

## Enhancing Capital Adequacy in Banks Using AI and Machine Learning: A Predictive Approach to Risk Management and Regulatory Compliance

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### Abstract

This paper examines the application of Artificial Intelligence and Machine Learning in estimating capital adequacy at banks, thereby addressing the limitations of traditional risk assessment methods, which primarily rely on conventional models and data. Through XGBoost, LSTM, RC, and RL, the research demonstrates how AI and ML can be applied to measures such as risk assessments, capital movements, and regulatory management, as embodied by Basel III. The analysis shows that gradient boosting techniques provide higher predictive accuracy and lower error rates compared to ensemble models. However, exploration by country shows that models do not perform well in some jurisdictions due to differences in regulatory contexts and macroeconomic characteristics. The study also reveals overconfidence in low capital involving overestimations and argues that explainable AI (XAI) can help enhance model interpretability. It demonstrates that the application of AI and ML in risk management is feasible in the future, provided that policies are calibrated and coordinated according to regional differences and heterogeneity, thereby achieving regulatory objectives. Therefore, the study also enhances the understanding of the use of AI to improve financial stability and provide insights into the institutions and regulators for the evolving nature of the banking sector.

**Keywords:** Capital Adequacy, Artificial Intelligence (AI), Machine Learning (ML), Basel III, Risk Assessment, XGBoost, Explainable AI (XAI).

### 1. Introduction

Capital adequacy is one of the most crucial factors in determining a bank's financial position [1]. It ensures that financial institutions have adequate capital reserves, especially in the event of risk incurrence, and can continue to operate their businesses during a recession. A

well-capitalised bank ensures that it limits depositors, investors, and regulators' loss of confidence by offering security to the entire financial system [2].

Banks are established to undertake a variety of activities in a somewhat risky environment where factors such as credit risks, market risks, and operational risks might lead to operational distress [3]. Lack of capital can make banks vulnerable to shocks, forcing them to close down and triggering a systemic problem. The 2008 global financial crisis underscored the importance of robust capital measures, particularly in light of the insufficient capital base within several financial institutions that contributed to the economic crisis [4].

Consequently, the availability of capital is crucial in preventing the spread of financial crises, balancing the economy and encouraging sound banking practices [5]. Enhancing capital adequacy measures is crucial for achieving long-term financial stability and protecting against various adverse shocks.

Basel III is a new set of rules in the post-crisis landscape, developed by the BCBS to help maintain and regulate capital adequacy [6]. However, it was created in response to several defects in bank regulations, as evident in the 2008 financial crisis [7]. It also establishes rigorous minimum capital levels, capital adequacy buffers, and advanced measures to strengthen the defensive capabilities of the firms it covers.

A significant component of Basel III is the upgrading of capital standards, for instance, raising the common equity tier 1 (CET1) capital ratio and establishing leverage ratio measures [8]. Furthermore, Basel III complies with the minimum standards for liquidity measurement, such as the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR), to ensure that all banks have adequate short-term and long-term liquidity [9].

Basel III is also important in allowing banks to handle risks, meet increased regulatory demands, and increase the overall stability of the financial system [10]. However, the cost and the complexity impose a heavy burden, especially on low-scale banks that may not be in a position to provide the necessary resources.

Traditional approaches used by regulators to determine capital adequacy involve the application of formulas and historical statistics to assess a bank's position [11]. Although these approaches are systematic, they do not enable the identification of novel financial risks as they evolve.

One major weakness of the current models is the fact that traditional models are relatively rigid and may not capture the dynamics of today's real-world financial markets [12]. Stress testing methods remain unreliable despite their popularity, as they fail to account for black swan events or other severe market conditions [13]. Additionally, manual risk assessment is also inefficient, as it requires a significant amount of time, has a high likelihood of containing errors due to human bias, and does not proactively predict future events [14]. Traditional approaches are insufficient to meet these demands and provide real-time risk insights as financial systems evolve and become increasingly complex.

Traditional measures of capital adequacy have largely been done using analytical formulas and historical statistics [11]. However, these approaches are, in some ways, restricted in the current efficient market environment. It is usually rigid, takes time to analyse new threats, and poorly imitates specific market conditions [1]. For example, when the COVID-19 pandemic broke out, most banks discovered that historical models were not able to adapt rapidly to the sudden market changes and new risks that evolved in real time [15]. These conventional models did not capture new risk factors like unexpected supply chain breakdowns or huge shifts in consumer behaviour. In contrast, AI/ML techniques process actual data in real-time and regularly refresh risk assessments, which enable banks to quickly detect and respond to emerging risks [16].

**Table 1:** Comparative Analysis: Traditional vs. AI/ML

| Aspect                     | Traditional Approach                                       | AI/ML Approach   |
|----------------------------|--|--|
| <b>Data Utilization</b>    | Relies on static historical data                           | Continuously processes real-time data                              |
| <b>Risk Identification</b> | Detects risks only after they manifest                     | Proactively forecasts emerging risks                               |
| <b>Stress Testing</b>      | Limited capability to simulate extreme "black swan" events | Simulates diverse scenarios with dynamic stress models             |
| <b>Efficiency</b>          | Manual, slower, prone to human errors [11].                | Automated, high-speed, and minimizes errors through learning [17]. |

By integrating AI/ML methods, banks have the ability to address these limitations using improved data analysis, improved risk prediction, and dynamic stress testing, hence enhancing overall capital adequacy management [17].

