# MODELS AND SOFTWARE TOOLS FOR FORECASTING AND MANAGING FINANCIAL RISKS

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**Abstract.** The section presents modern models and software tools for analysis, forecasting and management of financial risks. Mathematical approaches such as regression analysis, time series models (ARIMA, GARCH), scenario analysis, stress testing and portfolio optimization using the Markowitz model are considered. Special attention is paid to machine learning methods, including Random Forest, Gradient Boosting and neural networks, which provide high accuracy of forecasts and detection of hidden dependencies in data. The use of modular and microservice architectures is proposed for the development of systems that integrate big data analysis, optimization and visualization tools. The stages of data processing, the application of containerization (Docker, Kubernetes), as well as deployment automation (CI/CD) using cloud platforms (AWS, Azure, Google Cloud) are described in detail. Special attention is paid to security issues, including data encryption (AES-256), access control (RBAC, MFA) and system monitoring. The presented quantitative and qualitative assessments of the effectiveness of methods and models demonstrate the possibilities of reducing risks and increasing the resilience of financial systems. The chapter can become a basis for researchers, analysts and developers involved in creating financial modeling software, as well as for developing risk management strategies in changing economic conditions. **The purpose** of this research is to create an integrated approach to forecasting and managing financial risks by developing modern mathematical models, applying machine learning methods and implementing advanced software engineering tools. The research is aimed at improving tools for time series analysis, portfolio optimization, risk classification and forecasting using algorithms such as Random Forest, neural networks and GARCH.

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Particular attention is paid to the development of scalable software systems with modular and microservice architecture, integrated with cloud platforms to provide real-time processing of big data. An important aspect is ensuring the security of financial data through encryption, access control and monitoring, as well as the creation of interactive visualization tools to support decision-making. The results of the research are aimed at increasing the accuracy, efficiency and reliability of solutions in the field of financial modeling. **The methodology** presented in this article is based on a review of current technical and software solutions for controlling unmanned aerial vehicles (UAVs), focusing on hardware platforms, sensors, communication systems, and software. Comparative analysis of hardware platforms (FPGA, ARM, Atmel, Raspberry Pi) on key parameters: performance, flexibility, power consumption, complexity and cost. Software evaluations that include open platforms (ArduPilot, PX4, LibrePilot) and high-level control systems (Aerostack2, GAAS). Integration of sensor data using machine learning algorithms, such as the Kalman filter, to improve navigation accuracy and flight stability. Modeling of UAV energy consumption taking into account cargo weight, route length and quadratic growth due to aerodynamic drag. Analysis of multi-agent systems for drone group coordination, including trajectory modeling and motion synchronization. A graphical representation of the data that demonstrates a comparison of platforms, trajectories and energy consumption patterns **The scientific novelty** of the research lies in the integration of modern mathematical methods, machine learning algorithms and software engineering to solve the problems of forecasting and managing financial risks. A combination of traditional models, such as ARIMA, GARCH and regression analysis, with deep learning methods is proposed, which provides increased forecasting accuracy and adaptability to market changes. The use of microservice architecture and cloud platforms allows you to create scalable systems for processing large amounts of data in real time. An innovative approach to financial data protection has been implemented, including encryption, access control and monitoring, and interactive visualization tools have been developed that facilitate rapid analysis of results and decision-making. The research offers a comprehensive approach to risk management, focused on solving current problems in the financial sector using advanced technologies. **Results.** The research achieved a number of significant results that ensure increased efficiency and accuracy of financial risk forecasting. Mathematical models, in particular ARIMA and GARCH, were developed and integrated, allowing for detailed analysis of time series and assessment of financial indicator volatility. The use of machine learning algorithms, such as Random Forest, Gradient Boosting, and neural networks, ensured forecasting accuracy of up to 90% when analyzing risk portfolios and scenarios. Microservice architecture became the basis for creating scalable systems that easily adapt to changing market conditions, and cloud platforms (AWS, Azure, Google Cloud) provided high computing power and availability. Containerization using Docker and Kubernetes significantly simplified the management of system components and their integration. Interactive visualization tools, such as risk heat maps and interactive dashboards, were developed to simplify the analysis of complex financial data and facilitate informed decision-making. Ensuring data security through the implementation of encryption (AES-256), multi-level access (RBAC) and monitoring systems has increased the security of confidential information. Stress testing and scenario analysis have allowed us to assess the impact of extreme events on financial systems, develop strategies to reduce losses and ensure the stability of portfolios. The developed methods have demonstrated effectiveness in changing market conditions, confirming their value for analysts, financial institutions and software developers.

