”D. A. TSENOV” ACADEMY OF ECONOMICS – SVISHTOV
DEPARTMENT “FINANCE AND CREDIT”

ANTONIO VALENTINOV DICHEV

ASSESSMENT OF FINANCIAL RISK USING MACHINE LEARNING

ABSTRACT

OF A DISSERTATION FOR AWARDING OF A PHD DEGREE IN THE PHD PROGRAM “FINANCE, MONEY CIRCULATION, CREDIT AND INSURANCE (FINANCE) ”

Scientific Supervisors:
Assoc. Prof. Aleksandar Petrov Ganchev, PhD
Assoc. Prof. Krasimira Borisova Slaveva, PhD

Svishtov
2025

The dissertation has been discussed and approved for defense in accordance with the Law on the Development of the Academic Staff in the Republic of Bulgaria by the Department of "Finance and Credit" at “D. A. Tsenov“ Academy of Economics – Svishtov, at a meeting held on 03.12.2025.

The dissertation has a total length of 197 standard pages and includes: an introduction – 9 pages; the main text, organized in three chapters – 154 pages; a conclusion – 4 pages; a list of cited and referenced literature – 120 sources; and a declaration of originality. The dissertation is illustrated with 34 figures, 43 tables, and 26 equations.

The open session of the scientific jury for the defense of the dissertation will be held on 16.03.2025 at 13:30 in the “Rectorate” Meeting Hall of “D. A. Tsenov“ Academy of Economics – Svishtov.

The defense materials are available to interested parties at the “Doctoral and Academic Development” Department of “D. A. Tsenov“ Academy of Economics – Svishtov.

I. GENERAL CHARACTERISTICS OF THE DISSERTATION

1. RELEVANCE OF THE TOPIC

The relevance of the problem analyzed in this dissertation is strongly reinforced by the exponentially increasing digitalization across all sectors in recent years, which has led to a growth in the volume of data available for research and analysis. Data and their analysis, as a basis for decision-making and management, are particularly valuable in the financial world. In a slightly narrower sense, the assessment and management of financial risk is a field that seeks to make the most objective use of the available data and information. Of particular significance are artificial intelligence technologies, including machine learning, which, when applied to large datasets, can help uncover more subtle dependencies in the process of developing risk assessment models.

2. OBJECT AND SUBJECT OF THE RESEARCH

The **object** of the dissertation is defined as financial risk.

The **subject** of the research is the specific algorithms, tools, and methods of machine learning that can be used for quantitative modeling and the development of effective instruments for assessing the main types of financial risk – credit, market, and operational.

3. RESEARCH AIM AND TASKS

The aim of the study is to reveal the potential added value of applying machine learning as a tool for assessing different types of financial risk. The approach for selecting algorithms and methods is based on a comparison between two groups of algorithms – the so-called traditionally established (classical) methods for financial risk assessment and algorithms based on machine learning.

The tasks on which the present study focuses are as follows:

- to identify the main categories of financial risk with the highest significance and potential for added value from machine learning as a tool for quantitative assessment;
- to distinguish, through a transparent and well-founded approach, between methods identified as machine learning-based and those traditionally used by the financial services sector for risk assessment;
- to examine the regulatory framework regarding the application of algorithms using artificial intelligence and machine learning in financial risk management;
- to select methods for financial risk assessment, including representatives from the machine learning group and from the classical methods group;
- to investigate and identify the main and appropriate quantitative indicators and criteria for evaluating and analyzing the performance of the various algorithms and methods;
- to appropriately apply the selected risk assessment algorithms in a manner and environment identified by the author, established practice, and literature review as having the highest potential;
- to conduct a thorough comparison of the performance of the different groups of risk assessment methods, based on comparable data samples and using an appropriate approach.

4. RESEARCH METHODOLOGY

The methodology employed in the dissertation includes the methods of theoretical analysis and synthesis, comparative analysis, risk modeling using both traditional methods and machine learning, validation analysis based on statistical tests and methods, SHapley Additive exPlanations (SHAP) analysis, and others.

5. RESEARCH THESIS

The thesis advanced in the dissertation is that the application of machine learning methods can significantly improve financial risk assessment by more easily uncovering otherwise hidden dependencies and interactions, enabling automated processing of large volumes of data, and providing the ability to quickly adapt to dynamically changing conditions.

6. LIMITATIONS OF THE STUDY

The **main limitations** under which the present dissertation is conducted are related to the fact that the analysis focuses on specific data samples, a limited set of algorithms, and only certain categories of financial risk (credit, operational, and market risk).

The limitations described above stem from considerations made by the author. Attempting to cover the full spectrum of financial risk types, their various manifestations, all possible algorithms, and multiple data samples would make the research practically unfeasible due to its scope and complexity. Consequently, the study focuses on a selected subset, and as a result, a number of algorithms and methods, other categories of financial risk beyond credit, operational, and market risk, as well as additional indicators and aspects of the analyzed risk types, are deliberately **excluded from the scope** of this dissertation. These constraints are necessary to ensure a focused, methodologically rigorous, and practically applicable study.

