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OPTIMIZING PROJECT DEVELOPMENT RISKS AND MARKET VOLATILITY USING DEEP LEARNING METHODS

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This study addresses computer modeling challenges by focusing on the risks in IT projects, with particular emphasis on managing investment processes under conditions of uncertainty and incomplete information. The growing number of IT projects in recent years has brought new challenges to assessing and managing associated risks. As technology advances and IT initiatives expand in scale, uncertainties in investment processes have intensified, requiring more sophisticated evaluation methods. The study introduces a RIC methodology for calculating the risk function of investment projects, incorporating fluctuations in projected cash flows. Investment project development is often characterized by uncertainty and a lack of robust statistical data, necessitating advanced analytical approaches for sound decision-making. This research applies modern scientific techniques, including machine learning and convolutional neural networks, to develop an algorithm for risk assessment in investment projects. The proposed algorithm provides practical recommendations to improve the evaluation and management of investment-related risks. The findings of this study offer valuable tools for planning and risk analysis, making them applicable to various stakeholders engaged in investment activities.

Keywords: investment risk, IT projects, fuzzy fields, information uncertainty, Big Data, CNN models, machine learning.

ТЕРЕҢ ОҚЫТУ ӘДІСТЕРІН ПАЙДАЛАНУ АРҚЫЛЫ ЖОБАЛАРДЫ ДАМЫТУ ТӘУЕКЕЛДЕРІН ЖӘНЕ НАРЫҚТЫҢ ҚҰБЫЛМАЛЫЛЫҒЫН ОҢТАЙЛАНДЫРУ

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Бұл зерттеу компьютерлік модельдеу мәселелерін шешуге арналған, әсіресе ақпараттық технологиялар (АТ) жобаларындағы тәуекелдерге, сондай-ақ белгісіздік және толық емес ақпарат жағдайында инвестициялық процестерді басқаруға ерекше назар аударады. Соңғы жылдары АТ жобаларының санының өсуі тәуекелдерді бағалау және басқару бойынша жаңа қиындықтарды тудырды. Технологиялар дамып, АТ бастамаларының ауқымы кеңейген сайын, инвестициялық процестердегі белгісіздіктер күшейіп, неғұрлым күрделі бағалау әдістерін қажет етеді. Зерттеуде инвестициялық жобалардың тәуекел функциясын есептеуге арналған RIC әдістемесі ұсынылған, ол болжанған ақша ағындарының ауытқуларын ескереді. Инвестициялық жобаларды әзірлеу жиі белгісіздікпен және сенімді статистикалық деректердің жетіспеушілігімен сипатталады, бұл негізделген шешімдер қабылдау үшін заманауи аналитикалық тәсілдерді қолдануды талап етеді. Бұл зерттеуде инвестициялық жобалардың тәуекелдерін бағалау алгоритмін әзірлеу үшін машиналық оқыту және конволюциялық нейрондық желілер сияқты заманауи ғылыми әдістер қолданылады. Ұсынылған алгоритм инвестициялық тәуекелдерді бағалау және басқаруды жақсарту бойынша практикалық ұсыныстар береді. Зерттеу нәтижелері жоспарлау және тәуекелдерді талдау үшін құнды құралдарды ұсынады және инвестициялық қызметке қатысатын түрлі мүдделі тараптарға қолданыла алады.

Түйін сөздер: инвестициялық тәуекел, АТ жобалары, анық емес өрістер, ақпараттық белгісіздік, үлкен деректер, CNN үлгілері, машиналық оқыту.