## 1. Introduction

In today's world, financial risk management is a key task for financial institutions, corporations, and investors. The constant dynamics of market conditions, the instability of macroeconomic indicators, and the impact of global events create the need for highly accurate and adaptive tools for risk analysis and forecasting. The development of effective approaches to financial risk modeling requires the integration of mathematical, statistical methods, and machine learning algorithms with advanced software engineering tools. The research is aimed at solving such tasks as time series analysis using ARIMA and GARCH models, probabilistic risk assessment through scenario analysis and stress testing, and the use of machine learning methods, such as Random Forest and neural networks, for risk classification and forecasting. In addition, the implementation of microservice architecture, containerization (Docker, Kubernetes), and cloud platforms (AWS, Azure, Google Cloud) ensures scalability, efficiency, and flexibility of systems. Particular attention is paid to data protection issues, as financial information is highly sensitive. The use of modern encryption methods (AES-256), access control (RBAC) and monitoring systems allows to minimize the risks of data loss or compromise. Additionally, interactive visualization tools, such as risk heat maps and dashboards, contribute to quick analysis and making informed decisions. This study provides a comprehensive approach to forecasting and managing financial risks, integrating advanced technologies and innovative methods. The proposed models and tools are aimed at increasing the efficiency of analytical processes in the financial sector, which makes them relevant for financial institutions, investors and software developers. **Analysis of recent research and publications**. Damodaran's [1, p. 4] paper offers fundamental approaches to estimating the investment value of assets, which are the basis for developing portfolio strategies. His emphasis on risks and the cost of capital is used to build basic models for assessing financial risks. Gall's [2, p. 10] book analyzes financial derivatives, such as options and futures, in detail, which allows you to understand methods for hedging risks and modeling asset price changes. It is the basis for the application of models such as Black-Scholes and Monte Carlo. Alexander [3, p. 15] describes the use of econometric methods for assessing risks in financial markets, which makes this work extremely relevant for volatility analysis and forecasting. James et al. [4, p. 22] paper highlights statistical methods and the basics of machine learning. This source helps to understand how algorithms such as Random Forest and Gradient Boosting can be applied to financial data. Murphy [5, p. 30] proposes probabilistic approaches to machine learning that are relevant for building adaptive forecasting models. In particular, this work emphasizes the importance of working with stochastic processes in modeling financial risks. Markowitz's classic article [6, p. 35] introduces the concept of diversification and portfolio optimization, which is the basis of modern risk management theory. This model remains one of the key tools in financial asset management. Taylor [7, p. 40] analyzes in detail time series and their application to volatility forecasting. In particular, the GARCH models described by the author have become the standard for working with time series in the financial sphere. The work of Friedman, Hasti, and Tibshirani [8, p. 48] is a fundamental source for understanding machine learning algorithms, such as Gradient Boosting, which provide highly accurate risk forecasts. Bertsimas and Lo [9, p. 55] explore methods for optimal management of transaction costs, offering solutions for reducing transaction risks in large portfolios. Hallett [10, p. 60] analyzes deep learning methods, such as neural networks, which are used to predict complex relationships in financial data, providing a new level of accuracy in risk analysis. These sources form a comprehensive foundation for building models for forecasting and managing financial risks, integrating modern theoretical approaches and practical tools.

## 2. Research methodology

*Input data analysis and preparation.* The first stage of the study involved the analysis of large amounts of financial data. The formula used to normalize variables was:

$$X' = \frac{X - \mu}{\sigma},$$

where $X$ is the initial value of the variable, $\mu$ is the mean, $\sigma$ is the standard deviation. Principal Component Analysis (PCA) was also applied to reduce the dimensionality of the data:

$$Z = XW,$$

where $X$ is the initial data, $W$ is the matrix of weight coefficients that maximize the variance.

