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Prospects of Artificial Intelligence and Machine Learning Application in Banking Risk Management

Abstract: Artificial intelligence and machine learning have increasing influence on the financial sector, but also on economy as a whole. The impact of artificial intelligence and machine learning on banking risk management has become particularly interesting after the global financial crisis. The research focus is on artificial intelligence and machine learning potential for further banking risk management improvement. The paper seeks to explore the possibility for successful implementation yet taking into account challenges and problems which might occur as well as potential solutions. Artificial intelligence and machine learning have potential to support the mitigation measures for the contemporary global economic and financial challenges, including those caused by the COVID-19 crisis. The main focus in this paper is on credit risk management, but also on analysing artificial intelligence and machine learning application in other risk management areas. It is concluded that a measured and well-prepared further application of artificial intelligence, machine learning, deep learning and big data analytics can have further positive impact, especially on the following risk management areas: credit, market, liquidity, operational risk, and other related areas.

Key words: Banking, Risk Management, Artificial Intelligence, Machine Learning, Deep Learning, Big Data Analytics.

JEL Classification: C40, C45, C53, G17, G21, G28, G32.

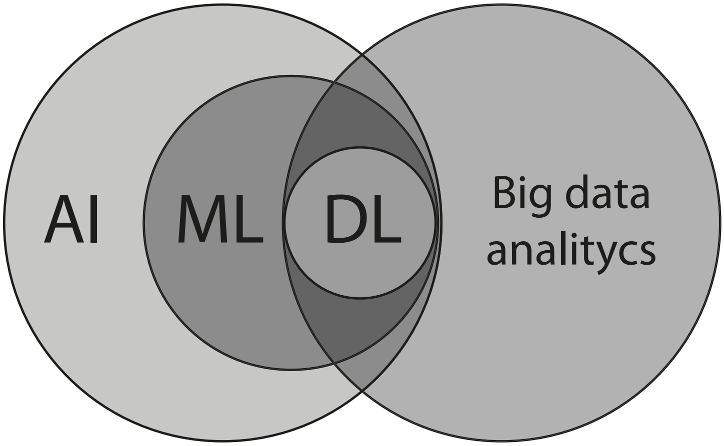
1. Introduction

Artificial intelligence and machine learning application in banking is constantly increasing. A similar trend can be seen in other areas of economy. Banking risk management is one of the finance fields with the strongest development during past decades, but the needs for further development of this area are constantly increasing. This is one of the reasons why artificial intelligence and machine learning is very important for today's banking risk management. Risk managers are having significant hopes in the possibilities of further banking risk management development, by the usage of artificial intelligence (AI) and machine learning (ML).

AI can be defined as the theory and computer system progress which is capable of conducting assignments and solve problems that usually need human intelligence as the prerequisite. ML is a subcategory of AI. In the training of the machine process, algorithms perform data analysis, learn from it and make decisions based on the stated experience it. Deep learning (DL) is a subcategory of ML. DL is conceived based on the human brain structure and work method. In the DL multi-layered artificial neural networks learn from the vast amounts of data. In the comparison to ML and DL, AI is the widest and oldest category, known from the 1950s. In the 1980s, ML began to flourish and very soon became one of the most important AI parts and very popular in risk management. During last two decades, DL has experienced a very strong development and it is a most sophisticate part of the ML. Big data analytics (analysis of huge and demanding datasets) is the technique that had a significant positive influence on AI, ML, and especially on DL, which is very demanding given the amount of data.

AI, ML and DL are already intensively used in banking risk management and we can see further increase of their usage. In credit risk, stated fields of AI have been strongly present during past decades. Many sophisticated classification algorithms are applied in the modern credit scoring (Lessmann, Baesens, Seow & Thomas, 2015). Some of the solutions that are in use for credit scoring are logistic regression, discriminant analysis, Bayes classifier, nearest neighbour, classification trees, Lasso logistic regression, DL, i.e. artificial neural networks, etc. (Leo, Sharma & Maddulety, 2019). The Support Vector Machine (SVM), which represents the supervised machine-learning algorithm, is used for the classification issues and has significant results in the credit scoring. AI, ML and DL (Addo, Guegan & Hassani, 2018) are in use also for other areas of the credit risk management, like stress testing (Jacobs, 2018), monitoring, but also in the estimation of the credit risk capital requirement parameters, especially: probability of default (PD) and loss given default (LGD). The stated parameters are in use also for the International Financial Reporting Standard 9 (IFRS 9) expected credit losses (ECL) impairment model.

