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Machine Learning for Financial Risk Management: A Survey

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ABSTRACT Financial risk management avoids losses and maximizes profits, and hence is vital to most businesses. As the task relies heavily on information-driven decision making, machine learning is a promising source for new methods and technologies. In recent years, we have seen increasing adoption of machine learning methods for various risk management tasks. Machine-learning researchers, however, often struggle to navigate the vast and complex domain knowledge and the fast-evolving literature. This paper fills this gap, by providing a systematic survey of the rapidly growing literature of machine learning research for financial risk management. The contributions of the paper are four-folds: First, we present a taxonomy of financial-risk-management tasks and connect them with relevant machine learning methods. Secondly, we highlight significant publications in the past decade. Thirdly, we identify major challenges being faced by researchers in this area. And finally, we point out emerging trends and promising research directions.

INDEX TERMS Machine learning, deep learning, financial risk management, financial risk management taxonomy, risk analysis, artificial intelligence in finance.

I. INTRODUCTION

Machine learning is making breakthroughs in Natural Language Processing, Computer Vision, and Robotics. These remarkable applications of machine learning have sparked a lot of interest in its application to other diverse areas where data is plenty. Financial Risk Management (FRM) is of course, not an exception. FRM tasks are generally challenging, with continuously evolving yet sparse and complex data. Quantifying and managing risk plays an important role in any organization. As businesses, especially, financial institutions, grow larger and more complex, the need for sophisticated statistical models to correctly quantify and mitigate risk has become more important than ever before. For big companies with very large portfolios and sophisticated financial products, accurately evaluating the exposure of the portfolio to the dynamic financial market is becoming increasingly difficult with previously implemented statistical or simulation methods. To address this shortcoming, there is a lot of work that is going on that deals with the application of advanced machine learning methods to datasets for FRM.

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Driven by the industrial demand for intelligent risk management systems and academic goals for developing highly-applicable machine learning algorithms, a growing number of researchers are exploring sophisticated ML approaches (e.g. Transfer Learning, Deep Reinforcement Learning) for tasks related to managing and mitigating financial risk. The depth of literature in solving specific FRM task is evolving rapidly. However, there seems to be limited work in providing an organized taxonomy to connect the explored machine learning methods within the overall FRM framework.

Although several surveys already cover the application of machine learning on specific FRM tasks [1]–[6], our survey provides a unifying view of the literature encompasses all major FRM tasks. For example, financial market movement prediction is covered by [1], whereas hedging market risks is covered in [2]. Many do not cover other significant exposures for the company, such as risks related to credit obligations or risks related to excessive claims. In contrast, we aim to unify the machine learning literature across different FRM tasks and identify the common challenges and research directions prevalent across the whole risk spectrum. Our work presents a holistic view of the ML literature from a single

FRM taxonomy that encapsulates all major financial exposure points for a company. To build the taxonomy, We follow the risk classification in which ''Insurance and Demographic Risk'' is included as the fourth risk type in addition to the traditionally recognized three financial risks (Market, Credit, and Operational) [7]. This helps us to encompass the challenges faced by financial institutions that also offer insurance as products.

The contributions of our survey paper are as follows:

- We present a comprehensive taxonomy of major FRM tasks and establish their connection with relevant machine learning problems. This taxonomy would help machine learning researchers navigate the complex domain of financial risks.
- We systematically survey a large corpus of existing literature on applying machine learning in risk management and reveal the best practices and common pitfalls in applying machine learning to each risk management task.
- We summarise the progress and highlight the common challenges present in the current implementation of machine learning in FRM. This provides insights to improve the existing models and make it more adaptable for practitioners and regulators.
- We propose future directions on tackling the common challenges identified by the literature survey. We hope these directions will benefit interested researchers and practitioners in developing more acceptable ML techniques in managing financial risk.

A. SURVEY ORGANIZATION

This survey is organised as follows: Section II provides a general background on FRM. This is followed by the categorization of the risk management tasks into different machine learning methods in section III. Section IV first introduces the FRM taxonomy, based on which we systematically review the ML applications for each major FRM task. Section V and VI identify major challenges and future research directions, respectively.

II. A BRIEF INTRODUCTION TO FINANCIAL RISK MANAGEMENT

Machine learning has been widely used in solving traditional quantitative finance problems, including return forecasting, risk modelling and optimal portfolio construction [8]. In this paper, we focus specifically on its use cases for financial risk management, which includes both risk modelling (the task of quantifying and predicting risk) and risk mitigation (the task of minimizing risk via optimal portfolio construction or hedging).

In [9], Horcher defines *risk* to be the probability of loss and *exposure* as the possibility of loss. Exposure to risk is often necessary for a business to prosper. Identifying risk and exposure form the basis of FRM. As risk and exposure are realized differently across different domains, they are measured differently. These measures are further discussed in Section IV. Interested readers can find more about the theory of financial risk and basic concepts related to FRM in [10]–[12].

A. THE RISK TAXONOMY

Different types of events can adversely impact a company's financial performance [7]. These events can include adverse financial market movements, loan defaults, unexpected insurance claims, fraudulent activities, loss of customers.

Based on the source of risk factors, it is conventional (see for example, [7]) to classify risk into four high-level categories: (i) market risk, (ii) credit risk, (iii) insurance and demographic risk, and finally, (iv) operating risk.

- *Market risk* refers to the uncertainties in the value of the company's underlying assets, liabilities, or income due to exposure to a highly dynamic financial market [7], [13]. Market risk includes risks such as interest rate risk, exchange rate risk, commodity price risk.
- *Credit risk* refers to the uncertainty involving its creditors' ability to perform their contractual obligation (loan defaults or bankruptcy) [14]. This is applicable for both retail lenders (lenders who provide loans to individuals or retail customers) and corporate lenders (lenders who provide loans to businesses).
- *Insurance and Demographic risk*, which is more specific to the insurance industry, refers to the variance in insurance claim experience due to unpredictable events (e.g. catastrophes, car accidents) as well as uncertainties involved with the demographic profile of its policyholders (e.g. mortality). This risk can be further broken down to Mortality Risk, Catastrophe Risk, and Non-Catastrophe Risk [7].
- And finally, *operational risk* refers to the risk of loss due to the unpredictability of business operation or loss of performance due to faulty or fraudulent business practices. Operational Risk can be further broken down into *business risk* and *event risk*. Business risk indicates the uncertainty related to business performance (e.g. uncertainty in earnings, demand volatility, customer churn, faulty business operations) and event risk includes uncertainty in events that have an adverse effect in business operations (e.g. fraudulent activities, change in regulations) [15].

The financial risk spectrum arising from different sources brings about the complex task of measuring and mitigating risk using various risk management strategies.

B. RISK MANAGEMENT STRATEGIES

Broadly, financial institutions apply two types of risk management strategies:

- *Risk decomposition* identifies each risk and handles it separately.
- *Risk aggregation* diversifies the risk exposure to minimize the overall risk exposure.

TABLE 1. Machine learning techniques with FRM applications.

Learning method	Learning task	FRM application
Supervised learning	Classification	Fraud Detection [19]
		Portfolio optimization [20]
		Credit Scoring & Bankruptcy prediction [21]
	Regression	Volatility forecasting [2]
		Sensitivity analysis [22]
		Claims modelling [23]
		Loss reserving [24]
		Mortality modelling [25]
Unsupervised learning	Clustering	Insurance pricing [23]
		Sensitivity analysis [26]
		Credit scoring & Bankruptcy prediction [27]
	Anomaly detection	Fraud detection [28]
	Dimensionality reduction	Insurance underwriting [29]
		Mortality modelling [30]
Reinforcement Learning		Portfolio optimization [31]
Semi-supervised learning		Sensitivity analysis [32]

Interested readers can find more in a standard textbook (e.g., [16]).

III. MACHINE LEARNING TECHNIQUES IN FINANCIAL RISK MANAGEMENT

Machine Learning is a computational method that uses past information to improve performance in a specific task(s) or make accurate predictions [17], [18]. These methods are generally reliant on optimizing a loss or reward function. Table 1 outlines the major types of machine learning methods and tasks, including their typical applications in FRM. The learning methods are briefly discussed below.

