24]. The objective of the learning process is the formation of the model that can make right predictions on new real-life data. Supervised learning is the type of learning that makes use of ground truth data so as to train a model of the relationship between the inputs and outputs [25]. The labeled supervised learning datasets are known as ground truth data. The trained models use their knowledge about the data in order to predict new and unobserved data as indicated in Figure 2.

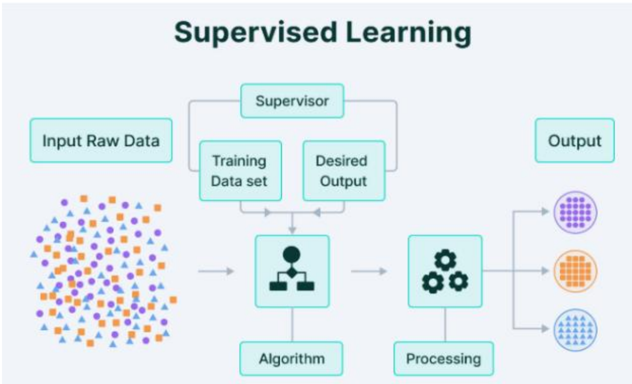

Fig. 2. Supervised Learning Approach

C. Supervised Learning Models

The learning process in a simple machine learning model is divided into two steps: training and testing. In training process, samples in training data are taken as input in which features are learned by learning algorithm or learner and build the learning model [26]. In the testing process, learning model uses the execution engine to make the prediction for the test or production data. In Supervised Learning there are various models are used as given below:

1) Support Vector Machine (SVM)

Support Vector Machine (SVM) is considered one of the strongest and the best accurate approaches in any machine-learning algorithm. It comprises mostly Support Vector Classification (SVC) and Support Vector Regression (SVR). The SVC has the concept of decision boundaries. A decision boundary is a line between two groups of instances with different values of a class. The SVC can do binary and multi-classification [27]. The closest point of the separation hyperplane is the support vector which characterizes the ideal separation hyperplane. The mapping input vectors on the separation hyperplane side of feature space are assigned to a single class that mapping input vectors on the other side of the plane are assigned to the other class.

2) K-Nearest Neighbor (K-NN)

K-Nearest Neighbor (K-NN) is a non-parametric supervised learning algorithm and it is primarily applied in the classification and may be applied in regression. It is free of any assumptions about the underlying distribution. Instead, it identifies the k closest examples of training examples in the feature space that are similar to the new observation and uses a majority label or mean of whether it is a task classification or regression to make a prediction of the target variable.

3) *Logistic Regression (LR)*

Logistic regression (LR) is another trending probabilistic based statistical model that is employed to address the classification problems. Logistic regression normally calculates the probabilities by use of logistic function also known as sigmoid function. Logistic regression hypothesis predisposes it to restrain the activity between 0 and 1 [28]. That is the kind of classifier that is applied to establish the correlation between the independent variables and the categorical dependent variable of a certain dataset.

4) *Random Forest (RF)*

Random forest refers to a group of decision tree [29], and it takes into account the result of each tree and only gives a combined final answer. Both decision trees are conditional classifiers: one visits the tree starting at the top and at each node a specified condition is tested against one or more features of the data under analysis. These work well when there is a large amount of data and are very effective when the problem is multiclass, but when there are more than a few levels then they can easily overfit.

D. *Unsupervised Learning*

The unsupervised ML methods facilitate the study of the raw data, aimless production of analytical data out of unlabelled data. The state of the art in unsupervised ML was improved by the existing advances in factor analysis, latent models, hierarchical learning, clustering schemes [30], and outlier detection. Certain later developments in unsupervised ML such as the development of so-called deep learning techniques have since improved the situation of the ML significantly since they do not demand such a careful engineering and a familiarity with the domain in which to build the features prior to processing the raw data.

E. *Unsupervised Learning Techniques*

Unsupervised learning techniques focus on uncovering hidden patterns, structures, and relationships within data without relying on predefined labels. These methods help group similar data points, reduce dimensionality, and reveal underlying trends that may not be immediately visible. Common approaches include clustering, association analysis, and dimensionality reduction, all of which support exploratory data analysis and enhance understanding of complex datasets. Unsupervised learning is especially valuable in domains where labeled data is limited, making it a powerful tool for pattern discovery and data-driven insights.

1) *Clustering*

It is one of the types of unsupervised learning whereby similarity measure is used to cluster data. The use of clustering algorithms is able to learn on the basis of audit information and the system administrator does not need to provide explicit description of various types of attacks [31]. Application of real-time signature detection with clustering algorithm. A frequency-based clustering algorithm called Simple Logfile Clustering Tool (SLCT) was used to generate the normal and abnormal network traffic. Two clustering schemes are employed: First, the normal and attack cases are detected by use of clustering scheme, Secondly, the normal traffic can be determined in a supervised mode by the use of the other scheme.