ОПТИМИЗАЦИЯ РИСКОВ РАЗРАБОТКИ ПРОЕКТА И ВОЛАТИЛЬНОСТИ РЫНКА С ИСПОЛЬЗОВАНИЕМ МЕТОДОВ ГЛУБОКОГО ОБУЧЕНИЯ

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Данное исследование посвящено решению задач компьютерного моделирования, сосредотачивая внимание на рисках в ИТ-проектах, с особым акцентом на управление инвестиционными процессами в условиях неопределенности и неполной информации. Рост числа ИТ-проектов в последние годы привел к появлению новых вызовов, связанных с оценкой и управлением сопутствующими рисками. По мере развития технологий и расширения масштабов ИТ-инициатив неопределенность в инвестиционных процессах усиливается, требуя более сложных методов оценки. В исследовании предлагается методология RIC для расчета функции риска инвестиционных проектов с учетом колебаний прогнозируемых денежных потоков. Разработка инвестиционных проектов часто характеризуется неопределенностью и недостатком надежных статистических данных, что требует применения современных аналитических подходов для принятия обоснованных решений. В данном исследовании применяются современные научные методы, включая машинное обучение и сверточные нейронные сети, для разработки алгоритма оценки рисков в инвестиционных проектах. Предлагаемый алгоритм содержит практические рекомендации по улучшению оценки и управления инвестиционными рисками. Результаты исследования предлагают ценные инструменты для планирования и анализа рисков, которые могут быть применимы различными заинтересованными сторонами, участвующими в инвестиционной деятельности.

Ключевые слова: инвестиционный риск, ИТ-проекты, нечеткая логика, неопределенность, Большие данные, модели CNN, машинное обучение.

Introduction. In recent years, the increasing number and complexity of Information Technology (IT) projects have posed significant challenges in assessing and managing associated risks. The rapid advancements in technology and the growing scale of IT initiatives have amplified uncertainties, particularly in investment processes, requiring more sophisticated and reliable evaluation methods. In today' s dynamic business environment, IT infrastructure and architecture are critical investments that command significant financial resources. These investments are crucial for constructing advanced production environments and operational IT architectures. The investments cover a wide spectrum, including projects, computers, telecommunications, and services. These are integral to enhancing a company' s productivity and operational efficiency. Yet, assessing the return on these investments poses a challenge, often taking years to realize their full benefits.

Recent scholarly and professional investigations have focused on evaluating the impact of IT investments on business performance. Various approaches have been suggested to assess these investments effectively and efficiently. *McKinsey* reports that IT infrastructure has undergone significant evolution-from small setups with few servers to massive data centers with thousands of servers. This transformation is driven by the need for robust systems capable of supporting essential business functions like transaction processing, customer data management, and complex decision-making processes. Investing in IT infrastructure brings substantial benefits. Well-integrated IT systems can improve real-time data collection, support extensive analytics, and enhance market responsiveness, thereby providing a competitive edge. For example, sophisticated infrastructure allows quicker establishment of sales offices in emerging markets and improved customer support.

Despite these benefits, the high costs and long commitments required for developing IT infrastructure present considerable challenges. The complexity of managing and integrating diverse technologies demands careful planning and strategic investments. Beyond individual companies, the strategic importance of infrastructure investments impacts broader economic activities. Enhancements in digital connectivity and transport networks facilitate business operations and can significantly boost economic growth by reducing costs, improving mobility, and bolstering competitiveness.

From the perspective of Ilin et al., the development and implementation of Enterprise Architecture (EA), including its IT components, significantly enhance transparency in business operations and agility in business re-engineering. They advocate for investment and assessment models that provide numerous advantages, such as enabling integrated comparisons of the impact of adopting IT solutions versus fragmented deployment, more precise calculations of investment project costs, reduced investment cycles for both physical and IT components, and the application of international software standards like COSMIC-ISO 19761 for practical implementation [1]. As well, a research by Purwita and Subriadi shows how IT investment valuations are influenced by both tangible and intangible benefits [2].

In another study, researchers analyzed Health Information Technology (HIT) investments in relation to hospital financial outcomes using econometric and microeconomic techniques. They optimized investment distribution based on productivity associated with each input, determining the appropriate investment levels for a global portfolio to achieve a desired confidence level [3]. Ali et al. underscores the significance of Information Technology Investment Governance (ITIG) as a vital organizational competency, highlighting its role in enhancing the relationship between IT investments and business performance, based on resource-based theory [4]. Berghout’ s research emphasizes the benefits of developing detailed business cases for IT projects, arguing that while resource-intensive, these cases are critical for organizations engaging in unfamiliar IT projects by providing a deeper understanding of the project’ s business value and supporting informed decision-making [5].

Further, Chen et al. proposes the development of an effective IT investment decision model for global organizations, aiming to demonstrate the framework’ s utility in supporting IT investment decisions [6]. Additionally, Witra et al. study on gender and IT investment decision-making reveals that women’s risk-averse behavior has significant implications for investment efficiency, especially in complex calculations [7]. Mirza et al. research suggests that female managers enhance asset efficiency and help organizations reduce unnecessary expenditures, particularly in developing economies [8]. Shin’s research further supports the idea that female directors strengthen board monitoring, impacting decision-making processes significantly [9]. Lee’ s research focuses on the critical need for businesses to understand how technology investments contribute to business outcomes, rather than just the technological aspects themselves. The study links IT spending to business growth and stresses the importance of prioritizing investments that produce tangible bottom-line results, navigating the so-called IT paradox effectively [10].