A. SUPERVISED LEARNING

This set of algorithms use labelled examples for training. The trained model can be used to make predictions for unlabelled examples. The supervised learning task is mainly associated with classification, regression, and ranking problems.

A major multi-class classification task in FRM is the task of credit scoring or bankruptcy prediction [33]. An example regression task is claim-frequency prediction [34], [35], where insurers try to predict the number of claims that will be made from a portfolio. Another highly cited regression task in FRM domain is volatility forecasting. This can also be seen as a supervised sequence learning problem [36], [37].

B. UNSUPERVISED LEARNING

Unsupervised learning refers to the task of detecting patterns from unlabelled data. In this setting, no labelled data is available. The unsupervised learning algorithms are built to solve specific problems (e.g. clustering, outlier detection, dimensionality reduction, anomaly detection) from unlabelled data.

Several models used for default or bankruptcy prediction in credit risk management rely on clustering the credit applicant profiles [27]. Clustering is also used to identify a representative set of policies from a large portfolio of annuity contracts [32]. Another unsupervised learning task, anomaly detection, is highly relevant for fraud detection tasks [28], [38]. Techniques for dimensionality reduction is implemented in the task of mortality modelling [30] and insurance underwriting [29].

C. REINFORCEMENT LEARNING

In reinforcement learning settings, the learner has the ability to actively interact with the environment. The objective of the learner is to maximise the reward over its set of interactions with the environment [39]. Due to its ability to consistently explore the environment to select the optimal strategy, researchers and practitioners have used reinforcement learning algorithms for risk-optimised dynamic portfolio allocation [31], [40].

D. SEMI-SUPERVISED LEARNING

Semi-supervised learning problems are common in settings where accessing labels is possible but expensive. These algorithms learn from both labelled and unlabelled data and make predictions on the unlabelled data [41]. Due to the complexity of acquiring labels in many real-life problems (e.g. finance, healthcare), the topic is highly relevant for applied machine learning research [42].

A strong application domain for semi-supervised learning algorithms in FRM is the task of approximating nested Monte Carlo simulation. Monte Carlo simulations are widely used in financial risk engineering (for example, VaR calculation, insurance pricing) but are computationally expensive for large portfolios. Therefore, several ML-based methods are used to approximate the result of full portfolio simulation based on simulation results of a much smaller subset [32], [43].

E. DEEP LEARNING

Deep learning is a form of machine learning that extracts multi-layered representations of the features, approximating a non-linear composite function that forms a hierarchical transformation of features into labels. This learning method is highly suitable for understanding patterns from complex non-linear interactions in the data [44].

Since its inception, deep learning methods have seen steady growth in the literature, along with some major waves of advancements. During the first wave of its advancement in the 1940s-1960s, it was known as *cybernetics*. During the second wave of advancement in the 1980s-1990s, it was termed *connectionism* and finally, it took on the current name *deep Learning* since the beginning of 2006 [45].

Convolutional networks [46], one of the most notable innovations in neural networks, has achieved tremendous success in practical applications, especially in computer vision. These networks utilise a special linear operation called "convolution" to extract local translation-invariant features from images and time-series data. Another property of convolutional networks is that they can learn spatial hierarchies, which is highly relevant for data with complex hierarchical patterns (such as images or videos). Interested readers can find a comprehensive review of Convolutional networks and their application in computer vision in [47]. One dimensional convolutional networks can be used for sequence processing as well. This makes it applicable for financial time-series forecasting. Within FRM domain, convolutional networks can be used for volatility forecasting [48], fraud detection [49], or credit default prediction tasks [50].

Recurrent networks [51] are another major innovation in neural networks. Whereas convolutional networks specialise in processing grid structured data, recurrent networks are specialised for processing sequences of values [45]. Some notable variants of recurrent networks include basic Recurrent Neural Networks (RNN) [51], Long Short-Term Memory (LSTM) [52] and Gated Recurrent Unit (GRU) [53]. These networks are highly applicable to natural language problems where the data is generally sequential. Due to its specialty in sequence modelling, recurrent networks are also widely used in financial time series forecasting problems, e.g. volatility forecasting [36], [37] or loss reserving [54].

Deep reinforcement learning [55] is a recent innovation in deep learning that merges the principles of deep learning and reinforcement learning to create algorithms that can efficiently learn to interact with the external environment. It is highly applicable for areas where agents need to make decisions in a dynamic environment (such as financial markets). An example is financial portfolio optimization problems where agents need to dynamically redistribute portfolios within volatile financial markets to minimise risk and/or maximise return [40]. Interested readers can find a comprehensive overview of deep reinforcement learning and its recent advancements in [56].

Graph neural networks [57]–[62] are a special type of neural network that can be used for modelling data with complex graph structures. In finance, such data can come in the form of a knowledge graph, for example, built on the Financial Industry Business Ontology (FIBO) [63]. Graph neural networks have been applied in financial fraud detection tasks [64], [65].

IV. MACHINE LEARNING APPLICATIONS IN FINANCIAL RISK MANAGEMENT

FRM tasks can be organised into a taxonomy as shown in Figure 1. The taxonomy provides a framework for connecting relevant machine learning tasks with the previously mentioned risk categories. The following sections will detail each of the categories in the taxonomy.

A. MANAGING MARKET RISK

One of the key measures related to market risk is volatility, which is the standard deviation of the (log) return of an asset [66]. Such risk is often managed via *options*, financial derivatives that are used either as leverage (to maximise potential return) or insurance (to minimise potential loss). From the market price of an option, we can infer the market's expectation of the volatility, which is called the *implied volatility* [67]. Section IV-A1 will review some machine learning models for volatility.

Hedging is a common risk management strategy that uses a portfolio of options (or other contracts) to reduce risk exposure. Different Hedging strategies are adopted based on the sensitivity of the portfolio of assets with regards to various market factors (for example, future change of the volatility). Such sensitivity measures are called *Greeks* and are critical for hedging market risks of the portfolio [68]. Section IV-A2 will review machine-learning methods for sensitivity analysis.

To minimise these market risks and maximise business return simultaneously, businesses may also adapt dynamic asset allocation systems. This is also known as *portfolio optimization* [69]. Models for portfolio optimization are covered in Section IV-A3.

1) VOLATILITY MEASUREMENT AND FORECASTING

Volatility is a statistical measure to describe the dispersion of return of a financial asset or portfolio. It reflects the uncertainty of future asset prices in the financial market. Generally, higher volatility indicates higher market risk. It is the most important factor in determining the option prices. Generally, higher expected volatility leads to higher option prices. On the other hand, future market volatility cannot be measured exactly. Therefore volatility estimate is a central problem for market risk management.