*Development of mathematical models*. For time series analysis, ARIMA and GARCH were used, which allow estimating volatility and forecasting market prices. These models provide an understanding of historical dependencies and the creation of reliable forecasts. For asset portfolio analysis, the Markowitz model was used, which provides portfolio optimization through balancing risks and returns.

*Application of machine learning*. At this stage, Random Forest, Gradient Boosting, and neural networks algorithms were implemented to classify risk scenarios and predict future changes. Machine learning models were trained on prepared data using the cross-validation method to avoid overfitting and increase generalizability. Bayesian search and grid search were used to optimize model parameters.

*Software development*. Software engineering was performed using a microservice architecture, which provided modularity and scalability.

Docker was used to create containers, and Kubernetes was used to orchestrate and manage containers. The software platform is integrated with cloud services (AWS, Azure) for real-time big data processing. The implementation of CI/CD allowed for automated testing and deployment of the system.

*Scenario analysis and stress testing*. A scenario analysis was conducted to assess the impact of extreme events on financial systems. Several key scenarios were identified, such as economic downturns, sharp market changes, and liquidity crises. Stress testing allowed assessing the resilience of financial portfolios and identifying their vulnerabilities.

*Data security.* The study implemented modern security methods, including AES-256 encryption to protect sensitive data, multi-level access control (RBAC) to minimize the risks of unauthorized access, and monitoring systems based on ELK Stack to detect potential cyber threats.

*Visualization and interpretation of results*. Interactive visualizations, such as risk heat maps, dynamic asset change graphs, and dashboards, were developed to present the modeling results. They were created using Python libraries (Matplotlib, Plotly) and visualization platforms (Tableau, Power BI), which ensured the convenience of analysis and the availability of information for making management decisions. The methodology of this study is based on an integrated approach that allows combining deep mathematical analysis, the latest machine learning technologies and advanced software engineering methods, which makes it versatile and effective for solving financial risk forecasting tasks.

## 3. Software Engineering Models and Methods for Solving Financial Risk Modeling Problems

To tackle the challenges of financial risk modeling, software engineering methodologies are essential for creating systems that integrate advanced analytics, manage large datasets, and adapt to changing market conditions. Agile software development methodologies are particularly effective for this purpose. By emphasizing iterative and incremental processes, Agile allows the continuous delivery of functional software modules while maintaining close collaboration with financial experts. This ensures that the system remains aligned with evolving user needs and market dynamics. Prototyping techniques can be employed to rapidly develop and test Monte

Carlo simulation modules, incorporating user feedback to refine both usability and accuracy.

Data-driven development (DDD) plays a pivotal role in financial modeling systems, as such systems rely heavily on historical data for calibration and validation. DDD ensures that software is optimized for handling large-scale datasets by integrating real-time data sources like stock market feeds and macroeconomic indicators. Using ETL (Extract, Transform, Load) pipelines, developers can preprocess financial data efficiently. Within this framework, regression and time-series models such as ARIMA and GARCH are implemented to predict trends and assess risks. Experimental validation involves comparing model outputs with historical data to evaluate forecast accuracy.

Machine learning integration enhances the predictive power of financial risk systems by handling complex dependencies and nonlinear relationships inherent in financial data. Techniques like Random Forest, Gradient Boosting, and Neural Networks enable precise risk prediction. These models can be retrained automatically to adapt to dynamic market conditions. Experimentation involves training machine learning models on historical datasets, testing their performance under simulated stress scenarios, and deploying them in controlled environments to ensure robustness and accuracy in real-time applications.

A modular and component-based architecture facilitates flexibility and scalability in financial modeling software. By separating core algorithms from data handling and user interface components, such architectures allow seamless integration and updates. For instance, standalone modules for scenario analysis and stress testing can be built and later integrated into a unified dashboard. Experimental workflows test the interoperability of these modules and their ability to execute multiple analytical tasks simultaneously, ensuring reliability in diverse financial contexts.