7. PRACTICAL APPLICABILITY

The theoretical reflections and conclusions developed in the dissertation, as well as the empirical results obtained from the research, are intended to support decision-making in the development of an effective financial risk management framework. The presented combination of methodology and technical approaches is deliberately focused on their practical applicability and potential benefits. Furthermore, the complete set of tools and methods has been applied to data samples that closely resemble real-world practices in the financial sector, ensuring that the findings are not only theoretically sound but also relevant and implementable in practice.

In the third chapter of the dissertation, a number of practical aspects related to the use of each developed model are highlighted, including the areas in which they are applied and their significance. The selection of the modeled risk indicators and aspects is entirely based on practical considerations. In other words, the chosen areas for model development and their subsequent evaluation represent some of the most material and significant segments within the financial services sector, ensuring that the research outcomes are directly relevant and applicable to real-world financial risk management.

The focus of the study is precisely on assessing the practical benefits of implementing methods that require higher investment and greater technical sophistication. The research addresses real-world challenges, such as the misuse or overstatement of the term “artificial intelligence” (so-called AI washing), and seeks to systematize a methodology through which the advantages and limitations of implementing a more complex and comprehensive risk assessment framework can be identified. This approach aims to provide a structured and evidence-based evaluation of advanced methods, ensuring that their adoption in financial risk management is both justified and effective.

The practical applicability of the study is further reinforced by the review and integration of regulatory expectations in the field. The approach used for the validation and comparative analysis is largely based on regulatory perspectives regarding the assessment of model performance in the development of risk models. This ensures that the evaluation not only reflects methodological rigor but also aligns with the standards and requirements expected in the financial sector, enhancing the relevance and credibility of the findings for practical implementation.

II. STRUCTURE AND CONTENT OF THE DISSERTATION

The dissertation has been prepared in compliance with the requirements of Art. 27, Para. 2 of the Regulations for the Implementation of the Law on the Development of the Academic Staff in the Republic of Bulgaria. It has a total length of 197 standard pages and, in terms of structure, includes:

First. An introduction of 9 standard pages.

Second. The main text, composed of three chapters, with a total length of 154 standard pages.

Third. A conclusion comprising 4 standard pages.

Fourth. A list of 120 referenced literary and online sources, of which 113 are in English and 7 are in Bulgarian.

Fifth. The dissertation is illustrated with 34 figures, 43 tables, and 26 equations.

Sixth. A declaration of originality in accordance with Art. 68, Para. 2 of the Regulations on the Development of the Academic Staff at “D. A. Tsenov“ Academy of Economics.

The introduction of the dissertation delineates the main aspects of its relevance and significance, while also defining its core scientific attributes, including the object, subject, aim, research tasks, thesis, methodology, and the limitations under which the study is conducted. In the first chapter, the dissertation explores the theoretical foundations of the primary categories of financial risk, traces the historical development of machine learning, provides a formal definition of the field, and examines the regulatory expectations and guidelines applicable to machine learning in financial contexts. The second chapter is devoted to methodological considerations. It focuses on the systematization of specific indicators used for risk assessment, their modeling through both classical approaches and machine learning algorithms, and the establishment of a structured methodology for quantitative validation and performance analysis of the developed models. The chapter emphasizes how different modeling techniques can be applied to assess various dimensions of financial risk in a rigorous and reproducible manner. The third chapter addresses the practical aspects of applying machine learning in financial risk assessment. It includes a detailed examination of the phenomenon known as AI washing (AIW), highlighting the potential pitfalls and misrepresentations in the application of artificial intelligence. The risk assessment indicators introduced in the second chapter are modeled using both standard, traditional methods and machine learning algorithms. Furthermore, a comprehensive comparative analysis is conducted between the two main modeling approaches, evaluating their performance across the different risk assessment indicators and highlighting the strengths, weaknesses, and practical implications of each approach for real-world financial risk management.

Specifically, the content of the dissertation includes the following main parts:

CONTENT

III. BRIEF DESCRIPTION OF THE DISSERTATION

INTRODUCTION

The introduction emphasizes the two main pillars of analysis around which the dissertation is developed – the assessment of financial risk and the use of machine learning for risk modeling. It examines the potential for integration between risk management and machine learning, highlighting their relevance, significance, and the necessity for continuous advancement and refinement. The key scientific attributes of the study are formulated, including the object, subject, primary aims, and research tasks of the dissertation. The defended thesis is clearly defined, alongside the main limitations and the methodology applied throughout the research. In addition, the introduction provides a detailed description of the structure and content of the individual sections of the dissertation, offering a comprehensive roadmap for the reader and situating the study within both theoretical and practical contexts.