Figure 1: Connection and relation between artificial intelligence, machine learning, deep learning and big data analytics



Source: Authors

ML is used in the different areas of market risk management such as forecast volatility, interest rate curves, foreign currency risk estimation and other areas. For the liquidity risk management, there has been some research in the recent period regarding the application of the Artificial Neural Networks and Bayesian Networks (Leo, Sharma & Maddulety, 2019).

Regarding the application of AI and ML in the management of operational risks and group of related risks, significant results have been achieved worldwide in the following areas: cyber security, fraud prevention, and anti-money laundering.

Artificial intelligence and machine learning have a potential to support the mitigation measures for the contemporary global economic and financial challenges, including those caused by the latest coronavirus disease (COVID-19).

Since new financial technologies and digital banking are changing the financial world, risk management follows those trends. AI research and solutions should give significant contribution in this process (Kolanovic & Krishnamachari, 2017). Besides positive effects of the AI, ML and DL, challenges and open questions need to be taken into account. Some of them are related to the model risk ("black box" issues), data availability, gathering and protection, transparency, ethics, availability of skilled staff to develop and implement new techniques (Financial Stability Board, 2017).

The starting research hypothesis is that using worldwide experience, published papers and databases, prospects of the AI and ML application in banking risk management can be defined. Second research hypothesis is that based on the stated, recommendations and proposals for successful implementation of the artificial intelligence and machine learning in the banking risk management can be formulated so that maximal positive results could be achieved (and negative to be avoided) in the field of banking risk management, business, and economy as well.

Our methodology in this research is dominantly based on respectable publicly available historical and current global experience, research results, analysis and databases were used for this study. Among other, many scientific works of the experts, as well relevant institutions` (including regulatory bodies) publicly available documents relevant for this field will be considered. The research takes into account big and advanced, as well as small and developing banking sectors and bank characteristics. The focus is on the comparative overview and analysis of the thesis, as well as conclusions in this work. This is the reason to conduct the analysis of the actual AI and ML application in banking risk management, as well as planned improvements. The aim is also to define recommendations for a successful implementation of AI and ML in banking risk management. Linked to the previous, the next methods are particularly relevant: descriptive, inductive – deductive, analytical – synthetic, and comparative analysis. The paper highlights was presented at the International Scientific Conference: “Global Economic Trends – Challenges and Opportunities”, organized in Belgrade on November 30, 2020 by the Belgrade Banking Academy – Faculty of Banking, Insurance and Finance in cooperation with the Faculty of Economics, People’s Friendship University of Russia, Moscow, Russia and Balkan Institute of Science and Innovation of the University Cote d’Azur, Nice, France. The book of abstracts from the conference has been published.

2. Characteristics of the current banking risk management

Current banking risk management is taking care of a significant number of risks. Traditional risks like credit, liquidity, market, operational and other risks, which have been known for a long time still dominate in the worldwide risk management. On the other side some relatively newer risks, like information security risks are having more and more important role. Additionally, some traditional risks are changing form, characteristics and they are closely related with the new risks. Stated is closely related to the new trends in the contemporary economy (Fabris, 2020) and finance (Grubišić, Kamenković & Kaličanin, 2021): like digitalization, new financial technologies, cryptocurrency era (Panagiotis, Efthymios, Anastasios-Taxiarchis, & Athanasios, 2020), etc.

Depending on the methodology, purpose and moment, the list of banking risks could have some variations. A typical list of risks which an average bank deals with in a modern economy is presented below.

Types of banking risks:

1. credit risk, including:
    a. counterparty risk
    b. settlement/delivery risk
    c. residual risk and
    d. dilution risk
2. liquidity risk, including:
    a. market liquidity risk
    b. funding risk
3. interest rate risk
4. market risk, including:
    a. foreign exchange risk
    b. price risk on debt securities
    c. price risk on equity securities
    d. commodity and other market risks risk
5. credit valuation adjustment (CVA) risk
6. concentration risk
7. investment risks
8. country risk
9. operational risk, including:
    a. legal risk
    b. information system risk
    c. risks arising from introduction of new products or services
    d. outsourcing risk
10. compliance risk
11. reputational risk
12. risk of money laundering and terrorist financing
13. business and strategic risk
14. macroeconomic risk
15. model risk
16. information security risk
17. other risks