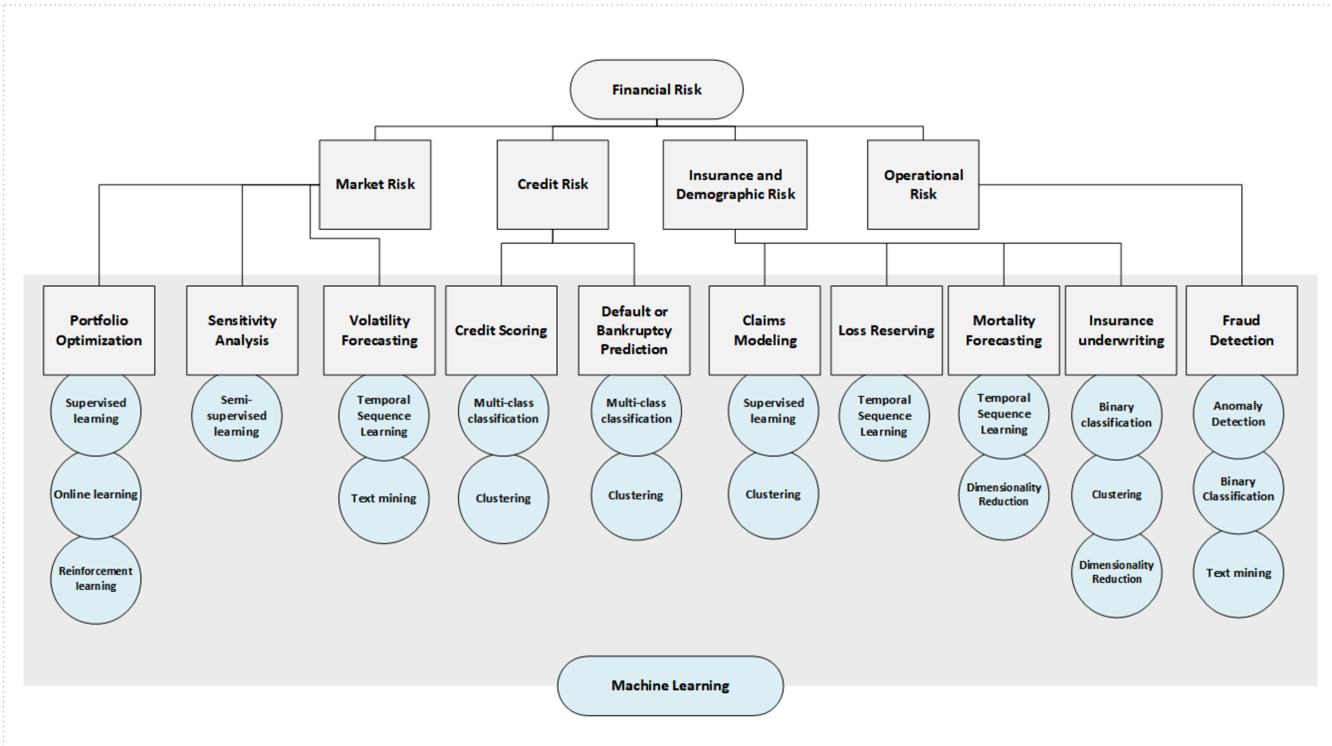

FIGURE 1. **Machine learning for FRM: task taxonomy.**

Volatility measurement: The primary variable on which volatility is calculated is the asset price. Firstly, the daily asset log-return, r_t is calculated from the asset price as $\ln(\frac{P_t}{P_{t-1}})$, where P_t denotes the asset price at time-step t [10]. Volatility of the log-returns measured over the period of length T is defined as

$$\sigma = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_t-\mu)^2}, \tag{1}$$

where μ is the mean of r_t over the period T.

a: TRADITIONAL METHODS

In this section, we discuss some traditional forecasting methods used for volatility modelling. These methods can vary based on their assumption on the stochastic nature of volatility. *Deterministic volatility models* follow the assumption that volatility is deterministic in nature. Some of these are discussed below:

- *Exponentially weighted moving average (EWMA)* models are exponential smoothing models that place higher weights on recent log-returns for forecasting volatility. The exponentially weighted moving average (EWMA) model can be expressed as:

$$\sigma_t^2 = (1-\lambda)r_{t-1}^2 + \lambda\sigma_{t-1}^2,$$

where λ is the exponential decay factor. The EWMA model is simple to calculate and also gives a more realistic estimate of the current volatility present in the market compared to the simpler moving average models. However, the EWMA does not account for some other realistic challenges present in financial time series. These are:

1) *Conditional Heteroskedasticity* refers to the time-varying volatility of financial assets. *Heteroskedasticity* is an important challenge for statistical modelling. It occurs when the standard error, ϵ of a regression model is non-constant over a specific period. The heteroskedasticity also depends on the past realization of the time series [70].
2) *Volatility clustering* occurs when periods of high volatility are interspersed with periods of low volatility [71].

- *Autoregressive Conditional Heteroskedasticity (ARCH)* was introduced to specifically address these challenges [70]. ARCH explicitly models the volatility as a function of the lagged residual errors. ARCH models the variance as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p}\alpha_i r_{t-i}^2, \tag{2}$$

where p is the lag amount and ω is a constant. A generalised version of ARCH, also called *Generalised Autoregressive Conditional Heteroskedasticity* (GARCH) model [72] is widely used by practitioners for modelling time-variant volatility of financial time series. The GARCH model extends the ARCH model to incorporate the lagged variance as well as the lagged residual errors from the mean process. The standard GARCH(p,q) model can be expressed as in Eq. 3. Interested readers can read about different variants of GARCH models in [73]–[75]. Importantly, the conditional variance, σ_t^2 is a deterministic function that is completely dependent on the return and variance in the previous time step.

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i r_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2; \tag{3}$$

Stochastic Volatility models, in contrast, assume that the volatility itself follows a stochastic path [76]. For example, a popular Stochastic Volatility model used for modelling volatility is Heston model [77]. The model assumes that the square of asset volatility (the variance of the log-return series) follows the Feller process [78]. In this model, the instantaneous volatility dv_t can be modelled by:

$$dv_t = \kappa(\theta - v_t)dt + \xi\sqrt{v_t}dW_t^v, \tag{4}$$

where θ is the long-run variance, to which v_t approaches towards at rate κ. W_t^v represents a Weiner process and ξ is the variance of the v_t.

Limitation of traditional methods Despite having high practicability in modelling volatility [79], limitations exist in both of these approaches. Firstly, there is an asymmetrical correlation of volatility to past return innovations [80]. Negative unexpected returns generally have a stronger effect on future volatility compared to positive unexpected returns. This asymmetric property of the series is not captured by the previously mentioned approaches. Secondly, these models are more suitable for univariate time series analysis, and does not take into consideration that volatility can be conditioned with other variables as well (e.g. financial news) [81]. This necessitates the need for a more robust data-driven approach of modelling volatility.

b: MACHINE LEARNING METHODS

Using Machine learning algorithms to improve traditional methods: *Hybrid machine learning techniques* can be implemented to improve the performance of the traditional GARCH-based and stochastic methods [80], [82], [83]. Artificial Neural Networks can be stacked with both GARCH and Stochastic Volatility models to produce more accurate volatility forecasting. Using the GARCH model output as one of the inputs for a Multi-Layered Perceptron model can not only make the prediction more accurate but also, the stacked model is more robust and consistent for different window sizes [82]. Integrating recurrent neural networks with stochastic volatility models can also significantly improve forecast performance [79]. Interestingly, there is also evidence to suggest that machine learning models (Support Vector Regression, Gaussian Process Regression and Neural Networks) can replace the parametric models altogether [2], [84].

Using neural network-based sequence learning methods for volatility forecasting: Long Short Term Memory (LSTM), is a popular variant of Recurrent Neural Networks that is used for sequential analysis [85]. LSTMs have been used for the task of volatility forecasting as well. Experiments suggest that LSTMs can outperform the traditional GARCH models and also provide more robust forecasts [86]. However, there are two challenges with implementing LSTMs for volatility modelling: firstly, long training time needed for convergence of these networks and secondly, the need for a high amount of data to get better performance. These challenges are widely prevalent on other application domains for LSTMs as well.

Using textual data as predictors for volatility forecasting: None of the aforementioned methods makes use of unstructured textual data (e.g. financial news, political news, pandemic news) in the prediction of volatility. Historically, only structured data (e.g. share volumes and prices) had been used to predict portfolio volatility with Machine Learning, but textual data can also be a significant predictor for market volatility [87]. There can be different sources of these text data related to the financial market. One source is the public discussion boards that reflect the public opinion about asset movements. Naive Bayes algorithm has been used to accurately predict trading volume and volatility based on message postings on these public discussion board [88]. News implied volatility, the uncertainty that arises from disaster news (e.g. war, market crash) can also be strong predictors of return volatility. Support Vector Regressors can be used for such predictions [81]. It is also observed that news articles (e.g. news regarding a company) can be good indicators for short-term prediction of underlying asset volatility [89]. Another interesting text source for these text-mining forecasting tools is social media data (for example, micro-blogging data present on twitter) [90]. Also, Google trends can be useful indicators for stock market volatility forecasts [91]. Evidently, there is a diverse set of data (both structured and unstructured) and machine learning algorithms that have been implemented for volatility modelling.

Natural language processing (NLP) techniques are increasingly being used to improve financial forecasting performances, as unstructured text data such as news articles and tweets may contain important information for financial decision making [92], [93]. A comprehensive survey on using text mining techniques on financial forecasting can be found in [94].

