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# Prediction of Banking Credit Risk Using Logistic Regression and The Artificial Neural Network Models: A Case Study of English Banks

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**Abstract**

In this comprehensive study, we delve into the utilization of Logistic Regression (LR) and Artificial Neural Networks (ANN) for predicting credit risk in the English banking sector over the period from 2021 to 2023. Through an in-depth analysis of quarterly financial and non-financial data from various banks, this research aims to discern which predictive modeling technique provides more accuracy and reliability. The comparison between LR and ANN models offers significant insights into their capabilities and limitations, potentially guiding future risk management and decision-making processes in banking. This study also addresses the importance of advanced analytical methods in improving the predictiveness of financial risks, thus contributing to the enhancement of banking operations and the promotion of financial stability.

**Keywords:** Artificial Neural Networks, Logistic Regression, Credit Risk Prediction, Banking Sector, Financial Stability

**JEL Classification:** C50, G21

## Introduction

The banking industry, at the heart of modern economies, is tasked with the critical responsibility of managing financial resources, facilitating economic growth, and ensuring financial stability. Central to its operations is the assessment and management of credit risk, a cornerstone of sound banking practices. Accurate prediction of credit risk is not just a technical necessity but a strategic imperative, defining the success and resilience of banking institutions in a dynamic and ever-evolving financial landscape.

This research embarks on an in-depth exploration of the multifaceted domain of credit risk prediction within the banking sector, with a specific focus on the application and comparison of two sophisticated predictive modeling methodologies: Artificial Neural Networks (ANN) and Logistic Regression (LR). The selection of these models is driven by their recognized prowess in the realm of predictive analytics, capable of unraveling intricate patterns and relationships within complex and multidimensional datasets.

The central objective of this comprehensive study is to undertake a meticulous examination of the effectiveness, applicability, and comparative performance of ANN and LR models in the prediction of credit risk. Beyond a mere academic exercise, this research is positioned to deliver actionable insights with direct relevance to the banking industry, offering a roadmap for better-informed lending decisions, enhanced risk management practices, and the safeguarding of financial institutions' health.

To attain this overarching objective, this research harnesses a comprehensive dataset derived from real-world banking data, reflecting the intricacies and nuances of the banking environment. By subjecting this dataset to the analytical prowess of ANN and LR models, this study seeks to uncover the hidden dynamics of credit risk, shedding light on the models' respective strengths, limitations, and potential applications in practical banking scenarios.

The subsequent sections of this paper will delve deeper into the intricate web of methodology, data analysis, findings, and implications, providing a comprehensive roadmap for stakeholders within the banking industry, regulatory bodies, and the academic community. As we traverse this terrain of credit risk prediction, the pivotal role of ANN and LR models as powerful tools for enhancing financial stability, optimizing lending practices, and fostering informed decision-making in the banking sector will become abundantly clear. In the era of data-driven finance, the ability to harness the full potential of advanced predictive models is not just a competitive advantage but a necessity. This research endeavors to illuminate the path toward more accurate, reliable, and efficient credit risk assessment, ultimately contributing to the resilience and sustainability of the banking sector in the face of evolving financial complexities and challenges.

### 1.1. Theoretical Background of Banking Credit Risk

The banking sector's pivotal role in the economy hinges on its ability to efficiently allocate financial resources to individuals, businesses, and governments. However, this intermediation process is accompanied by inherent risks, with one of the most prominent being credit risk, often referred to as default risk. Credit risk represents the potential financial loss that a bank may incur due to the failure of a borrower to repay a loan or meet their financial obligations as scheduled (Saunders and Cornett,2008:18).

### 1.1. Measurement of Credit Risk

To appreciate the significance of credit risk in banking, it is imperative to establish a robust framework for its measurement and management. One of the seminal contributions in this field is Altman's work on credit risk assessment, specifically his development of the Z-score model in 1968 (Altman,1968:600). This model utilizes financial ratios and discriminant analysis to predict the likelihood of corporate bankruptcy, offering a quantitative approach to evaluating credit risk.

Another essential tool in credit risk measurement is Credit Risk+, pioneered by Jarrow and Turnbull (Jarrow and Turnbull,1995:56). This model employs portfolio credit risk assessment, providing a comprehensive framework for understanding the credit risk of an entire loan portfolio. It combines default probability estimates with loss given default (LGD) and exposure at default (EAD) parameters. Credit risk, a fundamental concern in banking and financial institutions, represents the potential financial loss due to the inability or unwillingness of borrowers to fulfill their financial obligations as agreed upon. The measurement and management of credit risk are central to the stability and profitability of these institutions.