Materials and Methods. This research aims to establish a robust quantitative model to evaluate the effectiveness of IT investments in promoting business growth, using real-world data. The core proposition is that by strategically focusing IT investments on areas that generate substantial bottom-line results, businesses can optimize their expansion and performance. To achieve this, the study introduces a novel evaluation method named ”RIC” which incorporates three critical criteria:

1. **Risk Score:** This metric assesses the attractiveness of an investment based on its risk level. The score ranges from 0% (indicating very high risk) to 100% (indicating very low risk), providing a straightforward, quantifiable measure to gauge potential risk associated with each IT investment.

2. **Return on Investment (ROI):** ROI is used to measure the profitability of an investment by comparing the return or profit generated against the initial investment cost. This criterion is essential

for assessing the potential financial gains or losses from IT investments and supports decision-making by highlighting the efficiency and effectiveness of the expenditure.

3. **Criteria yet unspecified:** The third criterion, which will be detailed further in the study, complements the Risk Score and ROI to provide a comprehensive view of the investment's value.

The RIC method' s integration of these criteria aims to provide a multidimensional analysis of IT investments, enabling organizations to make informed, data-driven decisions that align IT spending with strategic business objectives. This approach not only seeks to clarify the direct impact of IT investments but also to guide companies in prioritizing investments that promise the most significant returns, thereby enhancing their competitive edge and operational efficiency.

This research commenced with the use of Python libraries to systematically gather and process investment-related datasets from a variety of sources, aiming to build a comprehensive foundation for the analysis. The primary dataset utilized was the ”Twitter Dataset” obtained from *Kaggle*, which encompasses approximately 1.5 million tweets and 1.2 GB. These tweets were analyzed to extract insights related to financial markets and investment trends.

Additionally, it's been integrated a substantial dataset provided by *McKinsey*, which includes detailed records of around 500 million interactions from regular users engaging with retail services. This dataset was pivotal in understanding consumer behavior and its impact on retail investment trends. The data collection also extended to financial markets, specifically through the use of data from *Yahoo Finance*. This source provided daily updates on a selected range of US-listed financial instruments. Although this dataset is comprehensive, it is important to note that it may contain some gaps, possibly due to the selective criteria used in data compilation, which could influence the availability of complete historical data.

To ensure a robust analytical framework, these datasets were meticulously cleaned and pre-processed to address inconsistencies and prepare them for integrated analysis. The aim was to correlate the risks derived from social media and consumer behavior with actual market movements, thereby providing a multi-dimensional perspective on investment strategies and market dynamics. This approach allowed us to harness big data analytics to derive actionable insights that could potentially guide investment decisions and strategy formulation.

Fig. 1 - RIC methodology

It has been considered quantitative methods as a cornerstone of the research, as a way to explore something better. In order to solve the investment problem, it has been created a method called RIC and uses three criteria (See Fig.1).

1. R stands for Risk (Risk Assessment)

2. I stands for Investment (Return On Investment)

3. C stands for Customer (Customer Satisfaction)

$$RIC = \frac{R + I + C}{3} \tag{1}$$

Each criterion is responsible for the main investment parameters: 1) both tangible and intangible; 2) tangible; 3) intangible, so that the method produces the best predictable result. In the realm of investment, accurately gauging the risk associated with stocks is paramount for determining their attractiveness and potential returns. The "Risk Score" is a fundamental metric developed to quantify this aspect, ranging from 0% to 100%. A score of 0% indicates a very high risk, suggesting that the investment is highly volatile or uncertain. Conversely, a score of 100% represents a very low risk, pointing to a stable and secure investment.

Investors rely on the Risk Score to make informed decisions by evaluating various factors that contribute to the risk profile of an investment. These factors include market volatility, which reflects the frequency and magnitude of price fluctuations; economic conditions, such as inflation rates, employment levels, and GDP growth, which can affect the overall investment climate; regulatory risks, involving changes in laws and regulations that could impact business operations; technological risks, particularly relevant in sectors where rapid innovation can render existing technologies obsolete; and operational risks, which encompass issues related to internal processes, systems, and people.