The Standardised Approach and the Internal Ratings-Based (IRB) models used in risk evaluation are also insufficient in terms of prediction accuracy [18]. These models can be based on historical data, but the latter does not always reflect the financial risks in future, especially during crises.

Furthermore, traditional approaches are unable to establish multivariate functions due to their linearity when applied to the factor risks inherent in financial markets [19]. People's tendencies to bring their subjective biases into risk evaluation and data interpretation also affect accuracy. However, these methods are still more reactive than proactive, meaning they focus on identifying risks after they have become threats rather than when they are merely a possibility [20]. Such limitations have underscored the need for the development of sophisticated data analysis methods to measure capital adequacy.

Artificial Intelligence (AI) and Machine Learning (ML) have the power to transform capital adequacy management [21]. Compared to traditional approaches, these AI-based models can analyse vast datasets of financial data instantly, identify more extensive risk patterns, and make predictions [22].

Other advanced models of machine learning, such as deep learning networks and reinforcement learning, may aid in the improvement of capital management by adjusting risk based on prevailing market conditions [23]. Furthermore, AI can be utilized for stress testing, thereby reducing reliance on manual assessments and enhancing the system's ability to identify risks [17]. Therefore, AI/ML can help banks make better decisions, follow rules and regulations strictly, and alert them when there is an issue relating to capital adequacy, thus making capital adequacy management more effective.

The use of AI and ML in capital adequacy assessment brings the following benefits in banking risk management and regulatory compliance [24]. Artificial intelligence enhances the efficiency of risk assessment, enabling banks to identify potential weaknesses before they escalate [25]. This enhances the capital utilisation plans for financial stability.

Additionally, compliance applications based on AI facilitate more straightforward and more efficient compliance reporting while also reducing the risk of mistakes [26]. With the help of AI, banks can continuously monitor and adjust their operations in response to new regulations in real-time [27]. The use of AI in capital adequacy management also promotes the advancement of new technologies in financial institutions, enhancing efficiency in the delivery of data analysis for decision-making on banking stability in today's and tomorrow's challenging financial environment.

The use of AI for assessing capital adequacy presents several factors that influence the industry and policymakers in financial institutions. The use of these tools helps banks manage

risks, make informed decisions about capital allocation, and comply with regulations based on real-time data, as well as model financial scenarios [28]. Consequently, institutions are well-positioned to detect evolving financial risks, mitigate operating risks, and maintain a competitive edge. For policymakers, AI enables the creation of structural frameworks that accurately reflect the market's nature, contributing to good governance [29]. Thus, cooperation between the banks' professionals and regulators fosters accountability, strengthens financial positions, and anticipates emerging trends that contribute to economic stability.

## 2. Literature Review

Capital adequacy is a crucial factor in the stability of banks in the global marketplace, as it ensures sufficient capital to cover potential losses resulting from financial risks [30]. Many current standards, including Basel I, Basel II, and Basel III, have developed essential capital adequacy standards aimed at protecting depositors' interests and maintaining financial system stability [31].

The Basel III agreement, which followed the 2008 global financial crisis, introduced new capital standards with a focus on risk-weighted assets (RWA), buffer ratios, and liquidity [32]. Currently, banks are legally required to maintain a minimum Common Equity Tier 1 (CET1) ratio of 4.5%, a total capital ratio of 8%, and a capital conservation buffer of 2.5% to mitigate shocks [33]. Similarly, in the context of Basel III, it was stated that the CCyB was given the power to use further capital during the credit cycle in order to prevent it [34].

However, there are still issues with the implementation and enforcement of capital adequacy measures. Challenges such as modeling risk, especially the interpretation of complex risk environments, and best practices concerning capital policies are likely to be daunting for banks. Furthermore, such frameworks are primarily founded on previous financial data and fixed risk models which makes it challenging for them to assess new risks in the financial sector such as volatility, cyberrisk, or systemic shock [35]. Such limitations also remind about the necessity of using AI and machine learning for improving capital adequacy assessment and concerns.

Traditionally, the banking systems have employed the risk-weighted capital adequacy solutions models to measure capital requirements [32]. It mainly focuses on credit risk model, market risk model and operational risk model that allocate risk weights to the various categories of assets. Among the most used techniques for regulating the banks' capital adequacy, one can

distinguish the Standardised Approach (SA) and the Internal Ratings-Based approach (IRB) based on the Basel frameworks [36].

The Standardised Approach involves using predetermined risk weights for assets in line with the set regulatory standards, which applies a uniform risk measurement model among banks [37]. However, this method is not very flexible, and it does not consider such institution-specific factors as its risk level. However, according to the study of [18], the use of the IRB Approach enables banks to build their internal credit risk models that factor in the past loss record and probability forecasts. However, the IRB Approach is more accurate and requires a significant amount of focus on regulatory requirements and high-quality data; therefore, it is not easy for small institutions to use.

Also, capital adequacy assessment has always included Value at Risk (VaR) and stress testing methods to determine possible losses under unfavourable conditions [38]. However, such approaches are associated with certain issues such as model risk, biased assumptions, and a lack of ability to incorporate current financial changes. Traditional methods are no longer as flexible as they should be, especially as financial markets continue growing and evolving rapidly [38]. Thus, experts recommend using AI and machine learning for capital adequacy tests.