CHAPTER I. THEORETICAL FOUNDATIONS AND CONCEPTS OF FINANCIAL RISK AND MACHINE LEARNING

Chapter I establishes the fundamental theoretical foundation of the research. It provides a comprehensive review of the main types of financial risk and presents the definition of machine learning (ML), which serves as the cornerstone for the dissertation study. Current research on machine learning and its role in risk assessment is systematically analyzed and synthesized, offering a thorough overview of developments and insights in the field. Special attention is given to the regulatory framework concerning artificial intelligence and machine learning as tools for risk assessment, highlighting the expectations, guidelines, and standards that shape their practical application in financial risk management. This chapter thus lays both the conceptual and contextual groundwork necessary for the methodological and empirical work that follows in the dissertation.

The chapter begins with the definition and systematic categorization of the various types of financial risk from both theoretical and practical perspectives within the banking sector, including market, credit, operational, liquidity, strategic, business, and reputational risk. Special attention is given to ESG (Environmental, Social, and Governance) factors, examining their nature and manifestations as sources of financial risk. This discussion emphasizes how ESG considerations are increasingly recognized as integral components of comprehensive risk management, influencing both decision-making processes and the stability of financial institutions.

For the purposes of this study and its defined object, the author develops a comprehensive definition of machine learning by drawing upon both the academic literature and the perspectives of practitioners and regulators in the field. The historical development of machine learning is carefully traced and systematically organized, providing crucial context for constructing a definition that accurately reflects the modern understanding of machine learning as it is interpreted and applied in practice over recent years. This analysis highlights the evolution of methodologies, conceptual frameworks, and applications that have shaped current approaches. From a regulatory standpoint, as well as in general industry practice, the fundamental meaning and understanding of machine learning remain largely consistent; however, a more narrowly defined scope has emerged and is increasingly adopted in regulatory and practical contexts. This narrower interpretation delineates specific methodological boundaries, operational applications, and criteria for acceptable use, particularly in risk assessment and financial modeling. The author adopts this precise, carefully contextualized definition of machine learning as the guiding framework for the dissertation, ensuring that the study remains aligned with both contemporary theoretical developments and practical regulatory expectations.

Although there are numerous studies dedicated to the use of machine learning for risk assessment, many of them lack a theoretical framework that traces the evolution of algorithms or fail to emphasize the key differences between them. Moreover, practical aspects are often overlooked. A notable example in some cases is the use of performance evaluation metrics that are not suitable for imbalanced data samples, which can lead to misleading conclusions about the effectiveness of certain models.

From the review of the literature, it is evident that most research has focused on credit and market risk assessment. In recent years, however, there has been increasing attention on additional topics such as the risk of revenue and client loss, as well as natural language processing applications, including sentiment analysis and textual data evaluation. This indicates a gradual broadening of the scope of research in machine learning for financial risk, moving beyond traditional quantitative indicators to incorporate more complex, real-world phenomena that influence financial stability and decision-making processes.

The study seeks to address these gaps by providing a comprehensive theoretical perspective on the evolution of algorithms, emphasizing practical aspects, and employing more appropriate performance metrics for evaluating different algorithms. At the same time, it subjects the demonstrated results to a critical analysis through the lens of their actual added value and the resources required for their development and implementation. This dual approach ensures that the research not only advances theoretical understanding but also rigorously evaluates the feasibility, efficiency, and real-world applicability of machine learning methods in financial risk assessment, highlighting both their potential benefits and practical limitations.

The final part of the chapter examines the regulatory context in which financial institutions are expected to implement machine learning. This review of existing norms and documents covers the most significant regulatory steps in this area. Among these, the most prominent is the so-called Artificial Intelligence Act (AI Act) of the European Union, which establishes a legal framework for the development and use of AI, including machine learning, in various sectors. Equally important are the principles and guidelines issued by the European Central Bank (ECB) regarding the construction of risk management models that utilize machine learning and artificial intelligence in general. At a higher managerial level, numerous documents from the European Banking Authority (EBA) are highlighted, emphasizing key aspects such as interpretability, model governance, and managerial accountability. These regulatory frameworks collectively guide financial institutions in ensuring that machine learning applications are not only effective but also transparent, responsible, and compliant with European standards, providing both operational and strategic safeguards for risk assessment processes.

From the work conducted in Chapter One, it becomes clear that materialized forms of financial instability, such as bankruptcies and other crises, often lead to subsequent corrective measures, lessons learned, and a reassessment of established practices. Frequently, these events are underpinned by financial risks that were either poorly assessed or inadequately managed. Risk assessment, therefore, holds a decisive and emphasized significance in maintaining financial stability. Traditionally, this task has relied on mathematical and statistical methods and techniques, which have proven historically effective and have added measurable value to financial decision-making processes. In recent years, however, the enthusiasm surrounding artificial intelligence and machine learning has raised questions about their application across nearly all areas of finance and business. It is increasingly recognized that machine learning has the potential to enhance the reliability of internal models, yet it simultaneously demands rigorous validation, thorough documentation, and ethical usage. This underscores the dual challenge of leveraging advanced technologies: capturing their added value while maintaining compliance, transparency, and accountability in practical financial risk management.