Understanding these risks is crucial as they directly influence the potential returns from an investment. By integrating the Risk Score into their analysis, investors can align their investment choices with their risk tolerance and investment objectives, aiming to optimize their portfolios for both risk and return. This approach to risk assessment not only aids in identifying potentially lucrative investments but also helps in mitigating potential losses, making it an indispensable tool in the financial decision-making process. ROI measures the profitability of an investment by comparing the return or profit generated to the initial investment cost. It helps assess the potential financial gains or losses associated with an investment.

$$ROI = \frac{Profit}{CostofInvestment} \times 100 \qquad (2)$$

Measuring customer satisfaction is a critical aspect of evaluating business performance and understanding the effectiveness of various investments. One common method to gauge this is through customer surveys or feedback mechanisms, which can collect detailed insights from customers about their experiences and satisfaction levels. These results are often quantified and reported as a percentage of satisfied customers. This percentage provides a direct indicator of how well a company is meeting customer expectations and needs. It is a valuable metric because it offers a clear, numerical benchmark that businesses can track over time and use to implement improvements. For instance, a high percentage of satisfied customers generally correlates with better customer loyalty, repeat business, and positive word-of-mouth, all of which are crucial for long-term success.

Businesses might utilize various tools for this purpose, including electronic surveys, feedback forms, social media interactions, and review platforms. By analyzing the data collected from these sources, companies can identify strengths and weaknesses in their products or services and make informed decisions to enhance customer satisfaction. This process not only helps in retaining existing customers but also attracts new ones by showcasing the company's commitment to meeting their needs and expectations.

Further it's been possible to conceptualize a model where the change in customer satisfaction over time is a function of various factors. Let $S(t)$ represent the customer satisfaction level at time t, measured as the percentage of satisfied customers. To model the change in satisfaction over time as a function of factors such as improvements in service quality $(Q(t))$, responsiveness to feedback $(R(t))$, and changes in customer expectations $(E(t))$ was developed an equation that can be:

$$\frac{dS}{dt} = k_1 \cdot \frac{dQ}{dt} + k_2 \cdot \frac{dR}{dt} - k_3 \cdot \frac{dE}{dt}, \qquad (3)$$

where:

- $\frac{dS}{dt}$ is the rate of change of customer satisfaction.

- $\frac{dQ}{dt}$, $\frac{dR}{dt}$, and $\frac{dE}{dt}$ represent the rates of change in service quality, responsiveness, and customer expectations, respectively.

- k_1, k_2, and k_3 are constants that determine the sensitivity of customer satisfaction to changes in each of these areas.

This model assumes that improvements in service quality and responsiveness directly contribute to increasing satisfaction, whereas rising customer expectations might decrease it. The constants k_1, k_2, and k_3 would need to be empirically determined based on data specific to a company or industry.

One of the RIC framework' s key advantages is its adaptability to integrate advanced machine learning models, such as convolutional neural networks (CNNs). While it's traditionally associated with image recognition, their utility in analyzing financial data lies in their ability to process sequential and structured datasets with remarkable precision. CNNs can be adapted to handle financial time-series data by treating the temporal progression of market events as layers of interconnected features. This approach enables the extraction of patterns and trends that might otherwise remain obscured. For example, in the context of the RIC framework, it could analyze multi-dimensional data inputs such as historical price movements, trading volume, sentiment scores, and macroeconomic indicators. The architecture's convolutional layers can identify relationships between these variables, while pooling layers reduce dimensionality, ensuring efficient computation. Dilated convolutions could further expand the receptive field, capturing broader market contexts without increasing computational overhead. See in Fig.2 more details of the model used for risk analysis.