AI and Machine learning are becoming standard in banking risk management due to their capabilities in analytical modelling, decision-making, risk identification, as well as real-time evaluation [38]. They are capable of handling large data volumes, extracting concealed risk patterns and also assisting in automated capital adequacy checks.

These machine learning approaches include decision trees, random forests, XGBoost and deep learning in creating efficient credit risk models for loan default [39]. In addition, the reinforcement learning algorithms select the right capital amount, which means the banks should maintain enough capital to cover the risks and potentially earn more profits.

Stress testing enables the AI models to present Economic Capital models, then compute returns, evaluating the effects of a range of adverse economic conditions [17]. In contrast to the conventional fixed initial assumptions models used in stress testing, AI is capable to learn current market changes and offer risk management data as they occur.

In the same manner, natural language processing (NLP) promotes automated regulatory compliance when analyzing the firm's financial reports, regulatory filings, and policy disclosures to reduce the risk of regulatory noncompliance penalties [40]. Risk management systems powered by artificial intelligence (AI) not only improve capital adequacy estimation but also enhance fraud detection, anti-money laundering (AML) monitoring, and cybersecurity risk estimation [41].

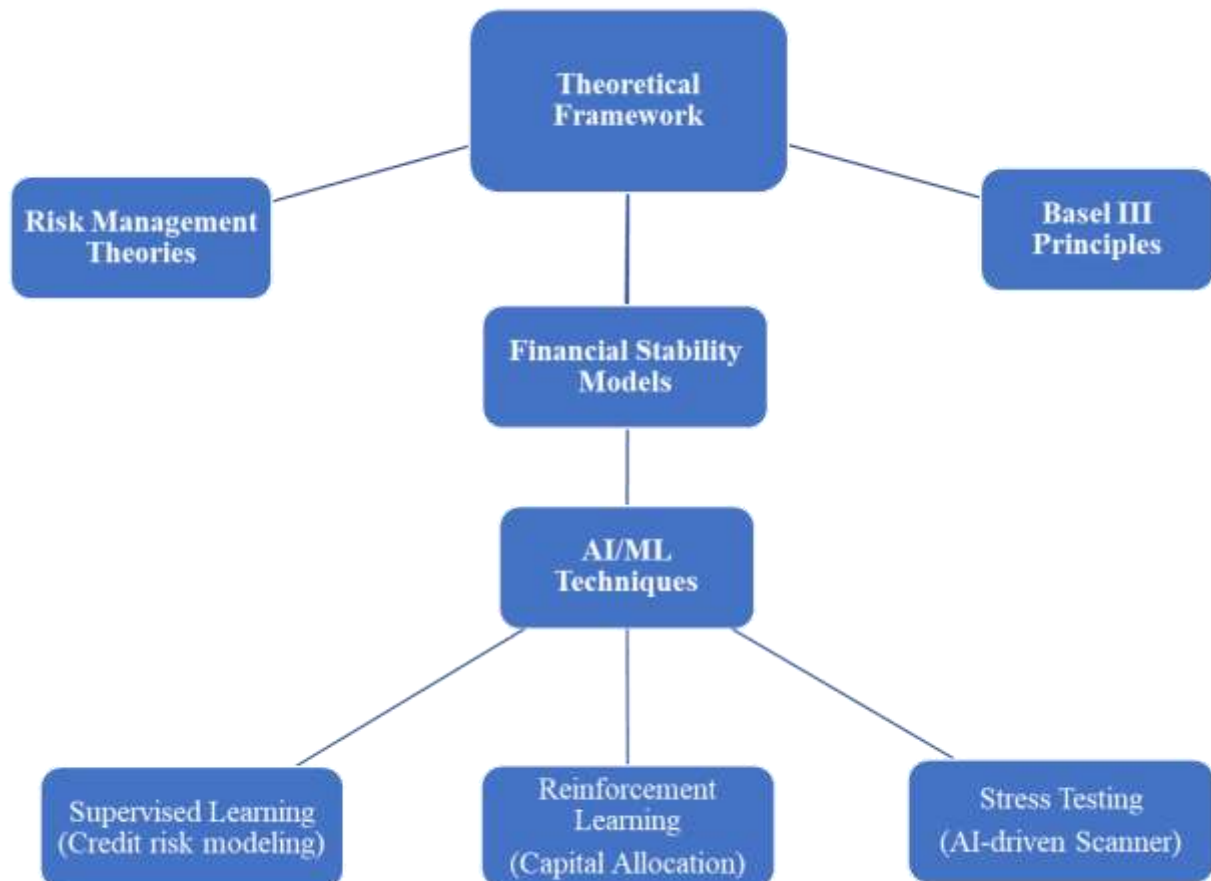
Techniques derived from AI have their advantages for summarising as well as analysis of crucial financial data, yet they also have their set of issues regarding regulation as well as ethical implications. Specifically, there is a concern regarding the explainability of conclusions produced by the AI models—also known as the 'black box problem'. Still, the lack of transparency, coupled with the data privacy and possible algorithmic bias in the case of a certain crisis becoming public, represents challenges for the regulators and banking professionals [42]. Some of the techniques like SHAP values or LIME can be used to make artificial intelligence system become more suitable for the regulated environment since they provide more transparent results of a decision made by the AI.

Despite the potential of integrating AI and machine learning for improving the capital adequacy assessments, some research gaps still exist. First, most of the existing studies were performed in the context of credit risk, or more specifically, credit risk forecasting. Reinforcement learning for managing capital reserves is also a relatively unexplored subject due to the necessity for real-world testing.