Credit risk, i.e. a potential of adverse effects appearance on the bank financial result and capital originated by the borrower's failure to fulfil its obligations to the financial institution (Basel Committee on Banking Supervision - BCBS, 2000, and BCBS, 2019c) is still strongly determining total banking risk management. Similar situation is with two components of the liquidity risk (European Central Bank, 2018): market liquidity risk and funding risk. Market risks are also in the group of most important banking risks. Operational risks (depending on the definition) imply a wide range of areas and risk components. They typically relate to the negative effects on the financial institutions` result and capital originated by omissions in employees' discharge of duties, internal acts and processes quality lacking, unpredictable external events, poor information system management and similar factors (BCBS, 2019c, BCBS, 2006 and Aldasoro, Gambacorta, Giudici & Leach, 2020). Operational risks have gained in importance during past decades, especially taking in account their connection with new trends in the financial services area. More details about risk definition can be seen in the BCBS comprehensive document: "The Basel Framework" (2019).

Banks need to adequately manage all risks to which they are exposed. In this process they need to take care that their risk profile is aligned with their risk appetite. In every moment banks need to have adequate level and structure of capital to cover their risks (Adrian, 2018, Milojević, 2014 and Milojević, 2016). On that note, some of the major formulas in the modern banking risk management are the following defined by the BCBS (2017, 2019a, 2019b, 2019c):

$$\frac{\textit{Common Equity Tier 1}}{\textit{RWA (Credit, market, operational risk)}} = \textit{Common Equity Tier 1 ratio} \geq 4.5\% \quad (1)$$

$$\frac{\textit{Tier 1 Capital}}{\textit{RWA (Credit, market, operational risk)}} = \textit{Tier 1 ratio} \geq 6\% \quad (2)$$

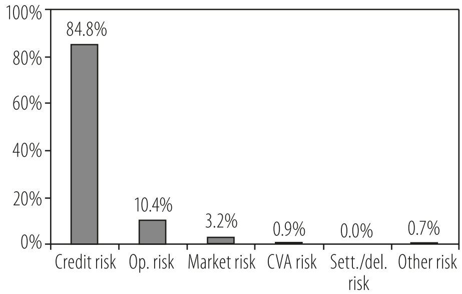
$$\frac{\textit{Regulatory Capital}}{\textit{RWA (Credit, market, operational risk)}} = \textit{Total Capital adequacy ratio} \geq 8\% \quad (3)$$

The difference between these 3 formulas is related to the regulatory prescribed amount and structure of capital for the risk coverage. Stated formulas are the basics for the capital and risk management, but they are supported with a wide range of the comprehensive requirements (Milojević & Redzepagic, 2020a).

As for risks which are relevant for the presented regulatory capital adequacy formulas, credit, market and operational risks are presented as parts of risk weighted assets (RWA). This is regulatory view, starting from the Basel II requirements

(BCBS, 2006), until today called "Pillar 1" requirements. On the other hand, the Basel standards prescribe that banks need to conduct Internal Capital Adequacy Assessment Process (ICAAP) where banks need to include, besides the already stated 3 risks, all other material risks to which they are exposed.

Figure 2: Risk exposures structure relevant for the capital adequacy of the European Union banks in the Q2 2020



Source: Authors, based on European Central Bank (2020)

Figure 2 shows a strong domination of credit risk in the risk exposures structure relevant for the capital adequacy of the European Union (EU) banks. Similar domination can be seen in the worldwide banking sectors, for quite a long.

To keep all risks under control and in the accordance with expected values, banks are applying various techniques, methods and tools. These techniques, methods and tools are more and more relying on the AL, ML and DL. Some of the most used techniques, methods and tools are the following:

- Risk limits;
- Risk assessment;
- Portfolio analysis;
- Scenario analysis;
- Sensitivity analysis;
- Stress testing;
- Ratings, scoring and classification;
- Expected credit loss;
- Value at risk;
- Expected shortfall;
- Back testing.

Risk techniques, methods and tools, as well as their connection with the AL, ML, DL and Big Data Analytics will be analysed in more detail in the next section of this paper. All stated elements are incorporated in contemporary risk management segments: identification, assessment, measurement, monitoring, mitigation, and reporting.