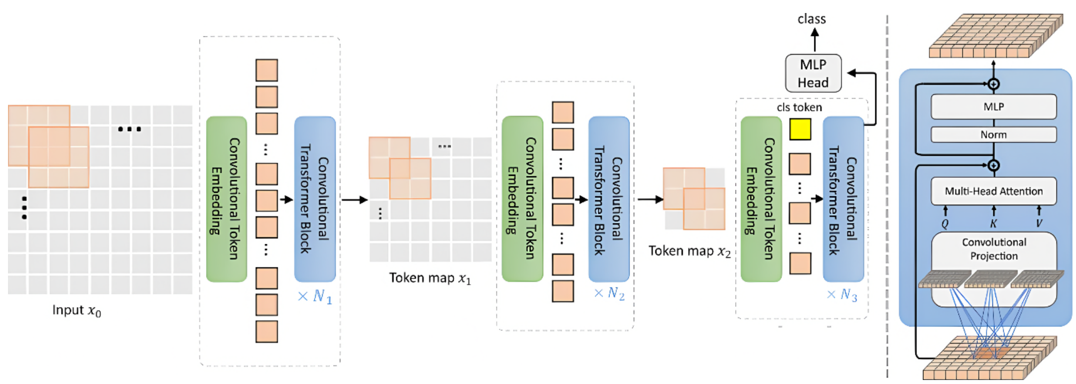

Fig. 2 - Design of the CNN model for this study

The CNN architecture was originally designed to address image generation problems. A key component of CNNs is the use of convolutions, which play a central role in feature extraction. Causal convolutions, in particular, are employed to preserve the temporal ordering of data, ensuring that the model's output at timestep *t* depends only on current and past timesteps, and not on any future information. Additionally, the architecture incorporates dilated convolutions, which skip input values at regular intervals. This design enables the receptive field to expand exponentially with depth, effectively capturing broader context in the data. CNNs have demonstrated remarkable success in tasks such as music audio modeling and speech recognition. Specifically, the dilated causal convolution layers in the architecture are instrumental in capturing long-term dependencies, making them well-suited for sequential data modeling.

Due to the nature of the model, which greedily selects the highest and lowest risk points within a range, a few challenges arise in identifying risks. Firstly, selecting CNN parameters involves balancing complexity and efficiency. Typical architectures use 3–5 convolutional layers with 3×33 times 33×3 or 5×55 times 55×5 kernels, a stride of 1 or 2, and ReLU activation Pooling layers, typically max pooling with a 2×22 times 22×2 window, are used to reduce spatial dimensions while retaining important features. The number of filters often increases in deeper layers, starting from 32 or 64 in initial layers and scaling up to 256 or 512 in later layers to capture complex patterns. Learning rates between 0.001 and 0.0001, tuned via optimizers like Adam or SGD with momentum, ensure stable and effective training. These parameter choices help build a CNN that generalizes well across different datasets, as shown in Table 1.

Specifically, the sizes of buying points (peaks) and selling points (valleys) are relatively smaller compared to holding points. In the dataset, buying and selling risks account for only 3% of the total data, highlighting a significant class imbalance. To address this imbalance, it's been proposed a sampling method that adjusts the data distribution based on the rate of rare events, ensuring a more balanced representation for effective model training, as shown in Fig.3.