2) SENSITIVITY ANALYSIS

Financial sensitivities, also called *Greeks*, are the partial derivative of a financial asset's value with regards to different attributes of its underlying asset. Some of the commonly used Greeks are Delta, Vega, Theta and Rho. These are briefly described in Table 2. Using these *Greeks*, actuaries can obtain a portfolio that is risk-neutral against different risk factors.

TABLE 2. Greeks for financial risk management.

Greek	Definition	Practical Use
Delta Δ	$\frac{\partial V}{\partial S}$, first-order partial derivative of an asset price V, with respect to its underlying asset price S.	Delta neutral hedging
Vega $\mathcal{V}$	$\frac{\partial V}{\partial \sigma}$, first-order partial derivative of an asset price V, with respect to the volatility of its underlying asset price, σ	Option pricing, hedging against implied volatility
Theta θ	$-\frac{\partial V}{\partial \tau}$, also known as *time decay*, is the first-order partial derivative of the asset's price with regards to time to maturity, τ	Option pricing
Rho ρ	$\frac{\partial V}{\partial r}$, first-order partial derivative of the asset's price with regards to the risk-free interest rate, r	Option pricing, Delta-Rho hedging
Gamma Γ	$\frac{\partial^2 V}{\partial S^2}$, second-order partial derivative of an asset price V, with respect to its underlying asset price S.	Delta neutral hedging

Role of Monte Carlo simulation in calculating Greeks: Calculating these Greeks for complex financial products is difficult when there is no closed-form solution for pricing these products. This necessitates the use of simulation models to estimate these risk measures. Monte Carlo Simulation is a widely used method for measurement of risk exposures (e.g. Greeks, VaR) when no closed-form solutions are available [95], [96]. A major application domain for this task is in large insurance companies offering products with financial market-linked benefits which are unpredictable (e.g.variable annuities products). Variable Annuities are life insurance products that provide various financial market-related guarantees to the policyholder. These products have an added challenge of valuation because the financial guarantees offered with the product are complex and there is no closed-form solution for modelling the fair market value or Greeks of such product. Therefore, insurers have to resort to techniques such as Monte Carlo Simulation. However, directly implementing Monte Carlo Simulation is not feasible to a large portfolio of these complex assets due to extremely high computation costs [43], [97].

Approaches for reducing Monte Carlo simulation time: These computational challenges can be addressed with two different classes of approaches: Hardware approaches and software approaches. Hardware-based approaches include accelerating the simulation process via the use of parallel processors. Multiple graphics processing units (GPUs) can be implemented for such a task for accelerating the process. However, the number of GPUs needed for full simulation of a large portfolio can still be very high. By contrast, software approaches can be much less expensive. These approaches accelerate the valuation process by utilizing statistical models/algorithms. In general, the runtime of the Monte Carlo simulation can be reduced by two algorithmic approaches. These techniques are mentioned in Table 3. The table enlists some relevant research work related to these algorithmic approaches for simulation time reduction.

TABLE 3. Techniques for reducing Monte-Carlo simulation time.

Strategy	Techniques
Reduce the number of scenario	Scenario Ranking [98] Representative Scenarios [99] Curve Fitting [100] Random Sampling
Reduce the number of policies	Cluster modelling [26] Replicating Liabilities [101] Replicated Stratified Sampling [102]

Using meta-learning methods to approximate Monte Carlo simulation: A new family of machine learning-based meta-learning algorithms has been proposed to approximate the expensive Monte Carlo simulations more accurately and in a significantly reduced time span [101]. This family of approaches is called *Meta-modelling*. A typical metamodelling approach involves the following four steps:

1) Identify a small subset of representative policies from a large set of contracts.
2) Implement a Monte Carlo Simulation to calculate the market value or Greeks of the representative contracts only.
3) Build a regression model (the meta-learner) based on the representative contracts and their simulated market value/greeks.
4) Use the meta-learner to extrapolate the fair market value or greeks for the full portfolio.

Typically, the metamodels consist of two important components:

- *Experimental Design Method:* The learning component of the model that identifies the subset of the variable annuity policies.
- *Predictive Model:* The regression model to extrapolate the final result of Monte Carlo simulation for full portfolio.

Table 4 enumerates the commonly used techniques for each of these meta-model components.

TABLE 4. Metamodelling techniques.

Component	Techniques
Experimental Design Method	Random Sampling Latin Hypercube Sampling (LHS) [103] Cluster modelling [26]
Metamodel	Kriging [32] GB2 Regression [22] Linear models with interaction [104] Regression Trees [105] Neural Networks [43]

Neural network-based approaches are increasingly gaining traction for meta-modelling due to their high robustness and accuracy [43], [106], [107].

Using neural networks for hedging with or without Greeks Interestingly, Neural-Networks can also be used to completely replace the meta-modelling approach for hedging VA portfolios. There are two ways that neural networks can be used for hedging:

- *Hedging via classical Hedging Principles:* In this approach, Neural Networks can be used to approximate the Greeks via metamodelling. Then, these Greeks are inserted into classical hedging formulas for determining asset ratios for hedging.
- *Direct Hedging via Neural Networks:* With this approach, neural networks are used to directly output asset ratios (e.g. stocks or bonds) required for hedging. The objective of the neural networks is to minimise the percentage change in the net position of the VA portfolio [108].

Datasets available for metamodelling research: Interested researchers can access synthetic datasets related to Metamodelling for sensitivity analysis in [109], [110]. These datasets include Monte Carlo simulation results and calculated Greeks for large synthetic variable portfolios.

3) PORTFOLIO OPTIMIZATION

Portfolio optimization refers to the process of allocating a set of financial contracts with specific weight distribution, to maximise the expected return and/or to minimise financial risk. We can define a portfolio by a set of real numbers $\{w_1, w_2, w_3, \ldots\}$ that corresponds to the weight of each asset in the portfolio, and their return by $\{r_1, r_2, r_3, \ldots\}$. The classical Markowitz mean-variance model [69] formulates the return and risk for an N-assets portfolio as:

$$\text{Return} = \sum_{i=1}^{N} w_i r_i$$
$$\text{Risk} = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i \sigma_{ij} w_j,$$

where σ_{ij} denotes the covariance between the i-th and j-th asset in the portfolio. The weights in the portfolio are also subjected to constraints:

$$\sum_{i=1}^{N} w_i = 1 \text{ and } 0 \leqslant w_i \leqslant 1.$$

The optimal portfolio is considered as the portfolio weight vector that minimizes Risk and maximizes Return.

Techniques for portfolio optimization: Optimizing portfolios over many assets is a difficult task due to the complex interdependencies present within different assets in a portfolio. Many analytical techniques can help to build a portfolio with minimum volatility.

a: TRADITIONAL METHODS

Mean-Variance optimization was the first analytical method to calculate the optimal portfolio with minimum expected volatility given a target return [69]. There are many variants of this method that consider more realistic constraints of the market. For example, [111] established that the transaction cost shall also be a significant constraint for portfolio allocation.

Multi-objective evolutionary algorithms (MOEA) have also received growing attention in portfolio optimization. There is a comprehensive survey on the implementation of different MOEA algorithms for solving portfolio optimization problems in [112].

b: MACHINE LEARNING METHODS

Supervised learning algorithms can be implemented for portfolio optimization problems. Support vector machines can appropriately identify the non-linear relationships among the market variables [20]. Performance of such supervised learning models were further improved by using novel regularization or cross-validation techniques [113]. Neural Networks can also outperform traditional models for portfolio selection [114].

Online Learning is also used for this task. An online portfolio selection strategy with the assumption of mean reversion relation of financial markets was implemented to find optimal portfolio weights [115]. A comprehensive literature on using different online learning approaches (e.g. Follow-the-Winner, Follow-the-Loser, Meta-Learning) for portfolio selection can be found in [116].

Reinforcement Learning methods are gaining traction in research related to portfolio optimization. CNN, RNN, and LSTM can be implemented to find optimal policies for the reinforcement learning task [40], [117]. Recurrent reinforcement learning method (RRL) has also been applied to simultaneously generate market activity signals (buy or sell) and the optimal asset allocation weights based on a downside risk-adjusted objective function [118].