3. Recommendations for the artificial intelligence and machine learning implementation plan in banking risk management

This part of the paper suggests prospects and recommendations for the successful AI and ML implementation in the banking risk management. The stated should include adequate strategy and implementation plan. Our idea is to define recommendations which could be helpful for different types of banks and markets. For the recommendations definition, the research has taken in account the needs and specifics of the various categories such as the following:

- small banks in developing stage;
- mid-sized banks;
- large international banks;
- developed markets;
- developing markets.

It can be stated that all banks, regardless of their size, length of business history, profile, strategy, development degree of the market, local or international orientation and level of risk management complexity can benefit from the AI and ML application in risk management. This is the reason why one of our aims is that research formulates the recommendations which would be helpful to banks in this process. The result should be that some banks which are now starting with AI and ML implementation in risk management or which are yet to start with it will find a significant number of proposed steps in this research which could be relevant for them. On the other hand, some big developed banks with highly sophisticated risk management have probably already finished a significant number of the steps indicated here, but this is an ongoing process so the room for improvement can always be found as well as new tasks and aims to be achieved.

Some of the crucial elements for a successful and comprehensive implementation of the AI and ML in bank risk management are the following:

1. Definition of the strategy, operative plan and project for the implementation of AI and ML in bank risk management.
2. Analysis which bank risks could be part of the scope of the AI and ML enforcement such as:
   a. credit risk
   b. liquidity risk
   c. market risk
   d. operational risk

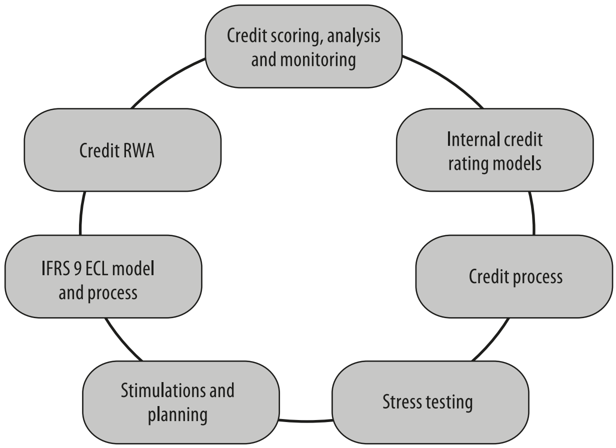
   e. risk of money laundering
   f. information security risk
   g. other risks
3. Analysis of the technical and human resources which are necessary for the enforcement.
4. Are the additional external resources necessary (recruiting, outsourcing, etc.)?
5. What are the legal and regulatory requirements and restrictions?
6. Budget and cost benefit analysis.
7. Involvement of all necessary organizational units such as:
   a. Risk management
   b. Credit analysis
   c. Information technology
   d. Legal
   e. Compliance
   f. Finance / controlling
   g. Anti money laundering
   h. Front organizational units: Corporate, Retail, Treasury, Investment, etc.
   i. Asset Liability Management
   j. Other (depending on the bank structure, organization, characterises and aims).
8. What AI, ML, DL and big data analytics elements, models and techniques will be applied?

Since credit risk is still the major risk in the banking and the risk with highest AI and ML usage during last decades, in the following segment, the research will put the special focus on this risk.

3.1. Credit risk management artificial intelligence and machine learning implementation

This chapter presents details of the proposal for the credit risk management AI and ML application. Based on our analysis, it can be seen that there is a possibility for significant AI and ML application results in the following credit risk management segments. Some of the segments are directly connected with core credit risk management functions, while some consider wider bank management integration (like credit process improvement, planning, etc.).

Figure 3: Major segments of the credit risk management AI and ML implementation



Source: Authors

Credit scoring, analysis and monitoring:

Phase 1: A bank can conduct testing of the various AI and ML techniques for this segment such as logistic regression, discriminant analysis, Bayes classifier, nearest neighbour, classification trees, Lasso logistic regression, DL, i.e. artificial neural networks, SVM, etc.

Phase 2: If the results of the phase 1 are good (like it is seen in the various analyses stated in this paper), the bank can start with AI and ML implementation in the bank processes regarding credit analysis and scoring. It can be done gradually, first as an additional tool, a parallel solution or similar.

If the bank decides to use DL (most sophisticate part of ML), it should count that this process will be demanding in terms of the amount of data. In this case, the big data analytics will have an important role so the bank should prepare all required technical and human resources for that task.

