# Application of Machine Learning Techniques to identify the Business Financial Risks

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## ABSTRACT

The success of any business is based on financial wellness. Therefore, if the financial risks (FR) are reduced or prevented the chances of profitability will increase for the firms. Businesses apply different technological techniques to resolve the issue of FR. In the current scenario the relevance and effective of Machine learning (ML) is greatly realized in all the sectors of businesses. FR is also one of the important areas that have received potential benefits from the applications of ML. Researchers in ML often find difficulty in understanding the concepts and taxonomy of FR. This research paper will facilitate the researchers to correlate the ML types and methods for solving different FR in businesses. A survey is conducted through online medium from Computer Science (CS) specialists in Information Technology (IT) firms to measure their understanding for FR concepts. These CS specialists are asked to apply their critical thinking for the application of the types of ML in solving types of FR in businesses. This study is an empirical research and recommendations for correlation are completely based on observations and findings from the survey.

Keyword: Financial Risks, Machine Learning, Computer Science, Empirical, Taxonomy, Information Technology
JEL Code: M41, C83, L20

## 1. INTRODUCTION

Machine learning (ML) is not a substitute to Artificial Intelligence (AI) but rather a subfield of AI (Naim, 2022). In general terms AI is defined like an ability of system to act, behave and respond like a human. Most important benefit of AI is to facilitate in complex decision making which is comparable to the actions and intellect of humans (Leo et al., 2019). ML can be understood as a tool for transforming (Naim, 2022) the system to think and respond like a human. To accomplish this objective, ML uses neural networks which practice sequences of algorithm that make system to respond and acts like human. ML has a great relevance in businesses especially in financial analysis (Naim, 2022).

ML has given a new and varied direction to finance in achieving feasibility in business operations (Lahmiri and Bekiros, 2019). Many firms have achieved competitive advantages after applying ML in their business practices (Leo et al., 2019). In the current scenario, it is found that firms are using AI, ML and Deep Learning (DL) at diverse level of business procedures and are realizing significant attainment and returns. Figure 1 shows the level and definition of AL, ML and DL (Wong et al., 2022).

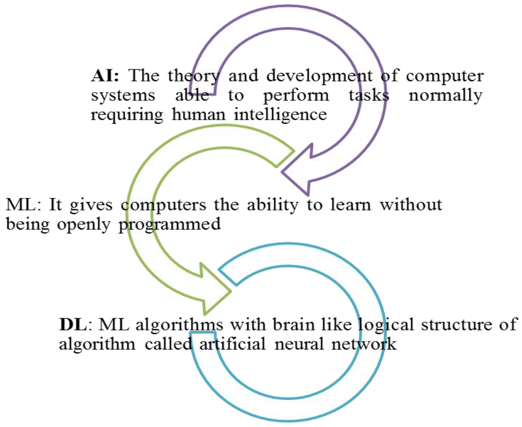


Figure 1: Definition of AI, ML and DL (Wong et al., 2022)
ML has four types and figure 2 shows the general depiction.

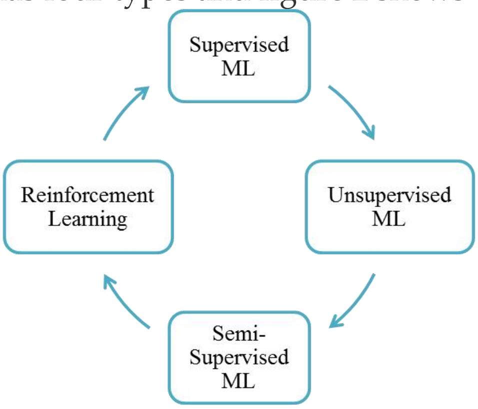


Figure 2: Types of ML (Wong et al., 2022)

ML has received overwhelming acceptance from users from all disciplines such financial analysts, social media analysts, advertising and media experts (Lahmiri and Bekiros, 2019). This is because of ML's advancements in using Natural Language Processing, Computer Vision, and Robotics.

The business practices which are based on quantitative analysis and have big data set extensively use ML types for solutions (Lahmiri and Bekiros, 2019).
Financial Risks (FR) is measured by the applications of ML and financial analyst take decisions to reduce risks and improve profit and financial efficiency (Naim and Hassan, 2022).