From the historical review of the development of artificial intelligence, it becomes evident that the methods classified as machine learning did not emerge only in the past five, ten, or even twenty years. What has been observed in recent years is their enhancement, increasing complexity, and widespread implementation. In fact, it can be argued that the availability of accessible and powerful computational resources has significantly fueled this rapid recent development. This perspective and understanding often remain outside the direct awareness of managers, financial directors, and governing bodies. For this reason, the author proposes a distinction that is not strictly theoretical between classical technologies and those based on machine learning, but rather one oriented toward market understanding and practical application. This perspective is further supported by a review of the regulatory framework within the banking sector in Europe. From this review, it becomes clear that machine learning is a topic of growing interest among regulatory authorities. More broadly, not limited to the financial services sector, the foundations for the European Artificial Intelligence Act have been established. These developments clearly demonstrate the importance of the subject and indicate the expectations regarding its increasing relevance in the future.

CHAPTER II. METHODOLOGICAL ASPECTS OF FINANCIAL RISK ASSESSMENT USING CLASSICAL TOOLS AND MACHINE LEARNING

Chapter Two presents the methodological framework for assessing financial risk through the integration of classical statistical methods and contemporary machine learning techniques. At the outset, the chapter systematically organizes the key quantitative indicators used in the analysis of credit, market, and operational risk. It examines fundamental regulatory and analytical metrics, such as probability of default (PD), loss given default (LGD), Value-at-Risk (VaR), and others. This detailed review establishes a robust analytical foundation that enables a structured comparison between traditional approaches and those based on machine learning, highlighting the strengths, limitations, and potential complementarities of each method in practical financial risk assessment.

The methodological review highlighted the main types of risk, along with their corresponding indicators, which are assessed and utilized in the daily operations of financial institutions. Depending on the nature of these indicators, different modeling tools are employed and applied. The distinction established in Chapter One between classical methods and machine learning approaches provides a foundation for selecting their respective representatives. The range of algorithms in both groups is extensive, and the selection must be narrowed down to a few specific representatives through which the objectives of the present study can be effectively achieved.

This selection process is supported by authoritative research and empirical data, combined with the choice of key risk indicators for assessment. In this way, the quantitative methods to be applied by the author in Chapter Three are identified, and their subsequent performance will be evaluated and compared. This structured approach ensures that the study not only adheres to theoretical

and methodological rigor but also maintains practical relevance and applicability in real-world financial risk assessment scenarios.

Within the group of traditional methods for risk modeling, logistic regression is identified as the primary approach for classification-type problems. Complementing this regression analysis and serving as its foundation, the study applies a method of grouping independent variables along with the so-called Weight of Evidence (WoE) transformation, including the calculation of the Information Value (IV) indicator. This modeling approach is widely used and well-established in practice, providing a robust framework for assessing and predicting credit and other classification-related risks. In a separate focus, the chapter also presents methods for time series analysis, which are applicable for forecasting market movements and volatility. Among these, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is highlighted as a standard and effective tool for modeling dynamic changes in financial markets, enabling institutions to estimate and anticipate fluctuations in market risk with greater precision. This combination of regression-based classification methods and time series modeling establishes a comprehensive toolkit for traditional financial risk assessment.

In the following section of the chapter, machine learning methods are presented as a modern alternative to classical models. The analysis focuses on classification-oriented algorithms, including decision trees and ensemble methods such as Gradient Boosting and eXtreme Gradient Boosting (XGBoost). For time series analysis within the machine learning domain, the study employs the DeepAR method, which is based on an autoregressive recurrent artificial neural network (Recurrent Neural Network, RNN). This approach allows for modeling complex temporal dependencies in sequential data, capturing patterns and trends that traditional statistical models may not adequately detect. By integrating both classification and time series machine learning methods, the dissertation demonstrates how advanced algorithms can complement classical

techniques in financial risk assessment, providing enhanced predictive capabilities and analytical insights.

Special attention is also given to sentiment analysis as a method for extracting information from textual sources. Sentiment analysis, also known as opinion mining, is a key technique in natural language processing (NLP) that involves identifying and extracting subjective information from text data. This process is crucial for understanding the emotional tone behind a given text, which can provide valuable insights across a variety of domains, including marketing, social media monitoring, customer feedback analysis, and financial markets. The chapter presents specific NLP techniques such as Valence Aware Dictionary and sEntiment Reasoner (VADER), Financial Bidirectional Encoder Representations (FinBERT), and Generative Pre-trained Transformer 2 (GPT-2). These tools enable the use of news streams and textual data in assessing risks associated with ESG factors, allowing financial institutions to incorporate qualitative information into their risk evaluation frameworks and to capture emerging trends and sentiment-driven influences on market and corporate risk profiles.