B. MANAGING CREDIT RISK

Credit risk is the uncertainty involving borrower's capability to fulfil obligations. This may involve individual borrowers defaulting on a loan or corporations going bankrupt.

The two most active research topics for credit risk management are bankruptcy/default prediction and credit scoring [14]. Credit scoring generally refers to the risk classification of retail borrowers (which includes personal loans or mortgages) whereas bankruptcy prediction generally refers to the prediction of bankruptcy of an institutional borrower (for example, a small business). Generally, from a statistical modelling point of view, both the bankruptcy prediction task and credit scoring task can be regarded as binary classification problems [33]. However, the predictors used for these modelling tasks are generally different. The predictors used for bankruptcy predictions are key financial ratios derived from the company's financial statements such as balance sheets or income statements [119]. In contrast, predictors used for retail credit scoring models are various financial and demographic information of the loan applicant (for example, credit history, account balance, employment status, age) [120].

a: TRADITIONAL METHODS

Initially, credit admission decisions were undertaken with a subjective evaluation which was highly dependent on the personal experience of the decision-maker. Statistical methods have gradually replaced subjective credit admission decisions in recent years. Historically, the most widely used traditional statistical methods for credit scoring has been Linear discriminant analysis (LDA). A comprehensive review of statistical techniques used for credit scoring can be found in [121].

b: MACHINE LEARNING METHODS

There is a large number of applied machine learning studies for predicting default by individuals or enterprises. The group of classifiers used for credit risk evaluation can be categorised into two families:

Supervised Learning Methods: Many studies have shown that single classifiers can effectively be used for predicting bankruptcy or for credit-scoring. Two mostly used single classifiers for this task are Support Vector Machines (SVM) [122]–[124] and Neural Networks [120], [125]–[127]. A multi-class SVM was proposed by [128]. Besides SVM, other classifiers were used, including CART model [129], Gaussian Process-based Classifiers [130], and Deep belief networks (DBN) [131]. The performance of these models can be improved with new feature selection techniques [132], [133].

Ensemble learning and hybrid models have also been extensively explored within this domain [134]–[136]. A comparative survey of different ensemble learning approaches (bagging, boosting, and stacking) used for this task can be found in [21], [137]. The high effectiveness of Support Vector Machines as a single classifier has inspired researchers to improve prediction performance further by using SVM as the base learner of their ensemble models [138]. There is evidence to suggest that Random Forest algorithms can outperform other single or hybrid classifiers for this task [139], [140].

Unsupervised Learning Methods: Clustering methods can also be used to identify the risk of bankruptcy or credit default. These methods can help to identify groups of loan applicants/ enterprises with similar characteristics. A cluster-based dynamic scoring model can achieve better scoring accuracy by implementing different classifiers for different clusters [141]. A comparative survey of different clustering methods used for this task can be found in [27].

Interested readers can find the list of credit risk related datasets in [14].

C. MANAGING INSURANCE AND DEMOGRAPHIC RISK

Financial institutions that offer insurance services for various types of risk bears a significant amount of financial risks themselves. It is critical for these companies to accurately quantify the exposure and take proper steps to mitigate these risks. Financial risk for insurance can arise from many sources, each requires accurate prediction modelling. For example, before providing a car insurance product to an individual, the insurer needs to accurately predict the number of claims the driver might make in the future. Error in the prediction would result in under-pricing of the insurance product, which would result in a financial loss for the insurer in the future. Also, life-insurers need to have an accurate estimate of the expected lifespan of demography before providing life-insurance products to the individuals belonging to the demography.

Some major tasks related to insurance and demographic risk include Claim Modelling, Loss Reserving, Mortality Forecasting [142], [143].

1) CLAIMS MODELLING

Claims modelling refers to the prediction of all future costs associated with insurance claims made by the policyholders. The two measures that determine this future cost is the claim counts (also called *claim frequency*) and the claim amount (also called *claim severity*) [34].

a: TRADITIONAL METHODS

Traditional statistical models for claims modelling mainly involve generalised linear models (GLM) [34]. Via these generalised linear models, the frequency and severity of claims are expressed as linear combinations of different rating variables that include policyholders' demographic attributes (e.g. age and gender), as well as behavioural attributes (e.g. driving behaviour, previous claims history). One common drawback with classical claims models is their unrealistic assumption that claim frequency and severity are independent [144]. Bi-variate regression models can be used to model the dependency between the frequency and severity of claims [145]. Bayesian learning methods are also shown to predict claim frequency with high accuracy [146].

b: MACHINE LEARNING METHODS

Supervised learning methods: Ensemble models (boosted trees) can outperform GLMs in predicting claim frequency and severity [147]. Also, neural networks can predict policy-level claim characteristics with high accuracy [23].

Telematics data for claims modelling: When car sensor data (telematics data) is available, it can reveal drivers' behavioural traits. Such data has been used to improve the accuracy of claim prediction [148]–[150] or improve related clustering tasks (e.g. clustering drivers with similar risk patterns) [23].

Interested readers can find a comprehensive survey of all machine learning methods and reference to related datasets used for this task in [23].

2) LOSS RESERVING

Loss reserving refers to the estimation of total reserves required to cover all future claims arising from insurance policies. This is an important task for different stakeholders in the insurance industry. Firstly, it benefits insurers in their underwriting or pricing decisions. Secondly, for investors, loss reserving is an important component of the income statement and balance sheet of the insurer. And finally, for regulators, the amount of loss reserves helps to address the financial soundness of the insurer [54].

a: TRADITIONAL METHODS

The most widely used traditional method for loss reserving is the chain-ladder method [151]. Some notable historical studies about this topic are mentioned in [143]. A comprehensive survey of the traditional methods for modelling stochastic claims reserves can be found in [152].

b: MACHINE LEARNING METHODS

Recently, several neural network-based methods have been proposed to replace or augment the traditional methods for loss reserving. Classical actuarial models can be embedded in neural networks to get more accurate predictive performance [153]. Even shallow neural networks can outperform the traditional Chain-ladder method in this task [24]. Sequence learning models based on gated recurrent units (GRU) [54] were applied to forecast aggregated loss reserves and it outperforms traditional models.

3) MORTALITY MODELLING

Mortality risk is a critical component to financial institutions offering products whose benefits are linked to the longevity of their customers' lives (e.g. life insurance products). An important measure for quantifying this is the mortality rate.

Mortality rate is a fundamental component for calculations involving the valuation of life insurance products. It is generally expressed as the expected number of deaths for every 1000 individuals in a specific population subgroup. The aim of this modelling task is to forecast mortality rate $m_{x,t}^{(i)}$ for age-group x, during calendar year t for the population subgroup i. Accurate mortality rate forecasting is a crucial task in minimizing the risk of contract longevity.

a: TRADITIONAL METHODS

The existing literature for mortality risk modelling can be categorised into two families. Firstly, discrete-time based models (for example, Lee-carter model [154], Cairns-Blake-Dowd model [155]) describe the evolution of mortality rates at the yearly interval. Secondly, continuous-time stochastic models ([156], [157]) describe an instantaneous force of mortality [158].

The most widely used traditional method for mortality rate forecasting is Lee-Carter Model [154]. An autoregressive moving average (ARIMA) model is fitted by [154] for modelling mortality index for a single population. The parameters of the Lee-Carter model is estimated with singular value decomposition (SVD) [159]. Also, a comprehensive survey on fitting generalised linear models (GLM) for mortality modelling can be found in [160].

b: MACHINE LEARNING METHODS

Recently, several ML techniques have been implemented for mortality modelling. Neural networks have been extensively used to augment the traditional methods for forecasting multi-population mortality. Neural networks can be used to extend the Lee-Carter model to predict multiple population mortality simultaneously [161]. Neural networks can also be used for the task of dimensionality reduction in multi-population mortality forecasting [30]. However, the use of temporal sequence-learning neural networks (for example, recurrent neural networks) to completely replace the traditional methods is still limited [25], [162].