Financial Risk (FR) is a concept explains the ability of any business to take care and deal the financial instabilities. These instabilities can be described as the liabilities and financial commitments any firm has to pay back. FR mostly ascends because of loss in business and financial markets, changes in stock market and in process, change in the currency value, etc. FR is important not only for financial analyst, business organizations but also for general economic scenario because it supports, synchronize and device commercial statistics and progressions. It also offers clear policies for exploring financial openings and assesses the performance of any firm. Figure 3 gives the types of financial risks with further segmentation.

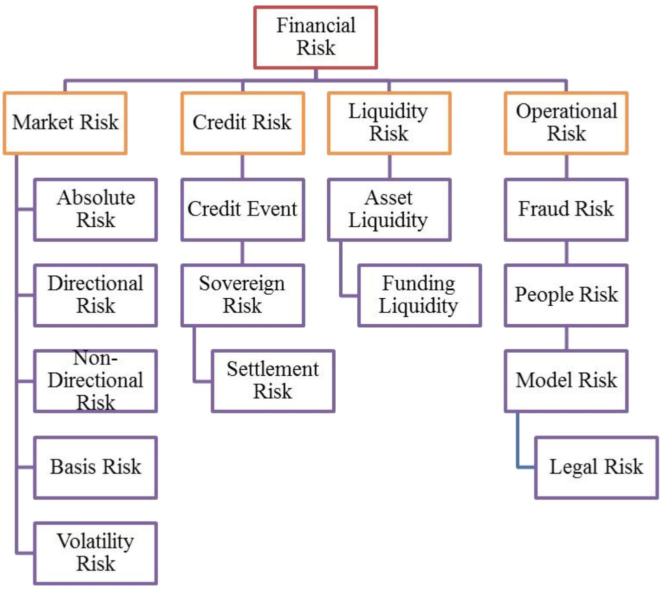

Figure 3. Types of Financial Risks (Wong et al., 2022)

FR is always a demanding area of research and application of ML to meet the challenge is not a new approach, (Naim et al., 2021). However, the application has used efforts and time in measuring, studying and identifying the FR clearly due to lack of conceptual knowledge in financial management in general and FR in specifically. In the current scenario, taxonomy to correlate and discover ML types to measure the FR has not been streamlined effectively (Wong et al., 2022).

Some previous research have used ML and explained the benefits of using ML in FR for specific firms but a general framework is yet to be explained that can be functional for any firm (Naim et al., 2022). FR is broadly segmented into four types for the understanding and conceptual distinction (Wong et al., 2022). These distinctions helped the research to define the types of FR in more specific manner so that definite type of ML can be identified to reduce the type of FR (Sanni et al., 2021). Reducing risk as well as managing risk is mostly a quantitative approach for the organizations (Naim and Alahmari, 2021). For large organizations this issues is not complex however for small scale firms, managing risks and reducing risk have always been a challenge. Big organizations can apply sophistical statistical methods to manage and reduce FR but for small firms it's also financial problems. In past many studies have focused on measuring the FR but this research paper explains the correlation and between ML and FR so that small firms can easily apply the types of ML to measure the FR (Naim and Kautish, 2022). Big organizations are also benefitted by this easy and effective framework (Bhatore et al., 2020).

We present a comprehensive taxonomy of major FR tasks and establish their connection with relevant machine learning problems. This taxonomy would help machine learning researchers navigate the complex domain of financial risks.

## 2. LITERATURE REVIEW

AI is facilitated by ML, as these tools help to leverage the objectives of technologies. Many times ML is synonymously used in place of AI due to the decision making capabilities until 1970s (Sanni et al., 2021). In later years ML grew as a separate branch and continues to become a popular tool for aiding various processes in business, medicine, and other disciplines (Bhatore et al., 2020). ML is witnessed to be applied for business research and modern techniques in business (Sanni et al., 2021).