Second, the risk regulation on AI's capital adequacy management is not well developed and unified. Nonetheless, while Basel III is strong in formulating certain regulatory guidelines and measures, it does not specifically address AI governance regulation, thus creating ambiguities that organisations have to solve. To this end, it is crucial to continue research in building experienced AI-based regulatory compliance models.

Lastly, there are drawbacks concerning datasets and interpretability that commonly affect AI models. Deep learning methods, which include neural networks, can provide high accuracy in predictions but can provoke a black-box effect for regulators. Further research on explainable AI (XAI) in capital adequacy assessment will help in improving the level of trust and understanding of the banking systems that employ AI.

Finally, although stress testing utilising AI techniques has some merits, there is a scarcity of studies on the integration of AI with other existing financial risk models. A combination of different methods could be more accurate in providing reliable measures of capital adequacy in varying economic situations.



**Figure 1:** Theoretical Framework

### 3. Method

AI and ML contribute significantly to capital adequacy management since they augment the process of risk evaluation, facilitate efficient capital distribution, and address compliance issues [43]. Traditional approaches include comparison with past records and use of basic computations that do not factor real-time risk into financial position. Nevertheless, AI/ML models can process large volumes of data and likelihood patterns, establish relationships in quantities, volumes and variance, and support organisational capital adequacy planning [17].

ML techniques like decision tree, gradient boosting, and neural network can analyse multilevel data of financial institutions to establish the loss exposure and chances of setting adequate capital reserves [44]. This is evident in reinforcement learning since it involves updating the reserve requirement of capital allocation as per the dynamism of the market [45]. Stress testing is one of the most useful tools in ascertaining a bank's ability to cope with unfavourable economic shocks. AI adaptation makes stress tests more fluid and sensitive to actual financial shifts [17]. However, one challenge that was observed when conducting the study was the ascertainment of AI-based stress testing models against past crises. If policy models are not calibrated against real economy shocks, then they might provide inflated estimates of system sustainability or overlook important stress signals. Moreover, incorporating AI/ML in capital adequacy assessment subsequently aids the financial institutions to shift from the risk management approach of reacting to situations and to meet the Basel III regulation, the stability and efficiency of a financial institution.

Capital adequacy forecasting models refer to the ability of banking institutions to satisfy the minimum capital requirements when tested on specific financial conditions [46]. These models employ AI/ML applications in making estimations concerning future necessary capital depending on the estimated and past data.

Logistic regression, decision tree, and gradient boosting are samples of the categorisation of a set of defined models under the supervised learning type that categorises banks into well-capitalised or undercapitalised risks [44]. Regression models predict how much capital is needed as a buffer in order to stay within compliance [47]. Time series techniques like LSTM model predicted the future changes in capital adequacy based on the volatile changes that were recorded in the past.

Stress testing models on the other hand is another method similar to the earlier that aims at determining the prospective possibility of a bank under adverse economic conditions [48]. Others include reinforcement learning that also enhances the capital allocation plans with dynamic levels of reserves. By the use of these models, the extent of risks that can hinder these banks from operating is easily measured hence improving on their stability.

In this regard, it becomes relevant to select AI/ML models for capital adequacy that strike a balance between high accuracy, interpretability, and compliance with regulations. As for the methods, decision trees are chosen due to the high accuracy of the presented models in the field

of classification and the ability to ensure compliance with regulatory requirements in terms of explaining the model's decision-making process [49].

As for LSTMs, they are good to be used in time-series forecasting as they are able to recognize long-term trends in the financial datasets. Online learning is applied for the dynamic capital distribution and adjustment of resource distribution in accordance with the market environment [50].

Risk assessment using a supervised learning approach, trend predictions via deep learning, and decision-making through reinforcement learning enable excellent capital adequacy [23]. It also contributes to implementing a preventive, precise, and compliance risk management system.

### ***Estimation Techniques***

#### *Decision Trees & Random Forests*

Decision Trees can work with categorical and numerical data, and their interpretation is relatively easy, which makes them suitable for financial risk analysis [51]. They categorize them based on capital adequacy risk categories and use multiple layers in terms of risk-weighted assets and other factors such as liquidity ratios. Despite that, they are fairly precise, DTs contain high potential for overfitting and are not designed for exploring large datasets [52].

Random Forests (RF) an ensemble learning algorithm address this issue through the construction of several trees and their outcomes are aggregated [53]. This will prove useful in improving the reliability of the results in terms of predictors, decrease in variability as well as increasing reliability of the model. RF is more beneficial in stress testing the system and credit risk as it establishes the relationship of many variables [54]. However, RF models have their disadvantage in that they are computationally intense and require hyperparameters optimisation for improved accuracy and reduced computation.

Therefore, the two forms DTs and RF models can be used to forecast capital adequacy as they are clearly defined and compliant with the regulation which takes into account the patterns of the financial data.

#### *XGBoost/Gradient Boosting*

Gradient Boosting Machines are Machine learning methods that use multiple weak learners to make predictions that are better. XGBoost is a boosted version of GBM with

superior performance regarding some angles, including speed, numerical stability, and dealing with missing data, making it suitable for use within the financial risk assessment [55].