4) INSURANCE UNDERWRITING

Insurance underwriting is a critical task for life insurers. It is the task of evaluating financial risk related to providing insurance coverage to a potential insurance applicant. This risk measure helps life insurers to decide on an insurance application and charge appropriate insurance price if it is accepted.

Exclusion prediction is an important objective for underwriting. This determines whether the insurance applicant should be excluded from making a specific type of insurance claim based on their historical records. Statistically, this can be seen as a supervised classification problem [163].

Supervised learning methods: Both logistic regression and gradient boosted trees have been shown to provide good predictive performance for this problem [163]. However, gradient boosted trees generally require fewer features than logistic regression to generate similar predictive performance for this task. This is important for downstream tasks, such as questionnaire optimization (only including questions related to important features). Some other notable algorithms include support vector machines [164] and neural networks [29].

Unsupervised learning methods: A semi-supervised learning framework has recently been implemented for insurance underwriting task which includes a soft k-means clustering method to identify clustered responses to the underwriting questionnaire [165].

Dimensionality reduction techniques, such as PCA have also been used for this task to get better predictive performance from the supervised learning models [29].

D. MANAGING OPERATIONAL RISK

Fraudulent Activities is one of the major sources of operational risk for companies, particularly those in the finance sector. It can take on many forms: for example, bank-activities related fraud (fraudulent credit card transactions [19], [166], money laundering activities [167]), insurance-related fraud (fraudulent insurance claims [28]), securities and commodities fraud or other frauds such as mass-marketing fraud or corporate fraud [168]. Financial fraud can be economically devastating for a business [169]. Therefore, financial fraud detection systems are becoming increasingly important for effective and timely fraud prevention [170].

Financial fraud detection systems use machine learning algorithms to distinguish fraudulent financial data from very large quantities of data [171]. These machine learning algorithms can be either supervised or unsupervised. Both of these different family of methods are discussed below:

Supervised learning methods: Many studies in the literature address fraud detection as a binary classification problem. Binary classifiers such as logistic regression [19], [168], neural networks [168], k-nearest neighbor [19], decision trees and support vector machines are widely used in this section of the literature [19], [168], [172]. Feature engineering methods can significantly improve the predictive performance of fraud detection models [173].

Researchers have also used several ensemble learning algorithms for fraud detection. Several meta-learning algorithms can be used for detecting fraud [174]. Bagging ensemble methods have also been used to address this problem [175]. Many text-mining based algorithms have also been proposed for detecting fraudulent activities [176]–[178].

It is important in fraud classification models to account for miss-classification costs since the cost of false-positive detection is not usually the same as the cost for detecting false-negatives [179].

Unsupervised learning methods: A significant number of works in literature addresses fraud detection as an anomaly detection problem [28]. A theoretical framework for similar anomaly detection tasks is provided in [180]. Deep learning models can also be used for anomaly detection task [181]. Generative networks, such as GANs have been used to simulate and detect fraudulent activities [182].

Recently, semi-supervised graph-based networks have been implemented to address the problem of few labelled examples in fraud detection datasets [183].

Application of NLP in fraud detection: NLP techniques have been widely used by researchers to mine text documents related to fraud detection. A major use case for NLP in financial risk management is the task of analysing linguistic features of annual reports. Ranking linguistic indicators (such as words) using decision tree-based approaches and then applying traditional classifiers, such as Support Vector Machines on the ranked words can significantly improve the accuracy of identifying fraudulent reports [184]. Numerous studies applied NLP to learn lessons from the Enron Scandal [185]–[187]. Review of NLP applications in financial statement fraud detection can be found in [188], [189].

V. CURRENT CHALLENGES

In this section, we identify some major challenges in applying machine learning for FRM. These challenges come from three areas: data, algorithm, and models. An illustration of these challenges in different FRM applications is given in figure 2. The figure indicates the relevant challenges for each FRM task mentioned in the previous section.

A. DATA

Most machine-learning methods, particularly deep-learning methods, are data-hungry. The success of machine learning depends heavily on the availability of high-quality training data.

1) DATA AVAILABILITY

Lack of public datasets: Data privacy and sensitivity is a major concern for the financial sector. Financial Institutions store a large volume of private and sensitive information which is generally highly regulated [190]. These data can not be shared across different organizations, therefore, the models need to be trained in silos. Also, for tasks such as insurance pricing or credit scoring, profiling of individual applicants is required, for which specific variables of consumers may have relatively high predictive power towards the model. However, if these variables are deemed to be sensitive or private, using these for predictions may have adverse regulatory consequences. It is highly challenging to build predictive models excluding sensitive information without damaging the predictive performance [191]. Some benchmark public datasets relevant for research in this domain are enumerated in Table 5.

Expensive data simulation techniques: Several FRM tasks rely on simulation methods like Monte Carlo simulation which is very flexible, yet extremely computationally expensive when it comes to large portfolios. This simulation step can significantly increase the time needed for calculating the greeks of a large portfolio [32]. For example, for a portfolio containing 100,000 policies, implementing a Monte Carlo simulation using 1,000 risk-neutral scenarios in 50 different market conditions for 360 monthly time step would require 1.8×10^{12} cash flow projections. This amount of cash flows would take approximately 2,500 hours to be computed by a computer that can process 200,000 projections per second [209]. However, the calculated Greeks are generally used for intra-day dynamic hedging, therefore the time available for each simulation is generally much lower. This challenge may be addressed with building a simpler model to approximate results of the Monte Carlo simulation, also known as, *meta-modelling* [210].

2) DATA QUALITY

Non-Stationarity: Many statistical methods used for FRM assume constant distributional properties of the underlying data [211]. However, it is widely accepted that real-life financial time series data may not follow a constant distributional

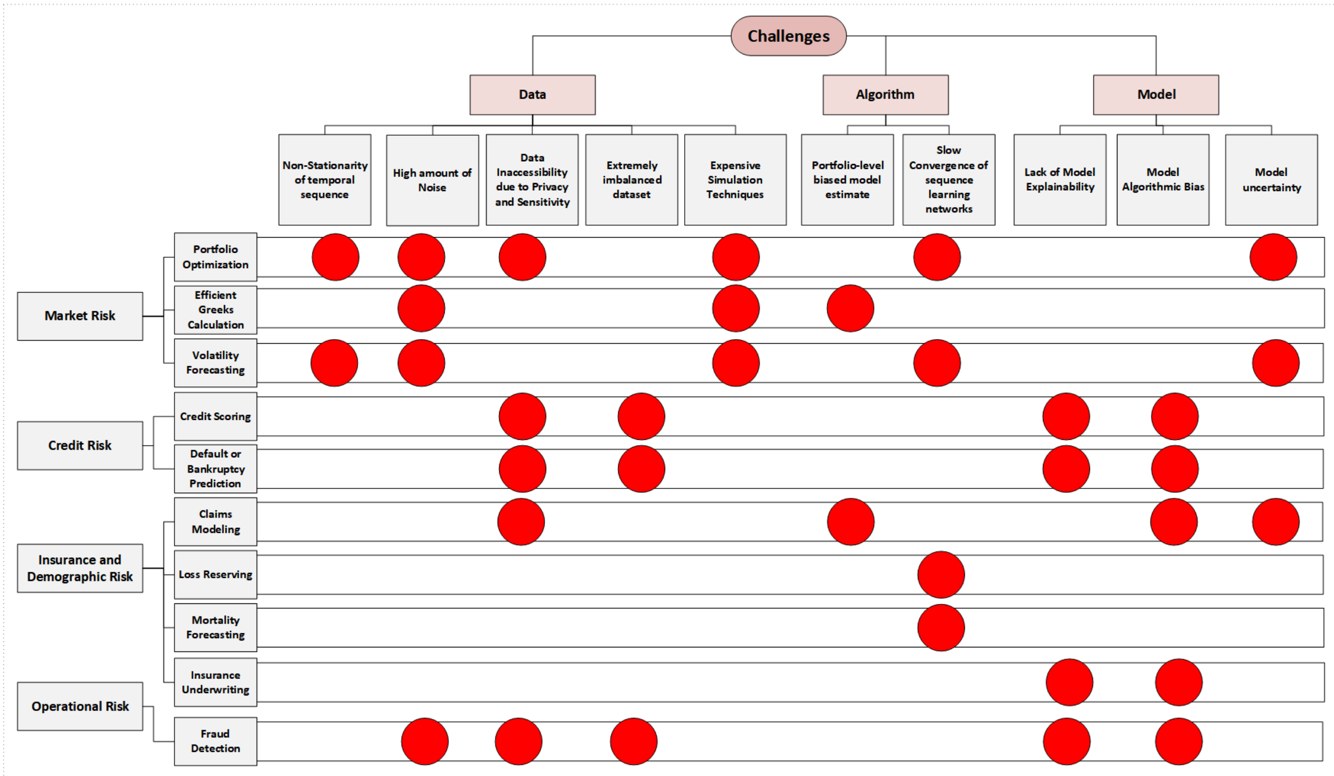

FIGURE 2. Major challenges in machine learning for FRM.