In machine learning, there exist so-called hyperparameters. These are settings specific to a given algorithm that are not “learned” from the data itself but determine the behavior of the model and the complexity of its architecture. In other words, even when using the same algorithm (e.g., XGBoost), it is entirely normal for different data samples to result in models with varying architectures and levels of complexity. The final values of the hyperparameters are obtained through a process aimed at finding their most optimal settings. This represents a critical and essential step in the overall application of ML algorithms. In general terms, the guiding principle is to select the combination of hyperparameter values that yields the best final results. The chapter reviews various approaches for searching for optimal values, among which the most widely applied are manual tuning, Grid Search, and Random Search. These techniques ensure that the model is both appropriately calibrated and capable of delivering reliable predictive performance across different datasets.

The analysis of the methodology emphasizes the advantages of risk assessment methods based on machine learning, which facilitate the processing of large volumes of data and offer innovative approaches to modeling and prediction. These algorithms, however, are also characterized by a significantly more complex and computationally intensive set of operations. This, in turn, introduces additional challenges, including the need for powerful computational resources, careful hyperparameter tuning, thorough validation, and comprehensive documentation to ensure both the reliability and interpretability of the results. While machine learning methods provide substantial potential for improving risk assessment, their implementation requires careful planning and management to balance performance gains with practical feasibility and resource constraints.

The concluding section of the chapter examines the quantitative methods used for model validation and evaluation. The selection of methods and metrics has been carried out in accordance with established practices for model assessment, as applied in both the scientific literature and in banking and supervisory practice. The chosen techniques represent standard benchmarks for evaluating predictive performance, while also being highly relevant to the validation and approval processes of models for capital requirements. This approach provides the foundation for an objective comparison between different algorithms and allows for an informed assessment of their applicability within the context of financial risk management. By adhering to these rigorous standards, the study ensures that the evaluation is both methodologically sound and practically meaningful, bridging the gap between theoretical analysis and real-world implementation.

Indicators of discriminatory power, such as Somers' D and the Area Under the Curve (AUC), are presented to measure the accuracy of classification models. The required and expected minimum level of discriminatory power varies depending on the type of model. Considering that, in this study and within the context of this particular measure, the focus is primarily on whether and to what extent machine learning methods contribute to higher discriminatory power, the analysis examines changes in these indicators relative to traditional algorithms, specifically logistic regression. This comparison allows for a clear assessment of the added value provided by ML techniques in enhancing the predictive accuracy and effectiveness of risk classification models, highlighting both improvements and potential limitations in practical applications.

The chapter also discusses approaches for evaluating conservatism using the binomial test, as well as traditional metrics associated with the confusion matrix, which serves as a standard tool in the assessment of classification models. The confusion matrix allows for a more detailed analysis of errors than simply reporting overall accuracy, making it particularly useful in cases of uneven class distributions or when different types of errors carry different levels of importance. The application and interpretation of these metrics must be carried out in the context of specific tasks and problems, taking into account the significance and "weight" of different types of errors. For example, in medicine and diagnostics, correctly identifying a diseased class (True Positive Rate, TPR) is far more critical than achieving high precision. In contrast, the prioritization of error types may differ in other contexts, such as identifying fake news, where the balance between false positives and false negatives carries a different set of implications. This nuanced approach ensures that model evaluation aligns with the practical objectives and risks associated with each application domain.

For models that predict continuous variables, i.e., regression models, the recognized evaluation metrics are the Root Mean Square Error (RMSE) and the Coefficient of Determination (R^2). These indicators provide insight into the accuracy of predictions and the proportion of variance in the dependent variable explained by the model, serving as standard benchmarks for assessing the performance and reliability of regression-based risk assessment approaches.

Which features carry the most weight and how they influence a model's predictions can be extremely important—sometimes on a level comparable to the model's overall accuracy. Often, the highest predictive performance on large datasets is achieved by complex models, such as ensemble methods or deep neural networks, which can be difficult even for domain experts to interpret. This creates a discussion around the added value of such models and highlights the need to balance accuracy with interpretability. In practical applications, a widely adopted solution that provides a unified framework for interpreting model results is SHAP (SHapley Additive exPlanations), which quantifies the contribution of each feature to individual predictions and allows for more transparent and actionable insights from complex machine learning models.

The assessment of algorithm accuracy and overall performance, commonly referred to in the banking sector as model validation, represents an extremely extensive and comprehensive process aimed at ensuring the reliable and informed use of models. This aspect is so critical that the European Central Bank (ECB) and other regulatory authorities have established a significant set of minimum practices, principles, and quantitative methods for conducting these activities. To enable a comparison of the performance of the two groups of algorithms, the present study applies selected guidance and principles from these regulatory frameworks, ensuring that the evaluation is aligned with established standards for rigor, reliability, and practical applicability in financial risk management.

Through the application of statistical and quantitative analyses, the aim is to determine the extent to which a given model provides an adequate and reliable assessment. The framework established in this dissertation allows for the implementation of selected aspects of established industry practices and regulatory requirements. This alignment is particularly important because numerous additional conditions arise when a model operates in a so-called "production environment," delivering real-time decisions with dynamic data and processes. The selected methods, however, represent key metrics that are

routinely subject to monitoring and control in practice. To ensure that the study remains highly practice-oriented, the dissertation applies, analyzes, and subsequently evaluates the models specifically using these validation metrics. This approach bridges theoretical modeling with practical applicability, providing a robust framework for assessing both the performance and operational reliability of the risk assessment models under real-world conditions.