XGBoost grows trees step by step, improving the quality of the last split and controlling the overfitting by means of penalties [56]. Due to these reasons, the model is very useful in forecasting capital adequacy in view of changing economic circumstances. It surpasses the traditional regression models in its ability to identify nonlinear relations involving such factors as leverage ratios, net interest margins, or loan default probabilities.

Nevertheless, XGBoost is computationally expensive and has many hyperparameters that should be optimised, like learning rate, the depth of each tree, and feature importance [56]. Nevertheless, it is more accurate at modelling interactions and predicting outcomes, and this is why it is used for risk-based capital adequacy assessment and stress testing in banks.

#### *Neural Networks (LSTM, RNN)*

LSTM and RNN are effectively suitable for the time series of stock price prediction [57]. As capital adequacy assessment is a progressive one, these models can observe the trends and determine the requirements for internal capital in the future better.

LSTMs do not entrap into the issues of long-term dependency that occur due to the high complexity of the RNNs [58]. This is useful in predicting the impact that macro environment components including; interest rate and GDP change on adequacy of capital over time. However, models such as LSTMs suffer from high computational cost and need a large number of samples for training [59].

Although utilizing neural networks yields a greater prediction capability, they come with the disadvantage of being less interpretable, which is a significant factor in regulation. Tools like SHAP (Shapley Additive Explanations) enable decision-making features to be explained [60]. However, the use of LSTM and RNN models enables banks to gain a deeper understanding of capital adequacy patterns, which can be beneficial to strategic management and risk control.

#### *Reinforcement Learning for optimal capital allocation*

Reinforcement Learning (RL) is a sophisticated AI method that can change the company's capital distribution according to changing financial risks [23]. Different from conventional paradigmatic approaches, where stock management functions in response to a

previously laid out plan of operations based on past trends, RL agents acquire the best strategies for capital from appropriate experiences.

Some of these techniques, including the Deep Q-Networks (DQN) and Policy Gradient Methods, are useful in adjusting the levels of the reserves to meet the necessary capital adequacy ratio based on the uncertain state of the economy [61]. RL models show different market conditions and policy constraints and learns strategies that can be beneficial for the long-term health of the investment portfolio.

Nevertheless, RL's implementation is challenging due to the need for large-scale simulations and high computational power. However, when training an RL model, the proper selection of the reward function based on the regulatory requirement and accepted level of risk is important [23]. However, when correctly deployed, RL improves the quality of decision making, which in turn allows banks to deploy capital more effectively while at the same time reducing systemic financial risks.

#### *Stress Testing*

Stress testing is an important part of assessments of capital adequacy; it allows the bank to assess the possibility of its business under adverse economic conditions [62]. Previous approaches in stress tests often depend on past crises, but AI in stress testing are superior to traditional methods since it uses machine learning algorithms.

XGBoost and LSTMs, for instance, can create stress test models based on macroeconomic factors, credit risk, and liquidity ratios [63]. These models aim at replicating scenarios of capital inadequacy, enabling the banks to rebalance capital in line with the forecasted solvency status. Real-time risk assessment, on the other hand, is also one of the benefits of using artificial intelligence in stress testing since it helps the institutions detect new emerging financial risks without delay.

Nevertheless, AI-based stress testing models depend on the availability of good data and also on the proper methodology of model validation. However, the adoption of AI in stress testing leads to increased predictive accuracy, better compliance with the requirements, and greater resilience of the financial industry to crises [17].

In times of crisis, like the 2008 financial crisis and again during unexpected market changes witnessed with the onset of the COVID-19 pandemic, these techniques were too slow and

inaccurate [64]. With AI/ML-driven models, real-time information is incorporated, and parameters are dynamically adjusted [65]. This reduces delays, minimizes human error, and better represents intricate market movements, even in unprecedented situations.

#### 4. Results

##### Banking Metrics for Germany (2001–2005)

Table 2: Banking Metrics for Germany (2001–2005)

| Index | Country | Year | Bank Deposits | Bank Net Interest | Bank Non-Performi | Bank Noninter | Bank Regulato | Bank ROA | Bank ROA | Bank ROE (After | Bank ROE (Before | Stock Price |
|-------|---------|------|---------------|-------------------|-------------------|---------------|---------------|----------|----------|-----------------|------------------|-------------|
| 0     | Germany | 2001 | 60.11213      | 1.085657          | 4.6               | 50.01545      | 12            | 0.19031  | 0.193711 | 4.938905        | 5.027161         | 22.99107    |
| 1     | Germany | 2002 | 61.91441      | 1.199346          | 5                 | 45.14739      | 12.7          | -0.08253 | -0.06942 | -2.18641        | -1.83919         | 28.96065    |
| 2     | Germany | 2003 | 63.60712      | 0.993525          | 5.2               | 53.95421      | 12.4          | -0.36976 | -0.38129 | -10.744         | -11.0788         | 38.05096    |
| 3     | Germany | 2004 | 63.186        | 1.039831          | 4.9               | 44.34132      | 12.4          | -0.07475 | -0.06483 | -2.53167        | -2.19551         | 25.24676    |
| 4     | Germany | 2005 | 65.42558      | 0.929148          | 4.1               | 56.22723      | 12.2          | 0.303123 | 0.464761 | 10.98832        | 16.84779         | 14.12969    |

The table presents some of the most significant banking statistics for Germany over five years, reflecting changes in deposit behaviour, profitability, and risk profiles. Bank deposits as a percentage of GDP rose consistently from 60.11% in 2001 to 65.43% in 2005, indicating an expanding deposit base relative to the economy. The net interest margin reached a peak of 1.20% in 2002 but had fallen by 2005, indicating tighter margins on core lending businesses. Non-performing loans, which indicate credit risk, varied modestly but decreased slightly by 2005, while noninterest income as a proportion of total income exhibited volatility, suggesting changes in revenue sources. Profitability, as indicated by ROA and ROE, exhibited a mixed pattern; profitability was positive in 2001 and recovered in 2005, but the losses in 2002 and 2003 are cause for concern regarding the consistency of performance. Lastly, stock price volatility was the greatest in 2003, capturing market uncertainty that year, and fell dramatically by 2005, implying stabilisation. Generally, these figures portray a dynamic environment with changing risk and performance profiles for German banks.