property (e.g. heteroskedasticity of log asset returns) and is highly variant across different timespans [6], [38], [212]. These changes are generally caused by various business or economic cycles [213]. The non-stationarity of the multi-variable correlations makes the problem even more complex. Also, observables such as variances and correlation coefficient can strongly depend on the length of the time window the time series is sampled from [214]. This non-stationarity property of financial time series data makes it difficult to apply machine learning models for forecasting.

Noisy data: A financial time series data is believed to contain a high amount of white noise or low signal-to-noise ratio, which makes the task of accurate forecasting extremely challenging [215]. Also, datasets used for fraud detection can be extremely noisy [216]. Implementing noise reduction techniques may improve the model performances for detecting the interdependence of financial markets [217].

Imbalanced dataset: For problems such as fraud detection, where the number of fraudulent activities is extremely low compared to non-fraudulent activities, the challenge of unbalanced data set is highly evident [176], [212], [218]. Since the class of interest (fraudulent activity) is extremely under-represented in the fraud detection datasets, the effectiveness of binary classifiers is reduced significantly [182]. This naturally makes the learning task using simple classifiers very challenging.

B. ALGORITHM

Biased portfolio-level estimates: Many machine learning models are trained to optimise the prediction on a *single* unseen data point, often assumed an iid sample of the underlying distribution. For FRM, however, the primary interest is not on individual contracts, but on the whole portfolio. A model predicting well on individual-level measurements may not predict well on portfolio-level measurements. In particular, it is well recognized that bias may be introduced when the portfolio-level estimates are derived from individual-level estimates [219]. Portfolio bias can come from two sources. First, the training data may be a small subset of the whole portfolio, and may not be representative of the underlying risk distribution. For example, in metamodelling of Monte-Carlo simulation, the training set size is limited by the simulation budget. Next, machine learning models tend to create biased estimates due to the use of regularization. Addressing these two sources of bias will be key to solve the bias problem.

Slow convergence of sequence learning networks: Although not specific to finance sector, several sequential networks (RNNs, LSTMs) are becoming increasingly common in financial forecasting (for example, volatility forecasting [37], loss reserving [54] and mortality forecasting [25]). This brings about the already known challenges of these networks, slow training time [220]. In other domains, researchers have proposed several alternative methods for sequential modelling, such as 1-dimensional

TABLE 5. Datasets for FRM research.

Dataset/ source	Description
Volatility forecasting and portfolio optimization:	
Yahoo! Finance [192] Bloomberg Markets [193] Wall street journal [194]	Multivariate time-series data that includes historical asset prices and other market data (e.g. adjusted price, trading volumes).
Two Sigma financial news data [195]	Unstructured text data (Financial news) regarding financial assets.
FRED Economic Data [196] The Economist [197]	Macroeconomic time-series data (for example, GDP, exchange rates, commodity prices).
Sensitivity analysis:	
Synthetic variable annuity datasets [198]	Monte Carlo simulation results of synthetic insurance portfolios with derived market sensitivities.
Credit scoring:	
Home credit default risk dataset [199]	Collection of datasets that include historical financial attributes of loan applicants (including previous loans, monthly credit balance, past payments).
Australian credit approval dataset [200]	Anonymised attributes of 690 Australian loan applicants used for credit approval decisions
German credit scoring dataset [201]	Dataset containing attributes of German credit applicants with a binary response variable indicating credit default risk
Claims modelling:	
French motor third-party liability datasets [202]	Two datasets containing claim frequency and claims severity of auto-insurance policies along with several demographic, behavioural, and vehicle-specific properties for each policy.
Loss reserving:	
NAIC Schedule P Triangles [203]	Multivariate time-series data that includes claims history of 50 insurance companies during accident years 1988-1997.
Australian private motor triangles [202]	Multivariate time-series data containing claims history of 2 lines of businesses of an Australian insurer during 1978-1995.
Mortality forecasting:	
Human mortality database (HMD) [204]	Time-series data that includes historical mortality rates for multiple countries during 1950-2016.
Insurance underwriting:	
Prudential life insurance dataset [205]	Dataset containing various attributes of life insurance applications and an ordinal response measure indicating varying levels of risk
Fraud detection:	
Credit card fraud detection dataset [206]	Dimensionality-reduced historical credit-card transactions of European cardholders on September 2013.
Fraudulent online transaction detection [207]	Two datasets containing several numeric and categorical properties of online transactions (for example, transaction amount, used card type, user device).
Fraudulent firm classification dataset [208]	Non-confidential financial data of 777 firms in India used for classifying possible fraudulent firms.

convolutions [221], attention-based models [222]. However, research in the application of these methods in the FRM domain is still limited.

C. MODEL

Model uncertainty: Many machine learning models are highly stochastic in nature. For example, neural networks generally use stochastic gradient descent techniques to find locally optimum weights [223]. These local optimas highly depend on the initialised model weights which are selected at random. This introduces uncertainty into the decisions made by neural networks which can adversely impact its acceptability in critical and highly regulated financial tasks [224].