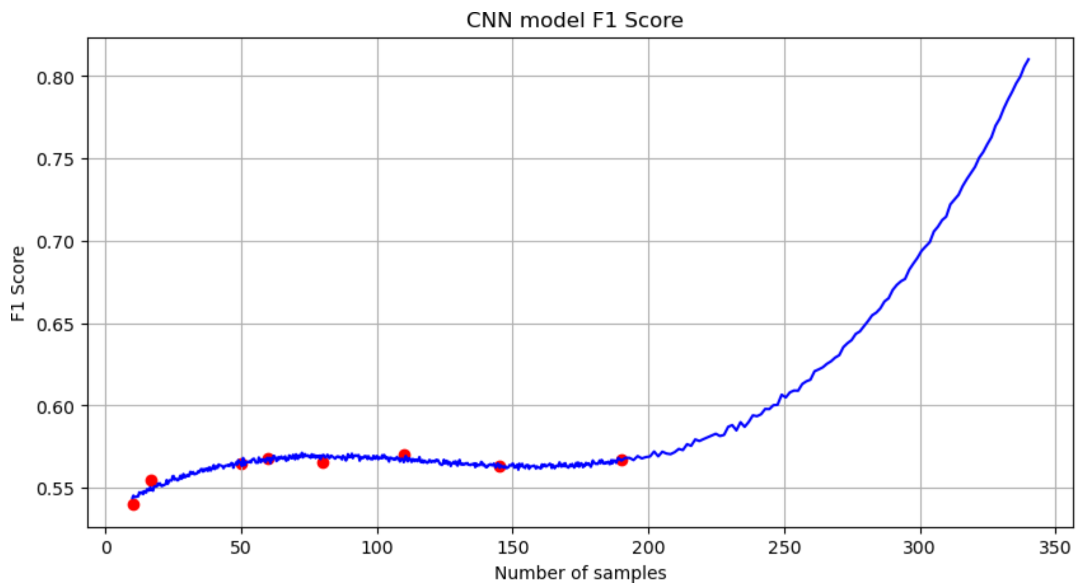

Fig. 3 - Evaluation of the CNN model after sampling

Table 1 - Comparison of CNN and machine learning models over 350 samples

Model	Accuracy	Precision	Recall	F1-Score
Proposed CNN Model	92.5	93.1	91.8	92.4
The Hybrid Model [14]	88.3	87.9	88.0	87.9
Random Forest [16]	85.7	84.5	86.2	85.3
Regression model [15]	84.2	83.0	85.0	84.0
Autoregressive (AR) model [19]	89.1	88.7	89.5	89.1

In the Table 1, the study highlights the superior performance of the proposed CNN model, which outperforms traditional machine learning models and a previous hybrid model in terms of accuracy, precision, recall, and F1-score. The improvement in performance demonstrates the effectiveness of the updated CNN architecture, likely due to better hyper parameter tuning, deeper layers, and optimized feature extraction techniques.

Results and discussion. To validate the effectiveness of the Risk, Investment, and Compliance (RIC) method in assessing investment opportunities, the study utilized historical data from several authoritative financial analytics sources.

Specifically, data spanning the past five years from Macrotrends [11], Infront Analytics [12] and Comparably [13] were employed to analyze the investment potential of ten selected companies across various industries.

This approach involved a systematic evaluation of each company' s performance and market behavior using the RIC. This formula integrates multiple financial indicators to produce a composite score reflecting the investment reliability of a company. The scoring system was categorized into three distinct risk levels:

- **30% and below:** Investments in companies scoring within this range are considered high risk, and thus not recommended;

- **31% to 60%:** Companies falling within this middle range are deemed moderately safe investments;

- **Above 60%:** A score above 60% indicates a high level of investment safety and is strongly recommended for investors.

For each of the ten companies, the RIC scores were calculated based on their financial data, market trends, and other relevant economic indicators provided by the chosen data sources. This approach allowed us to map each company onto the risk assessment scale effectively, as shown in Fig.4.

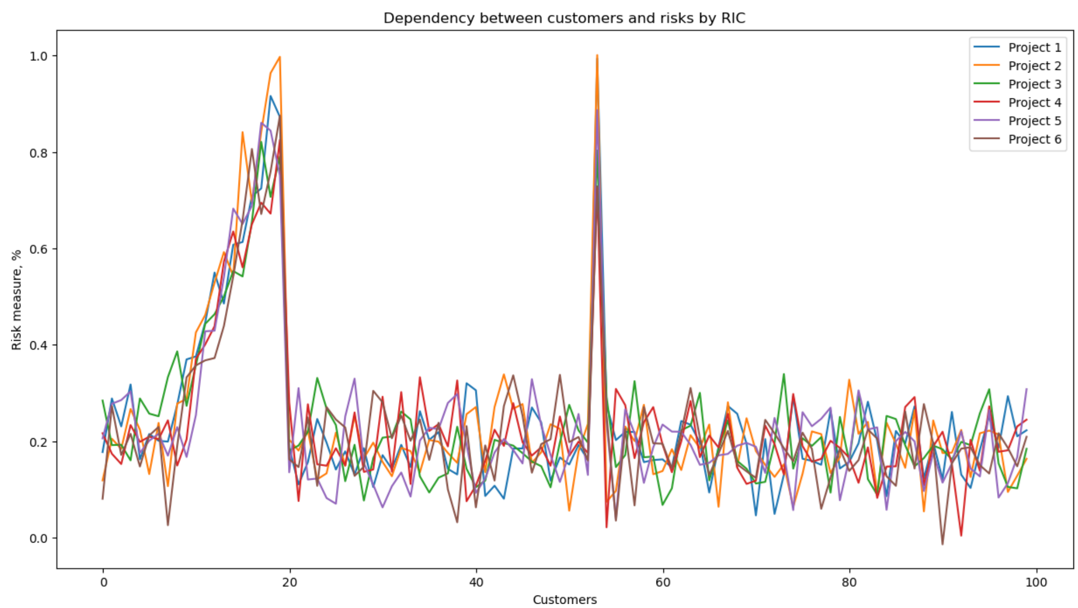

Fig. 4 - Risk measurement by customers

The machine learning (ML) model further enhances the analysis by leveraging these RIC metrics alongside other key data points to refine investment predictions. The ML model integrates both time-series analysis and sentiment analysis to capture trends and market sentiment, offering a more comprehensive assessment of investment opportunities. By utilizing algorithms and back testing procedures, the model incorporates confidence levels and simulates real-world scenarios, effectively identifying buying and selling points to optimize investment strategies. The combination of RIC and ML-driven insights provides a robust framework for evaluating investment risks.