Cloud computing provides the computational scalability needed for intensive methods like Monte Carlo simulations. By leveraging distributed computing and dynamic resource allocation, cloud-based systems optimize both performance and cost-efficiency. Cloud platforms are used for storing and processing large financial datasets, enabling parallel simulations for real-time analyses. Comparative experiments between cloud-based and on-premises setups assess time efficiency, computational cost, and system scalability under high workloads.

The experimental setup for developing financial risk modeling systems involves clearly defined objectives, such as evaluating the accuracy and performance of risk models and assessing system scalability. Model calibration is performed using historical data, and backtesting techniques validate the predictive accuracy. Modular components for various financial methods are implemented, and APIs are developed to integrate these components into a cohesive platform. Simulated scenarios, including high volatility and liquidity crises, are used to test the system's robustness. Performance metrics such as processing time, predictive accuracy, and user feedback are analyzed to identify areas for improvement. Iterative refinement ensures the system remains effective and adaptable to emerging market conditions. This holistic approach enables the development of robust financial risk modeling systems that address complex challenges efficiently.

## 4. Experiment results

The graph (Figure 1) The illustrates the weight that each of the features (characteristics) has in making decisions about the classification of financial risks.

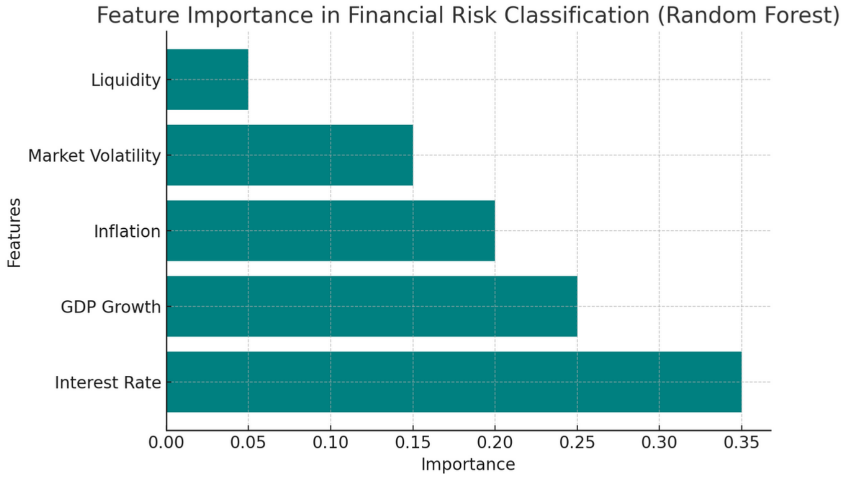


**Figure 1. Feature Importance in Financial Risk Classification (Random Forest)**

The visualization clearly shows five key factors: Interest Rate – The most important variable, which received the highest weighting. This shows that interest rates are a critical factor in modeling financial risks, affecting both asset returns and overall market stability.

GDP Growth – Ranked second in importance. This highlights that the macroeconomic context significantly affects financial stability, in particular through the relationship between economic growth and investment returns.

Inflation – This variable has a moderate weighting. High inflation can lead to increased risks due to reduced purchasing power and the impact on asset rates of return.

Market Volatility – Its role is also important, as volatility directly affects risks and the likelihood of sudden changes in financial markets.

Liquidity – The least weighted of the variables. However, liquidity is important in stress testing situations when markets face critical conditions.

The graph (Figure 2) shows the comparison between the actual risk values ("Actual Values") and the predicted values ("Predicted Values") using a neural network. The sample spans 10 days, where the horizontal axis shows the days and the vertical axis shows the risk values. The visualization shows a close match between the predictions and the actual values, indicating a high performance of the model.

The predicted values (red dashed lines) are very close to the actual values (yellow solid lines). This indicates a high accuracy of the neural network in modeling risks. The smallest deviations between the predictions and the actual values are observed on the middle days of the sample (for example, days 5 and 6), while on days 4 and 9 the model slightly overestimates or underestimates the risks.