*Quantitative Models for Credit Risk Assessment*: One of the foundational contributions to the measurement of credit risk is Altman's development of the Z-score model in 1968 (Altman,1968:601). This pioneering model employs financial ratios and discriminant analysis to predict the likelihood of corporate bankruptcy. By assessing a company's financial health based on metrics such as liquidity, profitability, and leverage, the Z-score model provides a quantitative approach to evaluating credit risk.

*Credit Scoring and Predictive Analytics:*Credit scoring models have become instrumental in assessing the creditworthiness of borrowers. These models utilize historical credit data, borrower characteristics, and financial behavior to assign credit scores that reflect the likelihood of default. One widely used credit scoring system is the FICO score, developed by Fair Isaac Corporation (Fair Isaac Corporation, 2021: Online). The FICO score considers factors such as payment history, credit utilization, and length of credit history to predict credit risk.

Furthermore, the advent of predictive analytics and machine learning has revolutionized credit risk assessment. Advanced statistical techniques, including logistic regression and artificial neural networks, can analyze vast datasets and uncover intricate patterns in borrower behavior (Hauser and Booth,2022:570). These models have demonstrated remarkable accuracy in predicting credit defaults and have been adopted by financial institutions worldwide.

*Regulatory Frameworks for Credit Risk Measurement* Regulatory bodies play a critical role in shaping the measurement and management of credit risk within the financial sector. The Basel Committee on Banking Supervision introduced the Basel II framework, emphasizing the importance of risk modeling and capital adequacy (Basel Committee,2006:Online). This framework allows banks to use internal models for credit risk assessment, known as the Internal Ratings-Based (IRB) approach, to calculate capital requirements based on their own credit risk assessments.The measurement of credit risk is a multifaceted endeavor that combines quantitative models, credit scoring systems, and advanced analytics. The ongoing evolution of credit risk measurement is influenced by both academic research and regulatory frameworks, ensuring that financial institutions can effectively assess and manage credit risk to maintain stability and profitability.

### 1.2. Macroeconomic Factors and Credit Risk

Beyond financial indicators, macroeconomic factors play a critical role in influencing credit risk. Economic downturns, characterized by high unemployment rates and reduced economic activity, often lead to an increase in credit risk. Researchers such as Yılmaz [4] have explored the relationship between macroeconomic variables and credit risk, highlighting the importance of economic indicators in predicting credit defaults.

In the wake of the financial crises and economic shifts globally, understanding the determinants of credit risk has become paramount for financial stability and growth. Credit risk, defined as the potential that a borrower will fail to meet their obligations in accordance with agreed terms, is influenced by a myriad of factors, amongst which macroeconomic variables have significant prominence. This essay explores the profound impact of macroeconomic factors on credit risk, highlighting inflation rates, interest rates, GDP growth, and unemployment rates, substantiating the discussion with empirical findings.

Inflation inherently decreases the purchasing power of money, impacting borrowers' ability to repay debts, consequently escalating credit risk. A study by Jiménez and Saurina (2006) demonstrated a positive correlation between high inflation rates and increased credit risk amongst banks. Their findings revealed that during inflationary periods, banks experienced a constriction in capital adequacy, propelling a surge in non-performing loans. Interest rates directly affect the cost of borrowing and the return on savings. Higher rates increase the cost of debt service for borrowers, potentially leading to higher default rates, as observed by Ali and Daly (2010). They found that spikes in interest rates were followed by increased credit risk, emphasizing the necessity for comprehensive risk assessment and interest rate risk management in financial institutions.

Gross Domestic Product (GDP) growth is an indicator of economic health. Negative growth or recession can signify a deteriorating economic climate, often associated with higher credit risk. A seminal work by Bernanke, Gertler, and Gilchrist (1996) illustrated that recessions typically see a contraction in credit availability, alongside an escalation in credit risk, due to decreased borrower solvency and deteriorating collateral values. Unemployment is inversely related to borrowers' repayment capacity. Higher unemployment rates exacerbate credit risk by diminishing consumers' disposable income, limiting their ability to service debts. Louzis, Vouldis, and Metaxas (2012) provided empirical evidence correlating rising unemployment with heightened credit risk in the banking sector, thereby affecting loan performance and financial stability. Macroeconomic factors play a critical role in shaping credit risk.