##### Model Performance Comparison

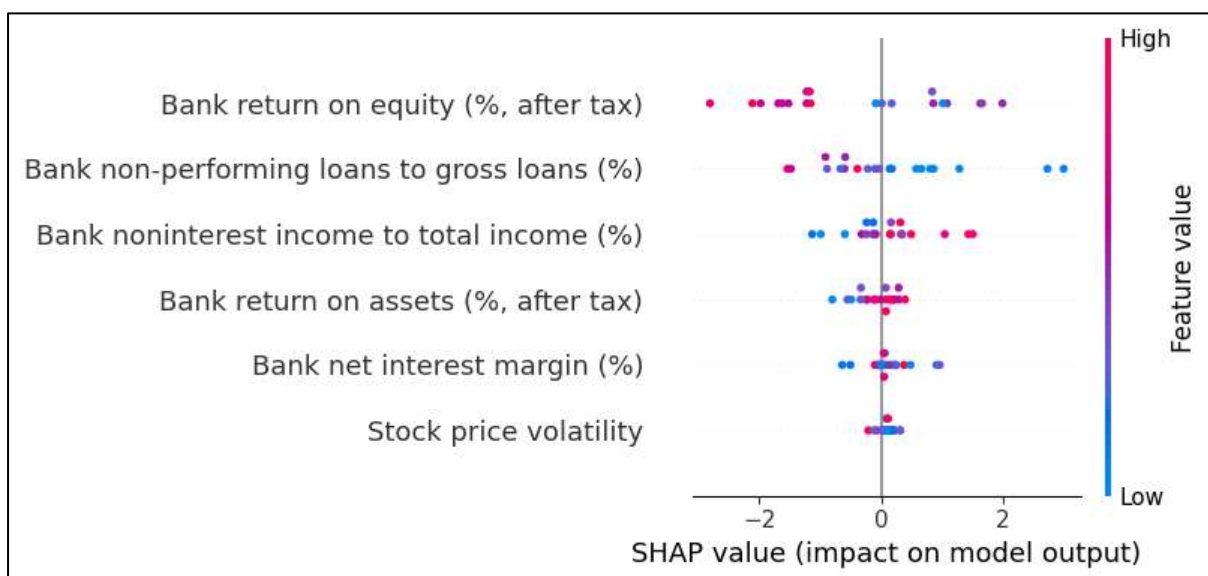
Table 3: Model Performance Comparison

| Model | R2 Score | RMSE |
|-------|----------|------|
|-------|----------|------|

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|               |             |             |
|---------------|-------------|-------------|
| Random Forest | 0.747577894 | 1.562519777 |
| XGBoost       | 0.847335615 | 1.215152256 |

The table presents a comparison of the performance of two prediction models: XGBoost and Random Forest. The  $R^2$  measure, which reflects the proportion of variance explained by the model, is more significant for XGBoost (0.8473) than for Random Forest (0.7476), indicating that XGBoost provides a more accurate fit for the data. Additionally, the RMSE (Root Mean Square Error) is smaller for XGBoost (1.2152) compared to Random Forest (1.5625), indicating more precise predictions with narrower average error margins. Overall, these statistics indicate that XGBoost outperforms Random Forest in this use case.



**Figure 2:** SHAP Plot

The SHAP plot displays the features that most significantly impact the model's predictions, ordering them by their importance. Bank Return on Equity (after tax) is one of the strongest influences, and greater values (colored in pink) typically add to the prediction. Other features, such as Bank Non-Performing Loans, tend to lower predictions when they have high values. The x-axis displays the direction and magnitude of the influence of each feature, and the colour scale indicates the actual feature values, allowing for a clear understanding of how every factor, whether high or low, contributes to the final model result.