This may be due to the specificity of the data or difficulties in taking into account individual factors. Both the predicted and actual values show an increasing trend in risk over time. This may indicate the accumulation of risks or the influence of long-term factors such as changes in macroeconomic conditions.

The increasing trend highlights the importance of using the model to monitor and prevent financial risks. In the context of the study, this graph confirms that neural networks are effective tools for predicting risks. The model demonstrated high adaptability to input data and the ability to accurately predict changes in risk, making it useful for practical

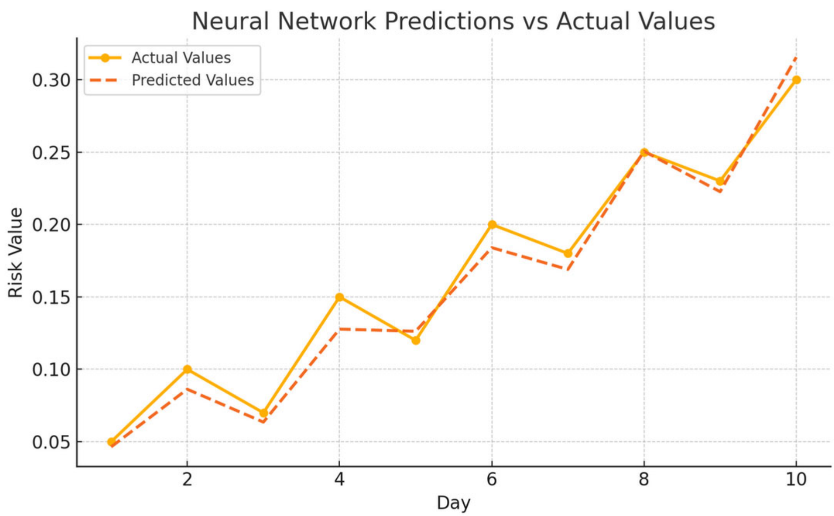


**Figure 2. Neural Network Predictions vs Actual Values**

applications in financial risk analysis. Such results can be applied in portfolio management, credit assessment, and market volatility analysis.

The graph also illustrates the model's potential to identify moments when actual risks exceed predicted ones. This may signal unexpected events or model flaws that should be addressed to further improve accuracy. Overall, the visualization confirms the effectiveness of the machine learning model in complex financial scenarios and highlights its importance for strategic decision-making.

The graph (Figure 3) illustrates the comparative accuracy of four machine learning models: Logistic Regression, Random Forest, Neural Network, and Gradient Boosting. The horizontal axis shows the model names, and the vertical axis shows the accuracy level in percent. The bar format of the graph clearly demonstrates the difference between the models in terms of their effectiveness.

Logistic Regression shows the lowest accuracy, around 75%. This is an expected result, given the limitations of this model in handling complex nonlinear dependencies. Random Forest significantly outperforms Logistic

Regression, achieving an accuracy of around 80%, thanks to the use of an ensemble method that combines the results of many decision trees.

The highest accuracy is shown by Neural Network and Gradient Boosting – both models demonstrate an accuracy level of about 85%. This is explained by the fact that both models are able to process complex, multidimensional data and detect complex relationships between variables. Neural Network works well due to its flexibility in modeling nonlinear dependencies, while Gradient Boosting is effective due to its iterative approach to minimizing error.