Internal credit rating models:

This segment can be closely related to credit scoring. Based on this, those two segments can be included in the AI and ML implementation project. Positive result in the credit scoring AI and ML implementation can be used for internal credit rating model improvements.

This can be done with rating validation analysis, back-testing, comparison of the result of the existing internal credit rating models and the new ones based on AI and ML. Positive results can lead to a gradual use, similar to credit scoring.

Credit process:

Positive results in the AI and ML credit scoring and internal rating implementation can bust the credit process and receivables disbursement. These processes are wider than the core credit risk management functions, but they are closely related to credit risk management. The aforesaid can result in faster credit process, lower costs, better conditions for the clients, improved capital allocation and support for the sustainable economic growth.

Stress testing:

Phase 1: By the usage of the already stated AI and ML credit risk management techniques, a bank can apply additional stress tests or improve the existing ones. In the first phase it can be done as an additional, parallel or a supporting analysis.

Phase 2: successful results of the phase one can lead to the stress test implementation in various bank processes: ICAAP, recovery plan, other bank stress testing, and the like.

Simulations and planning:

Positive results of AI and ML application, especially on stress testing, can be used for the simulation and planning improvement. This process can follow the stress testing of the AI and ML process, but it can also be connected to some of the following process like IFRS 9 and RWA AI and ML implementation. Positive results in the simulations and planning improvement lead to the total bank management improvement.

IFRS 9 ECL model and process:

IFRS 9 AI and ML implementation focus should be on the improvement of the PD and other ECL parameters, as well on parameters validations.

Credit RWA:

Phase 1: analysis, simulations and stress tests of the Credit RWA based on the standardized approach. Results can be used in the ICAAP.

Phase 2: After a successfully finished phase 1, if the bank has ambition to implement IRB approach and needed infrastructure and necessary preconditions for this demanding approach, analysis and preparation for the Credit RWA IRB approach implementation can start. Focus should be, among other things, on PD and other IRB approach requirements. AI and ML techniques can be compared and combined with other (standard) credit risk techniques. Positive results could be initially implemented in the ICAAP, which can have an additional special role (besides the usual ICAAP roles): it can be used as a kind of training for the IRB approach application in the regulatory credit RWA calculation.

Phase 3: After a successfully finished phase 2, the bank can continue with the IRB approach implementation, i.e. its foundation (FIRB) version. This demanding process can last for years and it should result in, inter alia, with regulatory credit RWA calculation based on the FIRB approach. AI and ML techniques can be helpful in this process, especially for PD.

Phase 4: If the bank successfully finishes FIRB approach enforcement in the regulatory credit RWA calculation, it can think about advanced IRB approach implementation (focus on LGD, etc.) and the help of AI and ML in this process.

If the bank is already using FIRB or AIRB approach, it can use the AI and ML techniques for its improvement, comparison, additional tests, validation, etc.

The stated process of AI and ML implementation in the credit RWA calculation can last for many years, especially due to the demanding FIRB and AIRB approach application in the regulatory credit RWA calculation. AI and ML can be very helpful in this process.

On the other hand, institution need to deal with challenges and open questions, like those related to the model risk ("black box" issues), data availability, gathering and protection, transparency, ethics, and availability of skilled staff to develop and implement new techniques. A well-structured AI and ML strategy and project enforcement with a clear and detailed plan ensure the necessary resources and the involvement of all indicated elements can be helpful in dealing with the mentioned challenges.

We end this chapter with a hypothetical model: an example of a gradual (phased) stress testing AI and ML implementation, combined and compared with an existing stress testing.

Table 1: Hypothetical example of the phased AI and ML stress testing inclusion in the ICAAP

in million EUR

Phase	Reporting date	Risk category	Stress test ICAAP capital requirement based on standard tools	Stress test ICAAP capital requirement based on AI and ML	Stress testing of capital requirement to be included in the ICAAP for the stated reporting period
T	30/06/2020	credit risk	100	95	100
T	30/06/2020	market risk	5	4	5
T	30/09/2020	credit risk	105	110	110
T	30/09/2020	market risk	3	4	4
T	31/12/2020	credit risk	107	105	107
T	31/12/2020	market risk	4	5	5
T+1	3X/X/2021	credit risk	Can be incorporated in the existing stress test	Can be incorporated in the existing stress test	110
T+1	3X/X/2021	market risk	Can be incorporated in the existing stress test	Can be incorporated in the existing stress test	4