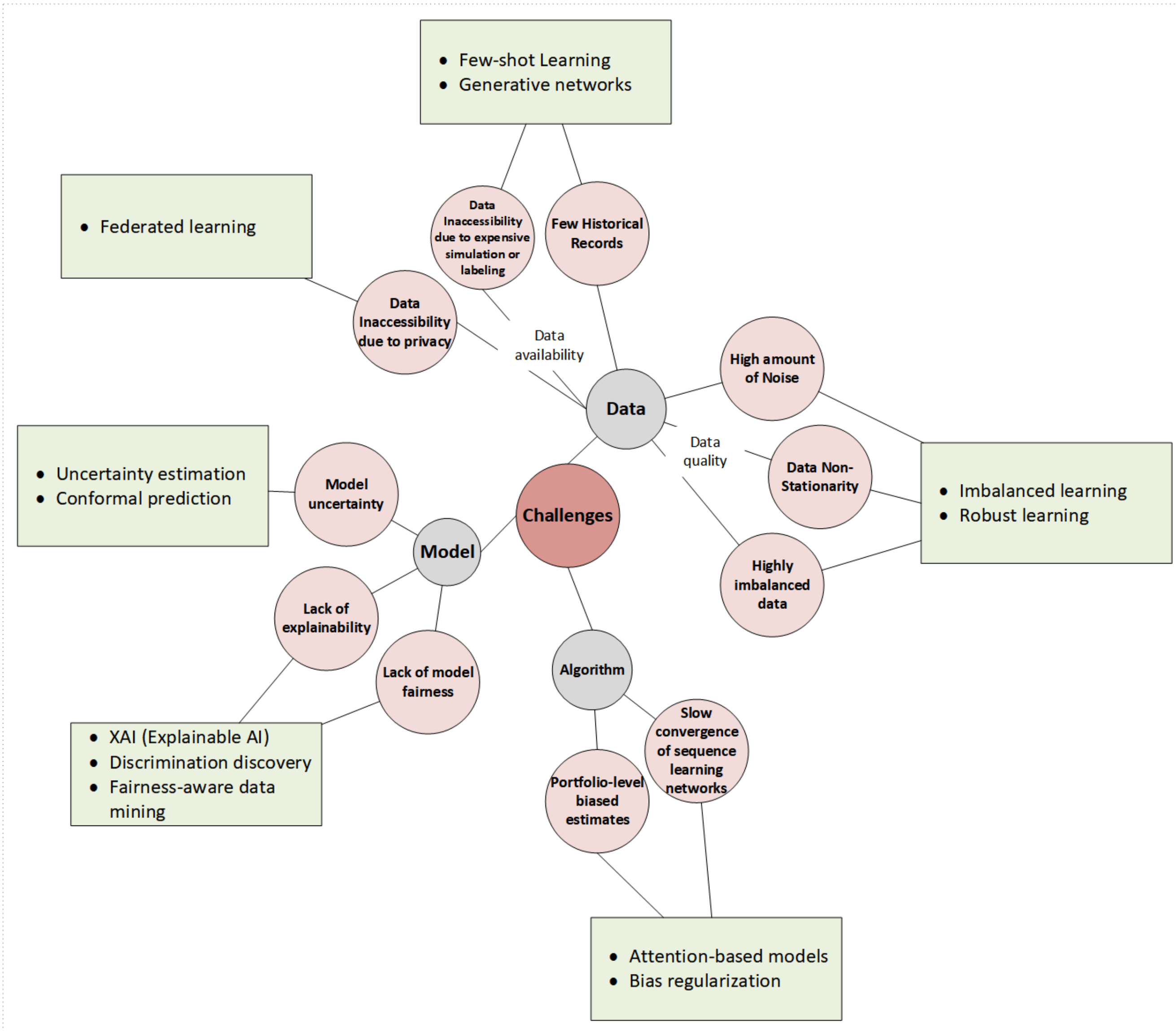

FIGURE 3. Emerging machine-learning research directions (in the light-green boxes) and how they may address challenges in FRM.

Lack of explainability: Model interpretability and explainability is a fundamental concern in the highly regulated financial domain. Models that profile individuals to make credit/pricing decisions are required to explain the rationale for their decisions for ethical and regulatory purposes. Model explainability is an active area of research, not just in finance but in other sectors as well.

Lack of fairness: Many machine learning methods used in finance rely on representational learning, however, external biases may instigate the credit rating or insurance pricing models to learn representations that may be discriminatory [224], [225]. This is an active area of research in applied machine learning [226], [227].

VI. FUTURE DIRECTION

Based on the challenges mentioned in the previous section, we can highlight some key research directions that can highly benefit the machine learning applications within the FRM domain. As illustrated in Figure 3, these challenges can be addressed with several ongoing research areas within machine learning literature. Some of these key research directions are discussed in this section.

A. FEDERATED LEARNING

Federated learning ([228], [229]) adopts distributed training techniques to avoid any data leakage. The aim of federated learning is to maintain data privacy and security by training a shared model without accessing data held by a different party [230]. To addresses the challenges of data privacy in finance, federated learning techniques can be used to enable multiple-party model training without exchanging the underlying private or sensitive customer or financial data.

Federated learning can be integrated with *differential privacy* techniques [231] to establish a stronger standard for individual privacy in modelling tasks on sensitive FRM datasets [232]. Differential privacy has been widely accepted by both researchers and practitioners as the de facto standard of privacy [233]. A standard technique for achieving Differential privacy is the Laplace mechanism, which adds noise without deteriorating final model performance [234]. Whereas federated learning techniques mainly focus on preventing sharing private data across multiple parties, differential privacy can add one more layer to overall model security by ensuring that the federated model weights can not be used to identify private information. Interested readers can find more about the recent developments of deferentially private federated learning in [229], [232], [235].

B. EXPLAINABLE AI

High-dimensional parametric models such as Neural networks are known to accurately identify latent correlations among features and labels. Most of the current work in literature focuses on applying these techniques mainly for prediction purposes, but very few attempt to find the causal relationship between features and model prediction. However, for many sensitive tasks in FRM, such as credit approval decisions or insurance pricing, causal explanation of model predictions can be of significant importance to both model developers and regulators [236]. Several existing approaches to identify causal explanation of decisions of complex predictive models used in credit risk management tasks have been reviewed in [236].

Model explainability and fairness both fit in the broader recognition of "responsible AI" by technology companies such as Google and Microsoft, which developed their own AI principles [237], [238]. Throughout machine learning literature, different methods to address model explainability has been proposed by [239], [240]. There is also a debate on how meaningful it is or when it is meaningful, to explain the decision of a highly accurate model [241]. Interested readers can find more about the recent developments in [242].

C. FAIRNESS-AWARE MACHINE LEARNING

Improvements in discrimination discovery and fairness-aware machine learning techniques can significantly benefit highly sensitive FRM tasks, such as credit approval or insurance underwriting decisions. A comprehensive review of fairness-aware machine learning techniques can be found in [243].

D. UNCERTAINTY ESTIMATION

To address the challenge of model uncertainty in a critical application domain like FRM, it is important to accurately estimate the measure of uncertainty involved with each model-driven decision. Measuring uncertainty related to neural network outputs is an area of active research. Prediction Intervals (PI) can be accurate indicators of uncertainty associated with point forecasts by neural networks [244]. This is highly beneficial for regression-based tasks in FRM. Also, some notable machine learning models that can quantify the estimated uncertainty of their prediction are SDE-net [245]. MC-Dropout [246], and DeepEnsemble [247]. A systematic review of neural network uncertainty and methods for measuring this uncertainty can be found in [248]. Such methods can enhance the acceptability of decisions made by machine learning models within this domain.

E. LEARNING FROM SMALL DATA

As discussed in Section V, many FRM tasks may suffer from the challenge of data unavailability due to data privacy, lack of historical records, or expensive simulation. This necessitates the implementation of models that can learn from few examples efficiently. One approach to address this issue is to generate representative synthetic datasets. For example, generative networks can be used to simulate datasets with fraudulent activities [182]. Insurance datasets may also be synthesised with such models for claims modelling or insurance pricing purposes [249]. Another approach is to implement learning techniques capable of learning effectively from a small number of examples. A comprehensive review of such small data learning techniques can be found in [250].

F. ROBUST LEARNING

For FRM tasks that suffer from statistically problematic data attributes such as non-stationarity or high amount of noise, robust learning methods may be implemented. Since these problematic data attributes (high noise or low signal-to-noise ratio) are not only specific to the finance domain, there is an active stream of research across different domains to learn from extremely noisy data. Robust learning methods may be implemented both in a classification context [251] or time-series context [252].

G. IMBALANCED LEARNING

For tasks that suffer from highly imbalanced classes, imbalanced learning techniques may be applied to address this issue. A comprehensive review of several machine learning methods to address the issue of class-imbalanced datasets can be found in [253].

H. OTHER RELEVANT RESEARCH DIRECTIONS

Improvements in attention-based models, such as the one proposed by [183] can help learn better representations for fraud detection models. These attention-based models are also known to outperform traditional recurrent neural networks, LSTMs, and GRUs for sequence modelling [220], which is highly relevant in financial forecasting tasks. Also, portfolio bias regularization methods (for example, [219]), can enable regression-based models to achieve better portfolio-level predictive performance when the primary objective is to estimate portfolio risk metrics.

VII. CONCLUSION

We have reviewed recent machine-learning applications in financial risk management. We identified areas that have been well-studied and also areas that require further research efforts. The well-studied areas include volatility forecasting, credit rating, bankruptcy prediction, fraud detection. In these tasks, advanced machine-learning models, including deep-learning models, have been extensively used. On the other hand, areas such as mortality forecasting, loss reserving, or claims modelling have not attracted an equal level of attention.

In terms of models, although important research challenges still exist in the more traditional statistical models, more high-value open problems involve the more advanced machine-learning models. The FRM domain has much to gain from leveraging recent breakthroughs in machine learning, particularly deep learning, applied to other domains.

These include the new uncertainty estimation methods in computer vision, robust algorithms for small, noisy, or non-stationary data.

Finally, some generic machine-learning questions are particularly central to FRM and will likely drive further machine-learning development. In particular, federated learning systems have the potential to ensure private and more secure learning using sensitive financial data. Explainability and fairness of machine-learning models are also essential considerations for FRM that require further research.

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