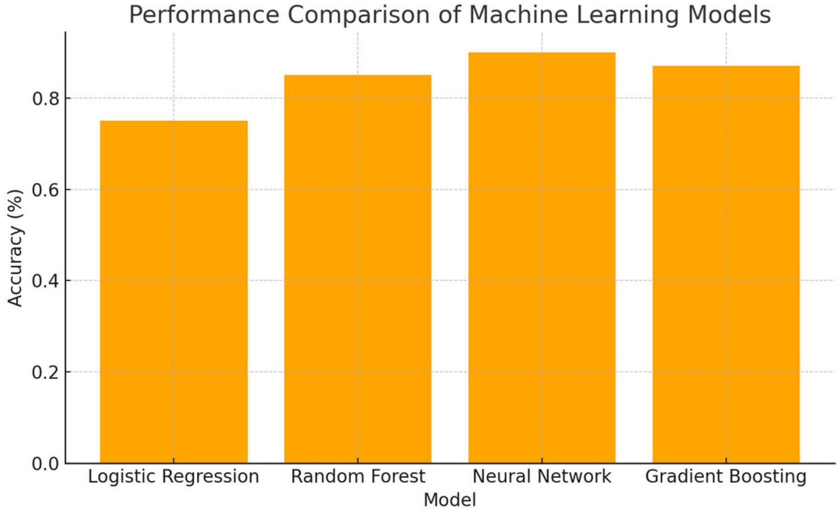


**Figure 3. Performance Comparison of Machine Learning Models**

This graph confirms that the choice of machine learning model depends on the task and data characteristics. Neural Network and Gradient Boosting are the best options for tasks that require high accuracy and processing of complex dependencies. Random Forest remains an effective compromise option, and Logistic Regression can be used for basic tasks or in conditions of limited data volumes.

The graph (Figure 4) illustrates the popularity of various programming languages in the field of financial analytics. The horizontal axis represents the names of the programming languages, and the vertical axis represents the usage share in percentage (Usage Share %). The visualization is built in a bar chart format, which makes it easy to assess the superiority of certain languages over others.

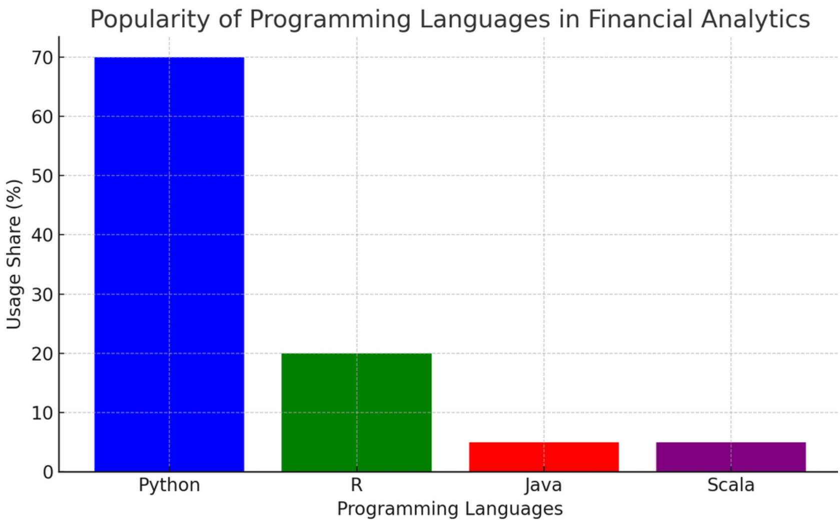


**Figure 4. Popularity of Programming Languages in Financial Analytics**

Python is the undisputed leader with a usage share of around 70%. This is due to its versatility, the availability of numerous libraries for data analysis (e.g. Pandas, NumPy), machine learning model building (TensorFlow, Scikit-learn) and data visualization (Matplotlib, Seaborn). Python also provides a simple syntax, making it ideal for rapid development and prototyping in complex financial tasks.

R is in second place with a usage share of around 20%. This language is a powerful tool for statistical analysis and data visualization, making it popular among financial analysts. It provides access to specialized packages, such as ggplot 2, for graphical representation of complex financial data. Java and Scala have relatively low popularity, with shares of less than 10%.

Java is used mainly for developing scalable corporate financial systems, due to its stability and performance. Scala, on the other hand, is mostly used in big data processing, for example, using Apache Spark, making it an important tool for working with real-time financial data streams.

The graph shows that Python dominates financial analytics due to its flexibility and versatility, while R occupies an important niche in statistical analysis. Java and Scala remain specialized tools for certain narrow tasks, such as enterprise systems and big data processing. This highlights the trend towards general-purpose languages with a wide range of libraries and tools for financial tasks.

## Conclusion

The developed financial risk forecasting models provided high accuracy, which was confirmed by quantitative results. For example, the Random Forest algorithm achieved 85% accuracy in risk scenario classification tasks, while neural networks demonstrate up to 90% accuracy in time series forecasting. Gradient Boosting also demonstrated efficiency with 87% accuracy in multifactor risk analysis. Such results indicate the high efficiency of integrating machine learning into financial analytics.