ML uses algorithms and neural network models to help computer systems in cultivating and enhancing the performance of business at all levels (Bhatore et al., 2020). In the year 1952, Arthur Samuel developed the concept of ML when he marked a principal processor culturing codes. The codes were for checker's game and later the firm IBM enhanced the game by applying ML technologies (Hoepner et al., 2021). In the late 1970s and early 1980s, AI research had focused on using logical, knowledge-based approaches rather than algorithms. Additionally, neural network research was abandoned by CS and AI researchers (Hoepner et al., 2021). Therefore ML was considered to be a practicing program for AI and there was no clear demarcation between ML and AI until then (Lahmiri and Bekiros, 2019). Presently ML is applied by many areas and disciplines for success and profit maximizations. Some of the breakthrough advancements occurred by the ML are self-driving vehicles, discovering the galaxy, and many more which are mentioned in figure 4.

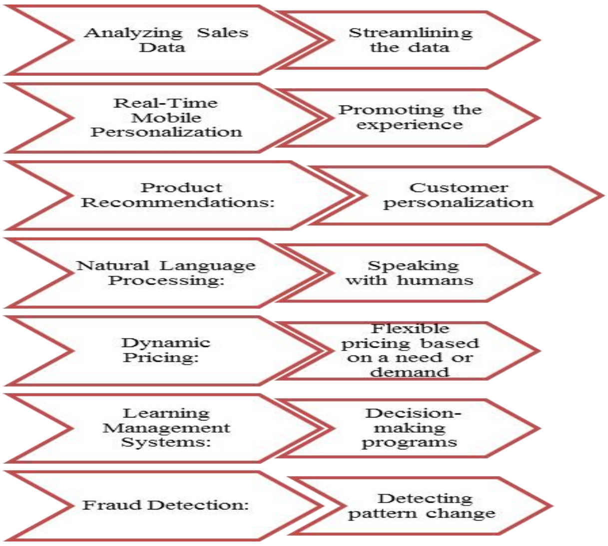


Figure 4. Benefits and Applications of ML in different areas (Lahmiri and Bekiros, 2019)

Another major contribution made by Stanford University while defining ML as “the discipline to make systems work without being programmed "(Lahmiri and Bekiros, 2019). ML has encouraged a new collection of concepts and technologies such as chatbot, IOT, algorithms for robots, supervised and unsupervised learning, etc., (Lahmiri and Bekiros, 2019). The term finance is as old as the start of civilization. The first finance application was in about 3000 BC. Empires like Babylonians Empire was the first ones to give the concept of banking and centuries later in 2013 the Nobel laureate Eugene F. Fama, explained the term modern finance in economics. He is popularly known as father of modern finance (Lahmiri and Bekiros, 2019). There are three broad categories of finance and later two more were added, so currently 5 categories of finance exist. These categories are public finance, corporate finance, and personal finance, social finance and behavioral finance (Leo et al., 2019).

Mashrur et al. (2020) explained ML for FR through the survey method but did not specify the target the computer science and ML expert for the responses for identifying the ML techniques for FR. (Lin, et al. 2011) illustrated the results of ML for Financial crisis and predicted the solutions through the survey but the research did not cover the FR through the types of ML. Researchers in Machine Learning often find difficulty in understanding the concepts and taxonomy of Business Financial Risks. This research paper will facilitate the researchers to correlate the ML types and methods for solving different Business Financial Risks. The target group for this research is the experts in Machine Learning, Computer Science Specialists and Software Engineers.

## 3. Research Methodology

The current study is based on the survey results from the computer science specialists and software engineers. The respondents were academicians from the southern universities in Saudi Arabia and professionals from Information Technology firms in Saudi Arabia. The survey questions have identified four types of ML types which are supervised, unsupervised, semi – supervised and reinforcement learning. The different types of FR were explained in the questionnaire and respondents, where asked to identify the ML types to assess the specific type of FR. Based on the responses the results show the methods of ML to measure the type of FR.