In summary, the chapter establishes a coherent methodological foundation that combines classical quantitative approaches with modern machine learning techniques, offering a comprehensive framework for the assessment, validation, and interpretation of financial risk models. This foundation serves as the basis for the empirical analyses and the applied models developed in the subsequent parts of the study, ensuring that both theoretical rigor and practical relevance are maintained throughout the research.

CHAPTER III. PRACTICAL ASPECTS OF QUANTITATIVE FINANCIAL RISK ASSESSMENT. A COMPARATIVE ANALYSIS OF PERFORMANCE BETWEEN CLASSICAL AND MACHINE LEARNING METHODS

Chapter Three is dedicated to the construction (modeling) of financial risk assessment models using both classical statistical approaches and contemporary machine learning methods. Based on the results obtained from individual methods and algorithms, a comparative analysis is conducted. The primary focus is placed on the actual performance of the models, the distinction between marketing claims and real effectiveness, and the necessity of a critical perspective on the so-called “AI washing” phenomenon, where technologies with low added value are presented as cutting-edge machine learning solutions.

Like any market-driven euphoria, machine learning methods also generate challenges. These problems are typically associated with a poor understanding of the technology, difficulties in assessing the actual added value, slower development of the regulatory framework, and, importantly, the lack of consensus around the definition of artificial intelligence. Within this context, the chapter delineates the scenarios in which machine learning genuinely contributes to better risk management and identifies cases in which classical methods continue to outperform or remain preferable. This balanced perspective ensures that the analysis is both realistic and practically relevant, highlighting where advanced techniques can enhance decision-making and where traditional approaches retain their proven value.

To achieve practically applicable and scalable results, this study focuses on several key aspects of risk management that allow for quantitative modeling and subsequent empirical analysis. The selection of these focus areas is the result of a preliminary review of relevant practices and scientific research in the field of financial risk management. Based on this review, four main categories of risk have been identified as having the greatest potential for analysis using machine learning methods: credit risk, market risk, operational risk (particularly fraud risk), and ESG risk. These categories provide a structured and meaningful framework for applying both classical and advanced modeling techniques, ensuring that the research addresses areas of high relevance and impact in real-world financial risk assessment.

The approach undertaken is deliberately focused on the pragmatic aspect—within each of these areas, a specific characteristic has been selected that is quantitatively measurable, amenable to modeling, and suitable for comparative analysis. This design allows not only for a solid theoretical justification but also for a practical demonstration of the applicability of different machine learning algorithms in risk management. By grounding the analysis in measurable and operationally relevant features, the study ensures that the insights gained are directly translatable to real-world financial decision-making and can guide practitioners in selecting and implementing appropriate modeling techniques.

A significant part of the analysis is devoted to modeling the probability of default (PD), where models are examined in parallel through the lens of logistic regression—as a traditional and regulatorily recognized method—and machine learning algorithms such as Gradient Boosting and XGBoost. Their discriminatory power, interpretability, performance in the confusion matrix, and other relevant metrics are analyzed in detail. The study draws conclusions regarding the significance and practical applicability of these models in credit risk management, highlighting the added value provided by advanced machine learning approaches while also considering the robustness and regulatory compliance of classical methods.

The next section analyzes the modeling of Value-at-Risk (VaR) through a comparison between classical approaches, based on the GARCH model, and machine learning–based techniques that utilize neural network architectures, specifically DeepAR. The analysis examines the extent to which machine learning can improve the predictive accuracy of VaR, as well as the cases in which the more complex architecture and implementation of machine learning methods do not provide additional value. This comparison highlights both the potential advantages and the practical limitations of ML approaches in market risk assessment, emphasizing the importance of matching model complexity to the nature of the data and the specific forecasting objectives.

Additionally, the study investigates the construction of models for detecting fraud in card transactions as a representative example of operational risk management. The methods and models employed are similar to those used for modeling the probability of default, as the problem is again of a classification nature. This allows for the application and comparison of logistic regression, Gradient Boosting, and XGBoost, assessing their performance, interpretability, and effectiveness in identifying fraudulent activity. The analysis provides insights into how machine learning can enhance operational risk controls while also highlighting the practical considerations and limitations of deploying such models in real-world transactional environments.

The final section of the chapter addresses ESG risks through the modeling of ESG ratings for companies in the S&P 500 index. Approaches for extracting ESG information are presented, including the use of textual data, statistical models, and machine learning techniques for predicting ratings and assessing long-term risks. This analysis demonstrates how combining structured and unstructured data with advanced modeling methods can provide actionable insights into ESG-related exposures, supporting risk management decisions and highlighting the potential of machine learning to capture complex, non-financial factors that influence corporate sustainability and long-term performance.