The application of the RIC yielded varied results across the board, reflecting a broad spectrum of investment reliability among the companies analyzed. Notably, the formula demonstrated its utility in distinguishing between high-risk and secure investment opportunities based on quantifiable metrics. Several companies scored above 60%, indicating strong financial health and market position, thus making them highly recommended for investment. Conversely, a few companies scored below 30%, suggesting significant risks that might outweigh potential returns, as shown in Fig. 5.

Fig. 5 - ROI data for a 5-year period

The results from this empirical investigation confirm that the RIC provides a robust framework for evaluating investment opportunities. By quantifying risk and correlating it with market and financial data, the formula helps investors make informed decisions grounded in comprehensive analytics [14]. Moving forward, there are obvious recommendations to refine the RIC parameters to enhance its predictive accuracy and applicability across different economic cycles and industry sectors. This ongoing validation process will ensure that the RIC remains a reliable tool for investment assessment in the dynamic global market (See Table 2). The machine learning model well complements the RIC framework by incorporating advanced analytical techniques to refine predictions and improve investment decisions. The model combines time-series analysis and sentiment analysis to identify patterns and gauge market sentiment, enriching the insights provided by the RIC.

Table 2 - Investment assessment of the global market companies (NASDAQ)

Company	R (%)	I (%)	C (%)	Result
Amazon	80	13.53	79	57.51
Microsoft	80	29.19	79	62.73
AMD	60	19.89	78	52.63
Intel	80	15.35	79	58.11
Nokia	80	2.54	67	49.85
IBM	80	9.13	68	52.37
Netflix	80	12.48	79	57.16
NVIDIA	70	24.73	85	59.91
SAP	90	8.87	83	60.62
Oracle	80	13.26	69	54.08

The machine learning module collects data from various sources to train predictive models. To preliminarily evaluate the usefulness of the data, the employment of time-series analysis and sentiment analysis provides a quick indication of whether valuable information is present. At this stage, the module is dedicated solely to Buy/Sell prediction tasks. To label the data, the authors devised a custom algorithm that greedily assigns points into three categories by identifying buying and selling points at the lowest and highest prices within a defined range. However, this labeling approach introduces significant class imbalance, leading the model to predominantly predict "hold," thereby failing to learn meaningful patterns. The results of this approach are illustrated in Fig. 6.

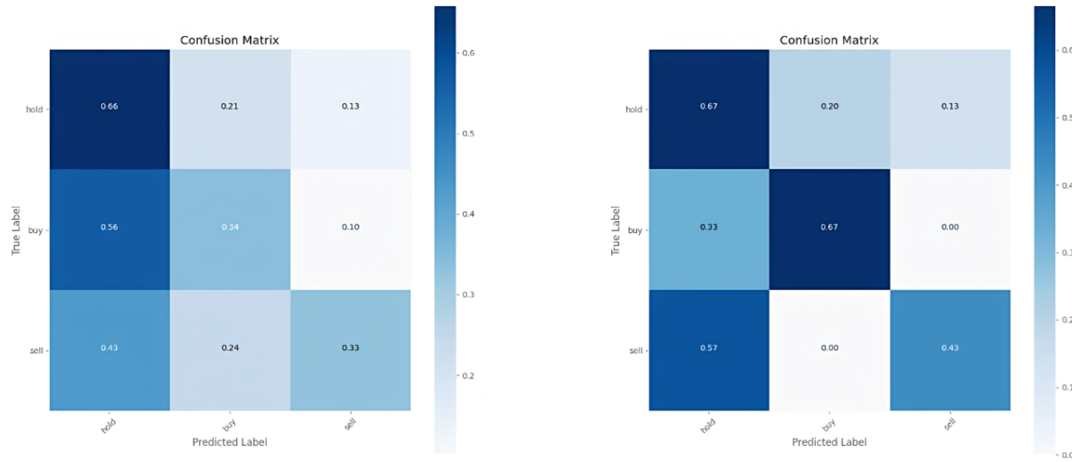

Fig. 6 - Predicted investment decisions for the companies

Given the inherent difficulty of the task, there's been a question whether the model could effectively identify upward and downward trends necessary for accurate predictions, particularly as the confusion matrix alone does not adequately capture its performance. To address this, the study adopted a more practical evaluation metric by simulating real-world conditions-investing funds and measuring potential returns. It's been considered to implement a back testing strategy that incorporates the model's confidence levels.