## 4. DISCUSSION

Most of the financial issues based on quantitative analysis are solved by ML, these issues are mostly related to profit maximization, predictive analysis, return on investments and FR. This research paper focuses on general understanding of FR types and ML types and the taxonomy of Business FR to identify ML types for measuring specific types of FR (Song, et al.,2014). There are four types of FR which are given in figure 3 in the earlier part of the paper. Each type of FR is segmented into sub parts of FR based on applications and conceptual understanding. These four types are market risk, credit risk, liquidity risk and operational risk

Market Risk has five subparts namely: Absolute Risk, Directional Risks, Non directional Risks, Basis Risk, and Volatile Risk (Leo et al., 2019). Absolute financial risk is measured by the total debt for certain or definite events. Directional risks explain the financial forfeiture ascends due to actual assets in the market. Non-Directional may occur because of any unexpected incidence. Basis risk happens due to mismatch in a hedging situation. Volatility risk is caused during the change of price of a collection. This brings financial instability.

Credit risk has three sub parts such as credit event, sovereign risk and settlement risk. (Leo et al., 2019). A credit event is an adverse variation in a debtor's ability when he is unable to payback and this prompts for credit default swap (CDS) contract. Sovereign risk is a national risk where the government has an obligation to pay back the debt due to risk in making investment in other nations. Settlement risk arises when one entity is unable to hold the cash for financial transaction and that eventually cause financial instability (Gotoh, et al.,2014).

Liquidity risk has two subparts such as asset liquidity and funding liquidity (Leo et al., 2019). Asset Liquidity arises when the asset is unable to be converted to cash when need for financial transaction or to pay debt. Funding liquidity risk is correlated to the financial institutions, where they are incompetent to settle debt or financial commitments (Li et al., 2009). Operational risk has four subparts namely, fraud risk, people risk, model risk and legal risk. Fraud risk depends on internal or external factors for illegal activity that can damage the image of the firm ( Naim, 2022). People risk also depends on internal and external factors when there is lack of human resources or negative behavior or lack of motivation or contribution that cause loss or errors in the process. Model risk is due to errors in designing that cause financial damage (Kou, et al.,2019). Legal risk is caused due to ethical issues or non-compliance regulations from the government.

The FR cause uncertainty to all types of firms and it is very important to reduce and implement a strategy. ML has successfully helped several firms for profit maximization and this research will focus on types of ML for measuring FR. Table 1 shows ML techniques and FR applications.

Table 1. ML techniques with FR Applications (Leo et al., 2019)

| Learning Methods | Learning Task | FR application |
|---|---|---|
| Supervised Learning | Classification | Fraud Detection |
| | | Portfolio optimization |
| | | Credit saving and bankruptcy policies |
| Unsupervised Learning | | Volatile forecasting |
| | | Claims modeling |
| Regression | Clustering | Loss Reserving |
| | | Mortality Modeling |
| | | Insurance Policy |
| | | Sensitivity Analysis |
| | | Credit saving and bankruptcy predictions |

ML is a computational method which is generally dependent on improving the functions and reducing the errors and losses. ML can be classified into supervised learning, unsupervised learning, semi supervised learning and reinforcement learning (Leo et al., 2019).

Supervised Learning is a type of ML as well as AI that apply the labeled dataset to practice algorithms which aid in classification and eventually predicting the results for the discipline of areas where it is implemented (Gao et al., 2021). Unsupervised Learning initiates ML algorithms without any human intervention. This ML subcategory prompts to study and cluster unlabeled datasets and the algorithms applied here determine the concealed designs or data groups (Xuan, 2021). Reinforcement learning is a ML practicing technique created on having required outcomes and removing irrelevant aspects. This subpart is very helpful in identifying the errors and it is focused on trial-and-error approach (Naim, 2021). Semi-supervised is a type of ML which is a blend of supervised as well as unsupervised type of ML and AI. The combination is based on the application of small type of labeled data and large unlabeled dataset (Hoepner et al., 2021).

## 5. RESULTS

Types of ML can be applied in measuring FR and taxonomy can be developed to correlate ML types for FR. The results show the type of ML corresponding to the FR. Figure 5 shows the general scenario of Ml for FR with the correlated taxonomy.