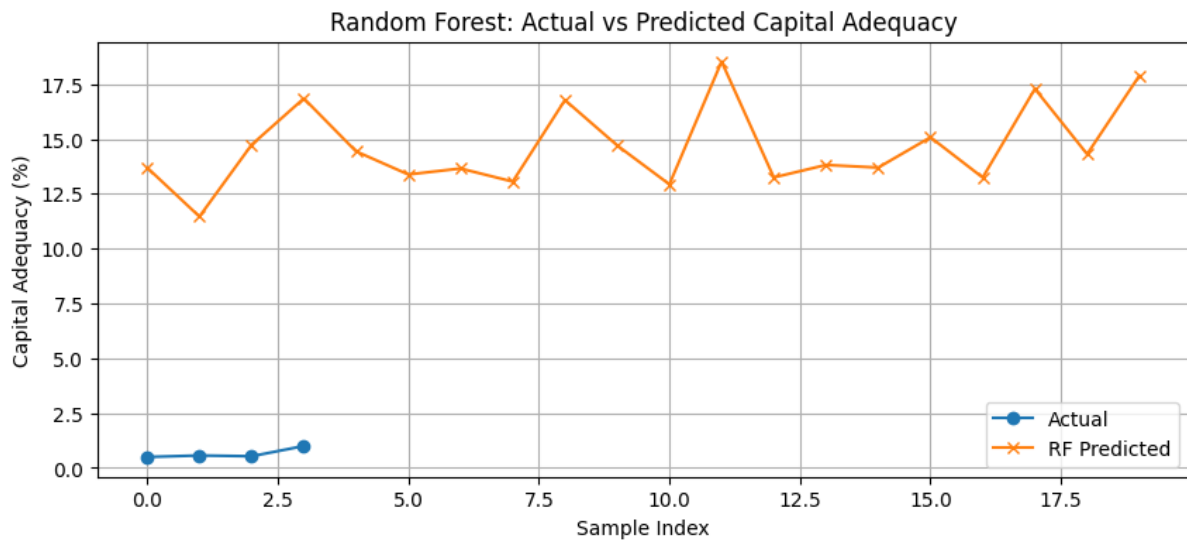
### Model Performance by Country

**Table 4:** Model Performance by Country

| Country        | R2          | RMSE     |
|----------------|-------------|----------|
| Germany        | -47.3168176 | 2.039257 |
| India          | -2.76304423 | 2.559838 |
| Japan          | -141.968848 | 2.626881 |
| United Kingdom | -226.312247 | 6.258901 |
| United States  | -4.96548069 | 1.729459 |

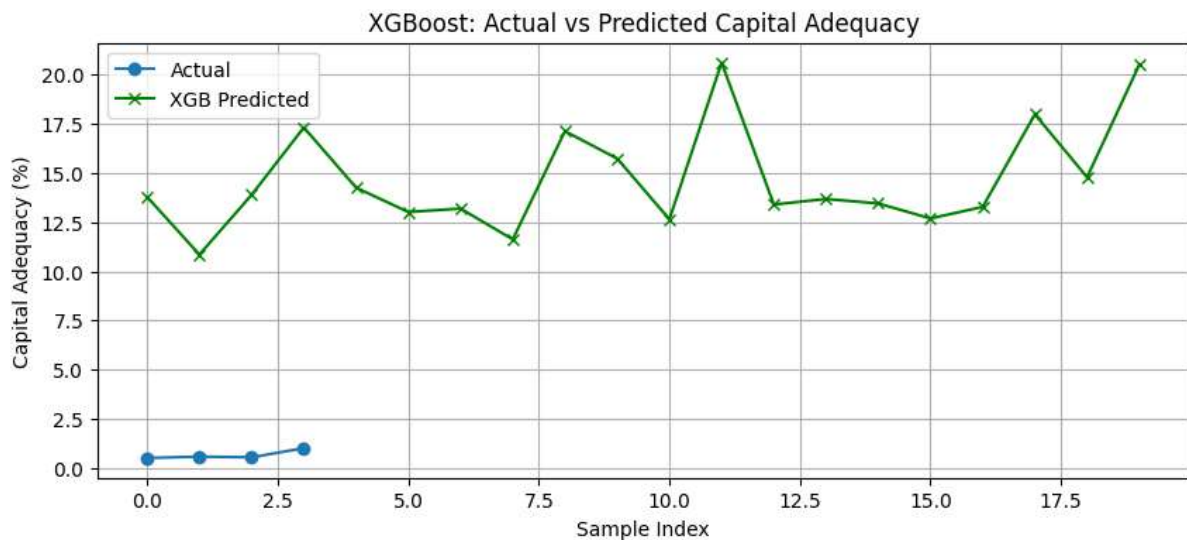
The table shows the models' performance across different countries, but the  $R^2$  for all of them is negative. This means that the AI/ML models are doing worse than a random prediction. This is a worry about whether the models will do well across different regions. The poor performance may be due to local legal differences, economic fluctuations, or poor data quality. For instance, the very low  $R^2$  value in the UK and Japan (-226.31 and -141.97, respectively) indicates that the models do not adequately capture the distinctive finance trends and regulations that are important in these countries without adjustment.

The RMSE values differ, ranging from the highest error in the United Kingdom (6.26), indicating significant prediction errors, to the lowest RMSE in the United States (1.73), suggesting comparatively better precision despite the negative  $R^2$ . In general, these findings indicate substantial difficulties with model performance between various regions.



**Figure 3:** Random Forest Model: Actual VS Predicted Capital Adequacy

The plot shows XGBoost and the actual values of capital adequacy. Actual values (blue) are relatively low, typically below 2%, whereas XGBoost predictions (green) vary widely, often exceeding these values by more than double, ranging from approximately 10% to over 20%. These results suggest that, like the RF model, the XGBoost model consistently overestimates capital adequacy, particularly in cases where actual values are low, indicating a misfit between the true and predicted values at low actual values.



**Figure 4:** XGBoost Model: Actual VS Predicted Capital Adequacy

The above figure 4 is showing the actual and XGBoost technique-predicted values of capital adequacy. The actual values are shown to be low, with some values even below 2%. In comparison, the predicted values are significantly higher and fluctuate between 10% and more

than 20%. This justifies the optimism of the XGBoost model, similar to the Random Forest model, in predicting superior capital adequacy, as it appears to overpredict in samples with low actual values, thus showing a disparity between the predicted and actual values in this category.