Source: Authors

In this hypothetical example, one of the potential phased and measured approaches is prepared and presented. It is assumed that, in the initial phases, the financial institution is testing few AI and ML techniques for the stress test and compares them against the standard stress test techniques which are already applied in this institution. The moment the bank is of opinion that one of the ML techniques (e.g. DL) can be adequate for the ICAAP inclusion, the "T" phase starts. During the "T" phase, a careful approach is applied, i.e. higher value between two stress tests (standard and ML) is used in final ICAAP calculation for the stated period. Here the bank is continuing various analyses of the ML stress test trustworthiness. At one moment (start of the "T+1" phase), the financial institution can decide that to have one unique stress test for the ICAAP, which is combined from the best ML and standard stress test elements. It can be valid for both presented risks (credit and market), but it is also possible for the new model to be valid just for one risk, while other risks are continuing to be calculated with the standard tools.

3.2. Other risk management artificial intelligence and machine learning implementation

Similar conclusions and recommendations indicated for the general risk management and particularly for the credit risk management are valid also for the other risks.

For example, in the market risk management, ML is used in different areas like forecast volatility, interest rate curves, foreign currency risk estimation, and the like. Additionally, most of the stated recommendations, phases and steps relevant for credit risk management are valid also for market risk management. These primarily relate to the recommendations regarding stress tests, capital adequacy calculation and/or RWA, simulations, ICAAP, recovery plan, and internal model development. The example given in table 1 is also valid for market risk.

As for the liquidity risk management, recent research involved the application of the Artificial Neural Networks and Bayesian Networks (Leo, Sharma, and Maddulety, 2019). AI and ML can be applied in stress tests, simulations, recovery and contingency plan. New analyses, tools, techniques and reporting can be established and these can be expected to significantly contribute to the Internal Liquidity Adequacy Assessment Process (ILAAP) and Asset Liability Management (ALM) improvement. This can have a significant positive impact on the crisis management improvement, especially in the time of the current COVID-19 challenges, which also has an impact on liquidity.

Regarding the application of AI and ML in the management of operational risks and a group of related risks, significant results have been achieved worldwide in the following areas: cyber security, fraud prevention, and anti-money laundering. For example, AI and ML, i.e. their segment of unsupervised learning algorithms can provide an input to operational risk models such as the institution vulnerability to cyber-attacks. AI and ML could be used for anticipating and detecting fraud, suspicious transactions, default, and the risk of cyber-attacks, which could result in improved risk management. During the implementation, institutions need to take care of the challenges like a potential oversight of new types of risks and events because we could `overtrain` on past events by using AI and ML tools (Financial Stability Board, 2017). This is the reason for a careful implementation of new AI and ML tools, combined and compared with the standard risk management tools and techniques which the bank already uses. Also, other challenges stated for the general risk management and particularly for the credit risk management, which are valid also for other risks, need to be taken into account.

The contemporary global economic and financial challenges, including those caused by the COVID-19 pandemic have accentuated the need for adequate AI and ML implementation in risk management. The stated techniques can be helpful in combating the current challenges.

Conclusion

AI and ML have a growing influence on the banking risk management. They have a potential to support the mitigation measures for the contemporary global economic and financial challenges, including those caused by the COVID-19. Measured and well prepared further application of AI, ML, DL and big data analytics can have a further positive impact, especially on the following risk management areas: credit, market, liquidity, group of operational risks and other related areas. The paper has defined recommendations and proposals for a successful implementation of AI and ML in banking risk management so that maximal positive results could be achieved (simultaneously avoiding the negative ones) in the field of banking risk management, business, and economy as well. The research highlighted challenges and open questions like model risk ("black box" issues), data availability, gathering and protection, transparency, ethics, availability of skilled staff to develop and implement new techniques. The paper has underlined the importance of the comprehensive, detailed, adequate and strict AI and ML risk management strategy, operative plan and project definition and application. The paper defines a roadmap for a successful implementation presented in the hypothetical model of a phased AI and ML application in risk management. The research suggests the crucial elements for adequate application. A phased and careful approach is in the focus of the paper recommendations. All presented herein should result in enhanced risk management, cost decrease, faster processes, and improved client services. The research results can be applied in risk management development by financial institutions. The paper could have a positive influence on future similar academic research of risk management.

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