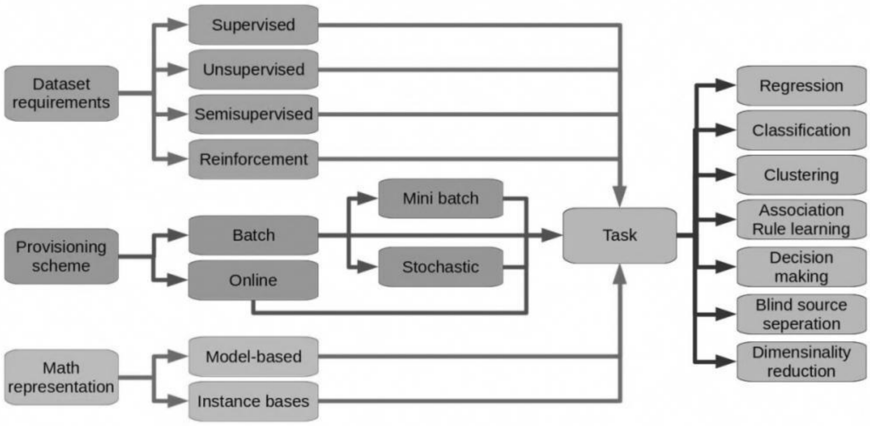


Figure 5. Taxonomy of correlation between ML for FR(Gotoh, et al.,2014)

Further table 2 shows the segmented FR and types of ML for types and application. However, the results will show the specific ML type for measuring and reducing a definite FR type.

Table 2. General scenario of ML types for measuring FR

| Financial Risk | | | |
|---|---|---|---|
| Market Risk | Credit Risk | Liquidity Risk | Operational Risk |
| ▪ Portfolio Optimization | ▪ Credit Scoring | ▪ Claim Modeling | ▪ Fraud Detection [Anomaly |
| ▪ [Supervised Learning, Online Learning, Reinforcement Learning] | ▪ [Multi Class Classification] | ▪ [Supervised Learning, Clustering] | ▪ Detection, Binary Classification, Text Mining] |
| | ▪ Default or Bankruptcy Prediction | ▪ Loss Reserving | |
| | | ▪ [Temporal Sequence Learning] | |
| ▪ Sensitivity Analysis | ▪ [Clustering] | ▪ Mortality Forecasting | |
| ▪ [Semi Supervised Learning] | | ▪ [Temporal Sequence Learning, Dimensionality Reduction] | |
| ▪ Volatility Forecasting | | ▪ Insurance underwriting | |
| ▪ [Temporal Sequence Learning] | | ▪ [Binary Classification, Clustering, Dimensionality Reduction] | |
| Machine Learning | | | |

The closed ended survey was conducted for CS and ML experts, where the questionnaire explained the FR concepts and subparts and was asked to identify the ML types to measure a particular type of FR. The results will show the four types of FR and which ML types are correlated to reduce and measure the type of FR. As mentioned in figure 3 above, four types of FR are further segmented into distinctive types. The four types included in the results are Market Risk, Credit Risk, Liquidity Risk and Operational Risk

Types of ML for Market Risk

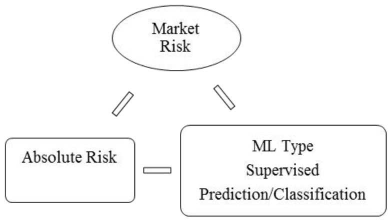


Figure 5. Absolute Risk

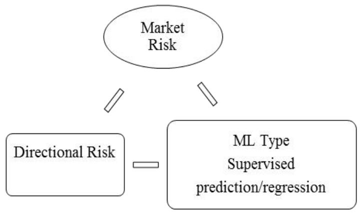


Figure 6. Directional Risks

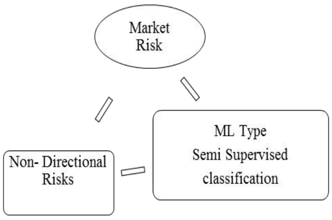


Figure 7. Non directional Risks

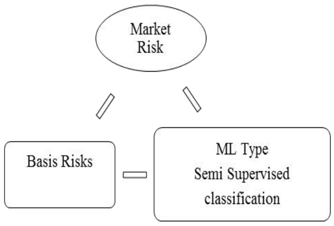


Figure 8.Basis risk

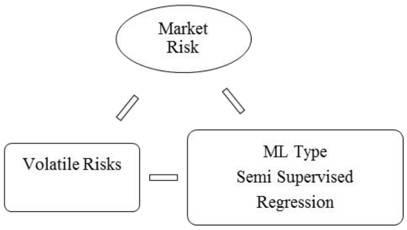


Figure 9.Volatile Risk

The results show that for absolute risk and directional risk, supervised learning can be applied for the FR measurement and for non-directional, basis risk and volatile risk; the best ML type should be semi supervised learning.