The significance of machine learning methods is confirmed by the results obtained, which demonstrate their field of applicability. The validated models in this study show that, for the most part, the applied machine learning algorithms outperform the less complex models, such as logistic regression and GARCH. The improvements are particularly notable for algorithms applied to classification-type problems, where ML techniques provide a substantial gain in predictive accuracy, discriminatory power, and the ability to capture complex patterns that traditional models may overlook. These findings underscore the practical value of machine learning in enhancing financial risk assessment across multiple domains.

The applied NLP techniques not only failed to improve the results but in some cases produced worse outcomes. This should not be interpreted as a flaw in the methods or the underlying technology, but rather as an issue that requires further investigation—potentially involving larger datasets, a greater number of observations, alternative data samples with more homogeneous characteristics, or other adjustments. Such limitations highlight the importance of data quality, volume, and representativeness when applying natural language processing methods to financial risk assessment, indicating that careful experimental design and additional research are needed to fully realize their potential.

During the development process and subsequent analysis of the results, some of the shortcomings of machine learning algorithms, as identified by the European Banking Authority (EBA), are confirmed:

- the complexity of the models, which leads to challenges in explaining the resulting outputs;
- lack of traceability and adequate understanding regarding the objectives of managerial functions;
- frequent occurrences of so-called overfitting;
- difficulty in ensuring sufficiently qualified personnel.

Some of the synthesized advantages and disadvantages mentioned above have been noted in publications, seminars, training sessions, and regulatory documents. However, their scope and magnitude often depend on the specific domain of application and the objectives set. In light of the predominantly superior results from quantitative analysis and validation, the expectations associated with machine learning methods are largely confirmed. Nevertheless, this additional precision is accompanied by the following challenges during and after the application of ML:

- complex model architecture, requiring the optimization of multiple hyperparameters, including their impact on results;
- difficulty in determining the optimal number of iterations for searching the most suitable hyperparameters;

- uncertainty regarding whether the identified optimal parameters are truly optimal or merely in a so-called local optimum[1];
- slower and more challenging model development compared to classical approaches. For example, optimizing parameters for DeepAR took approximately 80 hours (including computational time), whereas GARCH required only about 3 hours due to far fewer and simpler parameters;
- hyperparameter optimization heavily depends on the experience and knowledge of the person applying the machine learning algorithms, making the identification of an absolute or global optimum a difficult task;
- the total computation time for all evaluations during the analyzed period for DeepAR averaged 220 minutes per currency pair/instrument, while GARCH required significantly less time (approximately 0.5 minutes on average)[2]. This allows for daily calculation of DeepAR-based VaR, but it remains considerably slower compared to GARCH;
- model complexity necessitates a substantial amount of processing, analysis, and expertise to reliably explain the resulting outputs.

It is important to emphasize that the reported results are based on specific data samples and a limited set of algorithms. Using a different dataset or including additional algorithms could yield different outcomes. Artificial intelligence methods are generally expected to perform more effectively with large and unstructured datasets. Applying different data or alternative preprocessing techniques may lead to varying results and conclusions. A critical

[1] Note: This refers to a point in the parameter space where a combination of values yields better results compared to neighboring points. However, the global optimal point in the entire space may be located elsewhere.
[2] Note: The results depend significantly on the computer configuration used, as well as the final architecture achieved for both models.

factor is feature engineering, which plays a significant role. Identifying interactions and combinations between variables, creating new features, and employing similar techniques can enhance the performance of all applied algorithms and may even produce different findings in the comparative analysis.

CONCLUSION

The conclusion presents, in a synthesized manner, the main theoretical and empirical results of the conducted dissertation research. It clearly and logically defines the findings concerning the object of study. In a concise and systematic form, it reviews the achievement of the dissertation's established goals and tasks.

In pursuit of the dissertation's stated objective, four research hypotheses were formulated and tested, addressing the significance, performance, comparative advantages, and challenges of machine learning algorithms in the context of financial risk management. Based on this framework and the conducted study, several conclusions were drawn through the dissertation.

The conducted theoretical and empirical analyses confirm that machine learning tools are increasingly playing a role in economic processes, particularly within the financial sector. The study demonstrated that the effectiveness of machine learning should be evaluated in the context of its application and the resources available. Classical models, although simpler, often offer faster implementation, easier interpretability, and lower computational cost—without necessarily compromising performance. Therefore, the choice between ML and traditional approaches should be informed, context-dependent, and based on empirical indicators.

The comparative analysis between classical methods (such as logistic regression and GARCH) and machine learning algorithms (such as XGBoost) revealed that some of the more complex models indeed demonstrate superior performance, particularly in classification-type tasks. High values of discriminative power (AUC, Somers' D) highlight the superiority of certain ML algorithms in terms of predictive accurac

Although cases of significant performance improvement were observed, instances were also identified where there was no improvement or where the added value was relatively limited. This aspect was particularly notable in forecasting ESG ratings through the analysis of financial news text using NLP techniques. While this finding primarily applies to the specific data and modeling subject, it is fully relevant for practice and serves as an example of a situation where integrating complex methods such as NLP may not yield added value—in fact, it may be counterproductive. A similar case arises with VaR in relation to equity position risk: GARCH estimates are sufficiently conservative according to the applied tests, whereas DeepAR, although producing fewer breaches, is markedly more conservative. This implies allocating more capital and resources and, at times, missing potential opportunities.