2) *Dimensionality Reduction*

Dimensionality reduction techniques aim to simplify high-dimensional data by transforming it into a lower-dimensional space while retaining essential information. Methods such as Principal Component Analysis (PCA) [32], t-SNE, and UMAP reduce noise, highlight key features, and make complex datasets easier to visualize and interpret. These techniques improve computational efficiency, enhance model performance, and reveal relationships that may be obscured in higher dimensions. Dimensionality reduction is especially valuable in fields dealing with large, complex data, enabling clearer insights and more effective downstream analysis.

IV. CHALLENGES IN EARLY CLAIMS OF INSURANCE PREDICTION

In the contemporary insurance landscape, accurately measuring and managing claims risk is important for ensuring financial stability and operational efficiency, insurance companies face challenges in predicting claims occurrences and severities [33]. However, predicting when property insurance claims will occur remains a challenge for insurance companies due to limited information related to feature importance and an imbalanced number of claim data compared to policy data.

- **Large Data:** One of the critical challenges in early claim detection is dealing with large datasets containing hundreds or even thousands of features. Not all of these features are relevant, and attempting to process all of them can lead to computational inefficiencies and reduced detection accuracy [34]. Therefore, highly reliable feature selection techniques are essential to streamline the process and improve fraud detection outcomes.
- **Data Handling:** Modeling insurance loss data and classifying losses coming from different sources are important yet challenging tasks [35]. It is well known that the insurance losses coming from different sources are heterogeneous as reflected in multimodality, skewness, and heavy tail of the loss distributions. These features are difficult to deal with in actuarial practice.
- **Data Quality and Limited Early Information:** Early claim prediction often suffers from incomplete, sparse, or inaccurate data collected at the initial reporting stage. Essential details such as damage assessments, verification documents, or policyholder history may be unavailable or inconsistent, reducing model reliability. This lack of rich early features makes it difficult for predictive systems to distinguish between genuine, fraudulent [36], or high-risk claims at the beginning of the claim lifecycle.
- **Class Imbalance and Rare Event Prediction:** Insurance datasets typically contain far fewer high-cost, fraudulent, or complex claims compared to normal claims, creating severe class imbalance. This imbalance causes predictive models to favor the majority class, leading to poor detection of critical early claims. As a result, identifying rare yet high-impact claim scenarios become challenging, limiting the effectiveness and accuracy of early prediction systems.

V. Literature Review

According to the literature, the use of advanced automated methods considerably enhances the process of detecting fraud and claims adjudication in the context of property insurance. There are however still some issues with scaling these systems, making sure that models are accurate and testing them in the claim world.

Adavelli, Madhala and Rahul (2025) Proposed CI-HAF model is tested on the basis of real-world insurance datasets and compared to the traditional AI methods, (2025), by Adavelli, Madhala and Rahul. Some of the performance measures are claim processing time, fraud detection accuracy, precision-recall trade-off and computational efficiency. The experimental findings suggest that CI-HAF can increase the accuracy of detecting fraud by 15, decrease the time used in processing claims by 45% and increase the reliability of the risk prediction [37].

Cai et al. (2025) proposed an optimization model, which was compared with other machine learning algorithms through comparative analysis. The results show that the optimization model proposed in this study has achieved remarkable results in the task of patent classification. Compared with the baseline model, the optimized model has greatly improved the accuracy and other key assessment indicators. Especially when dealing with complex patent documents, it shows stronger classification ability. The results fully verify the great potential of DL technology in intellectual property management [38].

Sharan et al. (2024) suggested a fraud-detecting approach based on machine literacy to use in an Internet of Things context, which specifically targets insurance claims. The proposed solution utilizes real-time data provided by the IoT detectors and the actual claim history and uses machine learning methods such as finding anomalies, bracketing, and clustering in order to identify suspicious trends and raise a red flag on potentially fraudulent claims. The effectiveness and efficiency of the proposed approach are demonstrated, with an in-depth analysis on the basis of deconstructed and real-life data, as it suggests the potential to minimize fraud risks and enhance the truthfulness of insurance processes in the IoT setting [39].

Mahyoub, Ghareeb and Mustafina (2023) examined several ML methods to identify loan default before disbursing the loan to the applicant. This matter has been studied widely and used the predictive analytics to find out the relationship between attributes and the target variable. Predictive Analytics enables us to feed optimal set of features to the ML models. The study started with 122 attributes and ended up with around 30% of features as the ideal subset for housing loan default prediction [40].

Huang (2023) established the intellectual property information integration platform model and designs it from the aspects of platform function architecture and security guarantee. Finally, the PMF software integrated development environment is selected to implement the model system software from three main aspects: data management function, process control function and application management function. The study found that the system can achieve the expected purpose and function, and promote the development of intellectual property management [41].