## 5. Discussion

The findings of this research are valuable in offering important insights into the capability of using AI and ML models to measure adequacy capital, aligning with the emerging literature on the transformative value of advanced analytics in financial risk management. The improved accuracy of XGBoost over Random Forest highlights the XGBoost model's flexibility in capturing non-linear relationships between financial variables, thereby providing support for the overall conclusion of this study that gradient boosting methods excel at analysing complex financial data. Such findings are similar to those of this study, with research arguing that boosting methods are capable of managing the interactions of risk drivers, such as leverage, asset quality, and operational efficiency [55]. Similarly, using machine learning techniques like XGBoost, research established that dynamic markets can be well forecasted with improved accuracy compared to conventional techniques [66]. The differential regulatory frameworks, as well as the heterogeneous macroeconomic conditions, mean that even advanced AI models could be at risk when applied without due facilitation in native environments. It has been proven with evidence in the COVID-19 pandemic that areas faced even harder times with respect to such discrepancies, so they highlighted local training of the models [67].

Nonetheless, these outcomes are promising. However, the model's inability to generalise across country-specific data remains to be addressed due to heterogeneity in data and context. The poor performance exhibited in country-level predictions is consistent with this research [23], which suggests that most AI models are developed within homogeneous environments and, therefore, cannot effectively absorb the jurisdictional subtleties in regulatory frameworks and macroeconomic determinants. This is especially true in the context of capital adequacy, where differences in Basel III implementation, supervisory stringency, and economic volatility can have a significant impact on outcomes. The study emphasises that region-specific calibration is required to maintain model relevance and validity in cross-national applications, which aligns with this study that supports localised model training and the incorporation of jurisdiction-specific features [34]. In addition, it also emphasises the necessity of adapting AI applications to consider regulatory and operational variations among financial systems, enforcing the need for a more contextualised response [35].

A common issue in Model Assessment is overestimating capital adequacy, which is more evident in low capacity situations. These errors are indicative of the ‘black box’ nature inherent in artificial intelligence approaches, which is problematic when regulatory issues are concerned. Although SHAP boosts interpretability to a certain extent, the model exhibits a prediction bias during the low actual ratios, which requires better XAI solutions. In addition, the stress tests used in this study, which are relatively flexible and incorporate elements of artificial intelligence, failed to capture the main crisis events. This can only mean that more emphasis has to be placed on testing AI models against real financial crises to have a feel of what to expect in the actual world, so as to produce reliable and credible results. According to research, deep learning and complex ensemble models often lack the required interpretability in a financially regulated environment [58]. Similarly, research affirm that AI models may be overfitting and biased due to data scarcity and uncertainty within the economic environment [60].

It also follows the recommendations of previous studies against using AI models for stress-testing purposes. Although the XGBoost and LSTM models were able to construct more dynamic adverse scenarios than the static models, there were weaknesses in the models’ stress-testing aspect, as they did not identify capital shortfalls in actual crisis periods. This is in concordance with the study by [13], which pointed out that complex models may fail even in extreme events, such as those caused by a “black swan,” and have little relation to history. Likewise, it is listed several safety and credit topics related to AI, including the impact of expert judgment and the repetitiveness of stress, as well as the strength and quality of model results.

## 6. Conclusion

In summary, the study highlights the use of artificial intelligence and machine learning to enhance the effectiveness of capital adequacy management, which is a key issue following the realisation that relying solely on past data and rigid models is ineffective. This is achieved through the use of XGBoost, LSTM, and reinforcement, which provide an effective method for assessing the risks and capitals. XGBoost performed better than Random Forest, as it had higher  $R^2$  values and lower RMSE values, indicating that XGBoost has a better ability to model complex financial nonlinearities. However, specific difficulties were observed in extending the models to different countries, including negative values of  $R^2$  in countries such as Japan and the UK. This may be due to differences in regulations or the macroeconomic environment. Moreover, models overcame financial capital adequacy in low-capital conditions, which are

problems associated with the 'Black box' model and underscore the need for an explainable AI (XAI) to achieve better results. Both stress testing with the help of Artificial Intelligence and dynamic reinforcement learning can help to over-predict and prevent risks, meeting the demands of Basel III.

Thus, this study recommends that policymakers and financial institutions to integrate AI/ML technologies in capital adequacy planning and also work towards reducing regulatory disparities and ensuring model interpretability. Predictive measures may involve: developing models specific to the region, verifying the models against past crises, and the use of explainable artificial intelligence models to keep regulators informed. Further studies should examine the integration of AI and classical approaches in the banking field; investigate how AI can be governed; and analyse datasets from various countries in order to enhance external validity. Only in this way can AI be a useful tool to support the more measured, or explainable, and regional need of maintaining appropriate capital levels and financial stability.

Conventional approaches to capital adequacy assessment have generally used fixed formulas and historical data. These approaches, although systematic, are inflexible and reactive. For example, in the early days of the COVID-19 pandemic, numerous banks discovered that historical models were not able to adapt rapidly to the fast-evolving market conditions and new risks that emerged in real time. These conventional models did not account for unforeseen risk factors like unexpected supply chain disruptions or drastic shifts in consumer behaviour. On the other hand, AI/ML techniques handle real-time data and regularly revise risk assessments, enabling banks to identify and react to emerging threats in a timely manner.

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