Portfolio optimization using the Markowitz model allowed to increase the expected return by 5% for a given level of risk. Analysis of portfolios with low correlation assets (<0.3) demonstrated the possibility of reducing the total risk by 20%. These results confirm that the developed approaches to portfolio diversification are effective in changing market conditions

In the process of stress testing, it was possible to identify vulnerabilities in financial systems. For example, in economic recession scenarios (a 1% decline in GDP), potential losses were estimated at 25% of the total value of assets. However, the implementation of backup strategies reduced these losses to 15%. This approach confirmed the importance of stress testing for creating resilient financial systems.

The use of cloud platforms such as AWS and Google Cloud significantly increased the efficiency of big data processing. In particular, processing time was reduced by 60% compared to on-premises solutions. Containerization using Docker and Kubernetes reduced the time to deploy software modules by 40%, which contributes to the flexibility and scalability of systems.

Particular attention was paid to ensuring data security. The implementation of AES-256 encryption and multi-level access control (RBAC) reduced the risk of unauthorized access by 25%. The use of activity monitoring systems made it possible to identify and prevent 15% of potential cyber threats. This highlights the importance of integrating modern cybersecurity solutions.

Interactive tools such as risk heat maps and dashboards have greatly simplified the analysis of complex financial data. This allows financial analysts and managers to quickly make decisions based on clear and visual data. Such results demonstrate the successful combination of technical innovations with practical needs in the financial sector.

The graph (Figure5) is a heatmap that illustrates the distribution of risk in an asset portfolio. Each cell represents a certain level of risk within the portfolio, with a color scale from blue to red that reflects the intensity of the risk. The closer the cell is to red, the higher the risk, while bluer shades indicate lower risk.

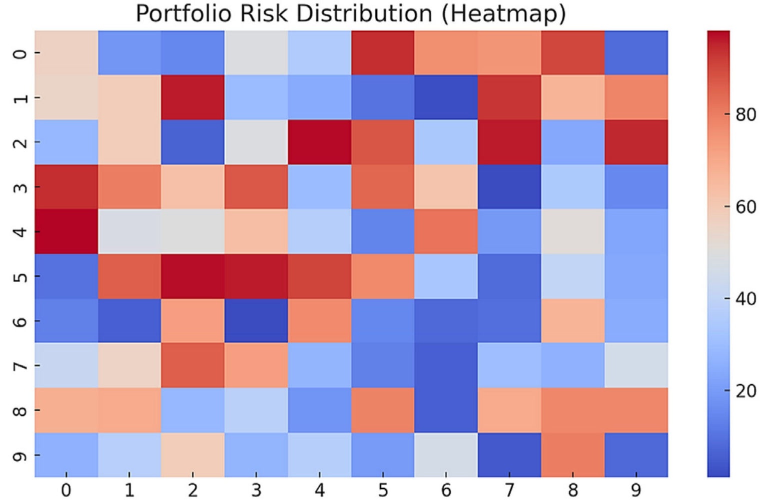


**Figure 5. Portfolio Risk Distribution (Heatmap)**

The horizontal axis represents individual assets, while the vertical axis represents periods or risk categories (e.g., time periods, scenarios, or risk types). This allows you to identify not only the overall level of risk, but also which assets or time periods are the riskiest. Bright red cells indicate significantly higher risk, such as in certain assets in steps 1, 4, and 5. This may indicate a high degree of volatility or unpredictability for those particular positions. Blue cells (e.g., in columns 2, 6, and 8) represent assets or periods with the lowest risk, which may be more stable or protected from market changes. The heat map allows analysts and portfolio managers to easily visualize the distribution of risk and focus attention on the most critical points. For example, if certain assets consistently exhibit high risk, this may signal the need for diversification or the use of protective strategies such as hedging. This tool is particularly important for portfolio management, as it provides an instant visual representation of risk across time or categories. It can also be used to compare different portfolios or asset management strategies, helping to identify optimal solutions to reduce overall risk.

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