The application of the RIC across various companies and industries has offered significant insights into the complexities of financial risk assessment. Leveraging data from sources such as Macrotrends, Infront Analytics, and Comparably, this study demonstrates the formula' s ability to categorize companies into low, medium, and high investment recommendation tiers based on their scores. This stratification serves as a vital tool for investors aiming to make data-driven decisions in a competitive market environment [15]. Another key finding of this study is the RIC' s reliability in delivering consistent risk assessments under diverse economic conditions [16-17]. The formula' s robustness lies in its capacity to integrate immediate financial metrics with broader economic indicators, making it an adaptable framework even in fluctuating markets.

One of the primary limitations of the RIC method lies in its reliance on historical financial data and predefined risk thresholds, which may not fully capture the dynamic processes of financial markets. The fixed risk categories (30%, 60%) are based on past trends and economic theories, making them potentially outdated in rapidly evolving conditions. Additionally, while the RIC effectively quantifies investment risk using financial indicators, it lacks the ability to incorporate qualitative factors such as market innovation, or industry disruptions, elements that can impact a company' s long-term performance. The RIC method operates under the assumption that past performance is indicative of future results, which may not always hold true in speculative markets [18]. While the integration of machine learning generally improves predictive capabilities, issues such as data imbalance and overfitting can limit the accuracy of uncertain forecasts.

To address these limitations, this study introduces machine learning (ML) techniques as a complementary approach to refine the framework.

By integrating ML models, such as time-series forecasting and sentiment analysis, the RIC can incorporate a more dynamic and adaptive methodology. For instance, the ML models analyze historical and real-time market data to identify patterns, predict future trends, and enhance the precision of RIC scores. Furthermore, advanced ML-driven algorithms allow for the consideration of qualitative factors by processing textual and sentiment data from news, reports, and social media [19-20]. This holistic integration of quantitative and qualitative metrics improves the RIC' s predictive capabilities, enabling it to provide a more comprehensive assessment of a company' s investment potential.

Future research should focus on optimizing the framework by incorporating these ML advancements and exploring additional data sources. By employing techniques such as neural networks, clustering, and reinforcement learning, the RIC can evolve into a model that adapts to market changes and investor behaviors in real time [21]. This evolution will enhance the tool's utility for investors seeking actionable insights in increasingly complex financial landscapes. The RIC method provides a foundational yet flexible framework for assessing and comparing the investment reliability of companies systematically. While this study affirms its utility and relevance, the integration of ML models and continuous validation with diverse datasets will be essential for maintaining its effectiveness. As financial markets become more interconnected and data-rich, the combination of the RIC framework with advanced ML techniques will pave the way for a new generation of investment assessment tools, capable of delivering better support.

Conclusion. The application of the RIC method in this study has demonstrated its efficacy in evaluating investment opportunities with above 80% risk score. By incorporating both tangible and intangible factors, the formula provides a comprehensive tool for assessing the attractiveness of investments. This practical approach is crucial for capturing the full spectrum of influences that can impact investment decisions. The findings indicate that the method enables quick and accurate determination of investment viability, supporting its use as a reliable decision-making tool in financial analysis. The success of this initial application suggests that the formula performs well across a diverse range of company types and sizes, from emerging businesses to large global corporations in the IT sector.

Given the positive results, future research is planned to refine and potentially expand the criteria used in the RIC method. Considerations such as Cost Benefit Analysis and Return on Assets could be integrated to enhance the formula' s accuracy and relevance. Such developments could lead to a more precise method for assessing investments, tailored to the specific needs and contexts of various companies, thereby supporting investors in making even more informed decisions. The continual improvement and testing of the method will be essential to adapt to the evolving economic landscapes and investment scenarios, ensuring that it remains a robust tool in the arsenal of financial analysts and investors worldwide.

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