Liu (2022) designed and implemented an intelligent management system based on J2EE technology research. Based on the research and analysis of the theories and practical achievements of local property management systems at home and abroad, combined with the future development trend of smart communities, an Internet-based local property management system is designed. Based on the property management of smart residential areas, the Internet of Things technology is fully utilized to realize intelligent management functions [42].

Vyas and Serasiya (2022) proposed the framework of a blockchain-based system to facilitate safe transactions and exchange of data between different interacting parties in the insurance network. Blockchain is a decentralized peer-to-peer technology through which healthcare claims can be safely, impartially, and transparently validated. Also, discuss how blockchain and smart contracts can be used together to improve organizational operations. More particularly, it will show how these technologies can be utilized to create a system that prevents certain types of fraud in the areas of vehicle, health-care, and life insurance claims, among others [43].

Table II provides an overview of prominent studies that are aimed at enhancing claims of property insurance, using AI, IoT, and blockchain. Research indicates that it has been successful in detecting fraud, processing their claims more quickly, and enhancing data security but still encounters difficulties such as data quality, integrating their systems, and scalability. It is expected that future work will focus on more automated, scalable and ML-driven claim management.

TABLE II. Summary of Recent Studies on Risk-Based Security Approaches

Reference	Study on	Approach	Key Findings	Challenges / Limitations	Future Directions
Adavelli, Madhala & Rahul (2025)	Fraud detection and claim processing in insurance	CI-HAF model evaluated on real-world insurance datasets; benchmarked against conventional AI methods	Improved fraud detection accuracy by 15%; reduced claim processing time by 45%; enhanced risk prediction reliability	Results based on selected datasets; may need broader validation across varied insurance environments	Expand CI-HAF to large-scale deployments; integrate with multi-source real-time data
Cai et al. (2025)	Patent classification using optimization models	Comparative analysis between proposed optimization model and traditional ML models	Shows superior accuracy and assessment indicators; strong classification ability for complex patent documents; highlights potential of DL in IP management	High computational cost for deep models; requires specialized data preprocessing	Apply model to multilingual patent datasets; integrate with real-time patent analysis tools
Sharan et al. (2024)	IoT-based insurance fraud detection	Machine learning using anomaly detection, clustering, and bracketing with IoT sensor data and real claim records	Effective at identifying suspicious patterns; demonstrated high efficiency using both simulated and real-world IoT datasets	Heavy dependency on sensor data accuracy; IoT integration challenges	Enhance scalability; incorporate advanced anomaly prediction using deep learning

Mahyoub, Ghareeb & Mustafina (2023)	Loan default prediction	Predictive analytics on 122 attributes to identify optimal subset of features	About 30% of attributes identified as ideal subset; improved ML model performance for housing loan default prediction	Large initial feature space; requires intensive preprocessing	Apply automated feature engineering; extend study to other financial loan products
Huang (2023)	IP information integration systems	Platform designed with PMF IDE focusing on data, process, and application management	System successfully meets functional goals; supports improved IP management operations	Limited to specific platform architecture; may need cross-platform flexibility	Enhance security layers; integrate AI-based IP analytics
Liu (2022)	Intelligent property management system	J2EE-based system integrating IoT technologies for smart community management	Achieves intelligent property management through IoT-driven automation	J2EE scalability constraints; IoT device integration complexity	Develop cloud-native version; include AI-enabled predictive maintenance
Vyas & Serasiya (2022)	Blockchain for secure insurance claims	Blockchain + smart contracts enabling secure, transparent transaction validation	Enhances fraud prevention in vehicle, healthcare, and life insurance; supports immutable data sharing	Blockchain adoption challenges; high implementation cost	Integrate AI-driven smart contracts; expand framework to cross-industry insurance ecosystems

VI. Conclusion and Future Work

The issue of properly predicting property insurance claims has gained more significance due to the increase in financial risk that the insurers are exposed to, the various customer behaviors, and the swiftly evolving environmental and regulatory landscapes. The current study shows that machine learning has a great potential to enhance the process of claim assessment, fraud detection and risk modeling through the application of supervised and unsupervised learning methods. In this paper, the detailed analysis of the insurance environment, the claim lifecycle, and ML techniques will help to understand that, the significant challenges still exist. Poor quality of data, scarcity of initial claim information, uneven loss distributions, and extreme imbalance in the classes remain as the impediments to the early claim prediction performance. In addition, big data, and features that are too complicated demand higher level preprocessing and optimization strategies in order to be reliable. On the whole, the research underlines that despite the fact that ML-based systems improve decision-making and operational effectiveness, closer data integration, scalable frameworks.

Future work needs to be done on the creation of more powerful and scalable ML systems which can blend heterogeneous data sources such as text, images and sensor data. The use of advanced methods in the form of deep learning, graph-based models, and automated feature engineering could assist in resolving the initial limitations of the data. To create more reliable and industry ready early claim prediction systems will require the improvement of real-time claim prediction, class-imbalance management and model validation across various insurance domains.

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