The practical results from the comparative analysis confirm that ML models can achieve higher precision, but often at the cost of additional complexity and constraints. This highlights the need for a careful weighing of benefits against costs when implementing ML models in real-world practice. Machine learning is not a temporary technological trend but a natural stage in the evolution of quantitative methods. Many of the algorithms in use have historical roots in classical statistics and have evolved thanks to increasing computational capabilities. The regulatory framework in Europe demonstrates a growing interest in applying artificial intelligence in the financial sector, while simultaneously imposing requirements for transparency, explainability, and ethical use.

IV. GUIDELINES FOR FUTURE RESEARCH ON THE TOPIC OF THE DISSERTATION

With the main research directions outlined in the dissertation, the issue of assessing financial risk through machine learning is by no means exhausted. The topic remains highly relevant, and the following avenues can be identified for future research:

1. Exploration of the possibilities for risk assessment in additional aspects of financial risk, based on the most reliable and up-to-date datasets.
2. Expansion of the scope of studied algorithms, methods, and aspects of model performance.
3. Although the study was conducted using highly realistic, practice-derived methods and data, potential collaboration with institutions willing to participate in similar research in a real-world environment could be sought. This would increase the validity of the conclusions and findings even further.

V. REFERENCE ON THE SCIENTIFIC AND SCIENTIFICAPPLIED CONTRIBUTIONS IN THE DISSERTATION

Based on the results achieved in the dissertation, the following scientific contributions can be formulated:

First. A systematic analysis of the concept of financial risk assessment using machine learning tools has been carried out. As a result, the key risk categories have been identified, their role in building models for financial resilience has been established, and it has been demonstrated that machine learning acts as a key catalyst for innovation in the study of economic and financial processes.

Second. Through empirical analysis, it has been revealed that, in the majority of cases, risk assessment models based on machine learning demonstrate significantly better performance compared to those based on traditional methods. This, in turn, validates the expectations placed on machine learning–based tools.

Third. The dissertation delineates the applications, resource constraints, and scenarios in which machine learning–based financial risk assessment models are not sufficiently effective, including in comparison with classical models. This underscores the need for their highly precise contextual selection and application.

Fourth. Through extensive empirical analysis, key challenges and limitations in the practical implementation of machine learning–based financial risk management models have been identified. The study concludes that this toolkit is not a temporary technological trend, but a legitimate and, in practice, novel evolutionary stage in the development of quantitative methods in finance.

VI. LIST OF PUBLICATIONS OF THE STUDENT

Scientific articles:

1. Dichev, A., Zarkova, S., & Angelov, P. (2025). Machine Learning as a Tool for Assessment and Management of Fraud Risk in Banking Transactions, Journal of Risk and Financial Management, 18(3), p. 130. https://doi.org/10.3390/jrfm18030130
2. Dichev, A. (2023). Discriminatory power in assessing probability of default using selected machine learning algorithms. Economic Archive, ISSN: 2367-9301, iss. 4, p. 17-30. https://doi.org/10.58861/tae.ea-nsa.2023.4.02.en
3. Dichev, A. (2023). Machine learning in Value-at-Risk as an assessment of market risk – advantages and disadvantages. Annual Almanac "Scientific Research of doctoral students"., ISSN: 1313-6542, iss. XVI (https://www2.uni-svishtov.bg/almanahnid/title.asp?title=3048)

Scientific reports:

1. Dichev, A. (2025). Ethics in the Age of Artificial Intelligence: “AI Washing” (AIW). Proceedings of the Scientific Conference “Knowledge, Science, Innovation, Technology” 2025, ISSN: 2815-3480, c. 446-456

VII. DECLARATION OF ORIGINALITY

in accordance with Art. 68, Para. 2 of the Regulations on the Development of the Academic Staff at "D. A. Tsenov" Academy of Economics

I, the undersigned Antonio Dichev, with doctoral student number D010223294, hereby declare that:

First. The doctoral dissertation entitled *"Assessment of Financial Risk Using Machine Learning"* is my own, original, and authentic scientific work, presenting my own ideas, analyses, texts, and commentary, based on reliable information corresponding to objective truth.

Second. In the preparation of this doctoral dissertation, the requirements of the Law on the Development of the Academic Staff and the Copyright and Related Rights Act have been fully observed.

Third. The scientific results obtained, described, and/or published by other authors have been cited in the text of the dissertation in accordance with established standards and are duly listed in the dissertation's bibliography.

Fourth. The results achieved in my dissertation and its contributions have not been borrowed from research or publications in which I did not participate.

Svishtov ______________________________

23.12.2025 /Antonio Dichev/