Types of ML for Credit Risk

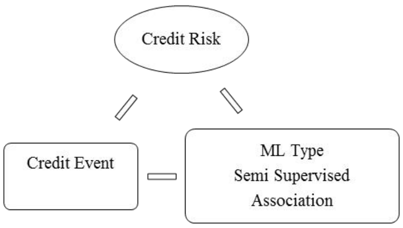


Figure 10. Credit Event

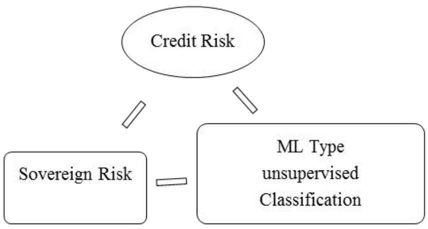


Figure 11. Sovereign Risk

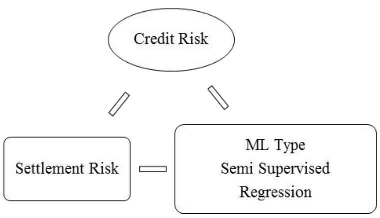


Figure 12. Settlement Risk

The results show for subparts of credit risk that for credit event and settlement risk, semi supervised risk should be applied and for sovereign risk unsupervised ML type should be pragmatic for the measurement.

Types of ML for Liquidity Risk

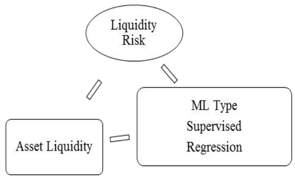


Figure 13. Asset Liquidity

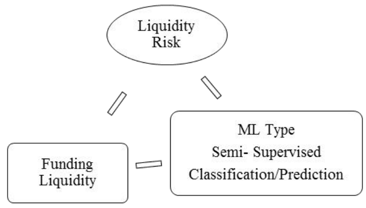


Figure 14. Funding Liquidity

The results for subparts of liquidity risk show that for asset liquidity supervised ML and for funding liquidity semi supervised ML type should be functional to measure the FR.

Types of ML for Operational Risk

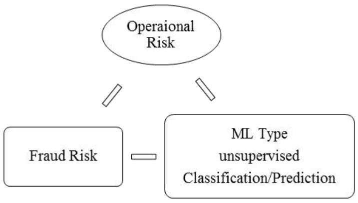


Figure 15. Fraud Risk

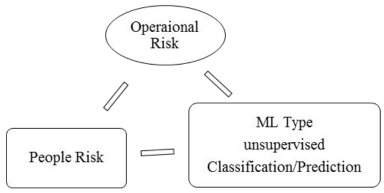


Figure 16. People Risk

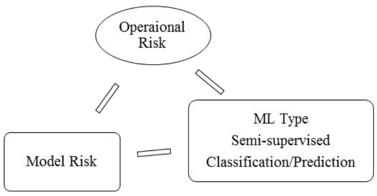


Figure 17. Model Risk

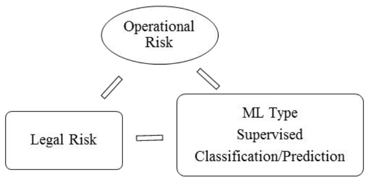


Figure 18. Legal Risk

The operational risk is measured under four subparts and results show that for fraud risk and people risk, unsupervised risk is more practical type and for model risk, semi supervised and for legal risk, supervised ML types are practical measurement tools.

## 6. CONCLUSION

We studied the definition of ML types and FR types and developed taxonomy to develop a correlation between ML subcategories and FR types. The general scenario is developed that given a simple but definite framework for FR types to be assessed by specific ML types. This research has facilitated the CS experts to apply the ML types to measure FR without making extensive research and also they do not need to develop a financial understanding to implement the ML type. In future the study will be conducted for exemplary approach where the research will measure the effectiveness of the application of these ML subclasses for FR forms.

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