### 1.3. The Role of Regulatory Bodies

The global financial landscape is intricate, and the role of regulatory bodies in shaping and directing this environment, particularly in credit risk management, is pivotal. These entities enforce standards and practices that ensure financial stability, protect consumer interests, and maintain confidence in the credit system. This essay examines the role of regulatory bodies in mitigating credit risk, supported by citations from scholarly sources and industry reports. Regulatory bodies establish guidelines to govern credit risk management. One such example is the Basel Committee on Banking Supervision (BCBS), which sets global regulatory standards for banks, including those related to credit risk. The BCBS's Basel III framework, for instance, emphasizes improved capital, leverage, and liquidity ratios, aiming to bolster banks' ability to absorb shocks from financial and economic stress (BCBS, 2017).

Consumer protection is crucial in maintaining trust in financial markets. Regulatory bodies, such as the Consumer Financial Protection Bureau (CFPB) in the United States, oversee lending activities, ensuring fairness, transparency, and integrity in credit practices. This oversight includes the regulation of credit risk-related disclosures and practices to prevent consumer exploitation and systemic risk build-up (CFPB, 2020).

Credit rating agencies (CRAs) play a significant role in assessing credit risk, influencing investment decisions and capital flows. However, the 2008 financial crisis highlighted the potential conflicts of interest and failures in CRAs' assessments. Regulatory bodies, such as the European Securities and Markets Authority (ESMA), oversee and regulate CRAs to ensure they adhere to stringent standards of integrity, transparency, responsibility, and accuracy in credit risk rating (ESMA, 2021). Advancements in technology are revolutionizing credit risk management. Regulatory bodies are increasingly recognizing the role of financial technology (FinTech) and regulatory technology (RegTech) in enhancing credit risk management efficiency. The Financial Stability Board (FSB) has been active in this realm, analyzing the implications of technological innovations on global financial stability and providing recommendations on regulatory and supervisory approaches (FSB, 2019).

## 2.Navigating Credit Risk Complexity in the United Kingdom's Banking Sector

Within the global financial architecture, the United Kingdom's banking sector stands as a pillar of both stability and potential systemic risk. Central to this paradox is the concept of credit risk, representing a financial institution's potential loss due to borrowers' failure to fulfill their contractual obligations. The landscape of managing this inherent risk has undergone significant evolution, more so in the wake of the 2008 financial crisis and recent global disruptions. This scholarly examination underscores the pivotal developments in regulatory frameworks, strategic risk management protocols, and the integration of technological advancements, all set against the backdrop of an increasingly volatile economic and geopolitical environment. Post-2008, the regulatory environment in the United Kingdom embarked on a journey of significant recalibration. Spearheaded by entities such as the Financial Conduct Authority (FCA) and the Prudential Regulation Authority (PRA), the emphasis has been on fortifying the financial sector's infrastructural resilience. The Basel III regulations emerged as a global standard, advocating for enhanced bank capital requirements, stress testing, and market liquidity risk. Beyond regulatory compliance, UK banks have harnessed a more strategic ethos in managing credit risk. Utilization of internal ratings-based (IRB) approaches, alongside the institutionalization of stress testing scenarios, reflects a shift from reactive risk management to a more proactive risk anticipation and mitigation philosophy (BoE,2021). Credit risk in the banking sector does not exist in a vacuum. The turbulence generated by events such as Brexit presents a tangible manifestation of how geopolitical shifts significantly impact credit risk parameters. These movements necessitate a holistic view of risk that encompasses a wide range of economic, social, and political variables (Sampson,2020:166). The advent of Artificial Intelligence (AI) and Machine Learning (ML) in financial risk management marks a transformative departure from traditional methodologies. By leveraging complex algorithms, banks can now predict potential defaults with a higher degree of precision, thereby enhancing their decision-making protocols (Financial Conduct Authority,2018:11). The COVID-19 crisis has stress-tested the entire financial sector's resilience, drawing attention to the need for robust credit risk buffers. The UK's strategic approach, characterized by regulatory forbearance and fiscal interventions, highlights the critical role of flexible policy frameworks in maintaining financial stability during systemic shocks (BoE,2020:18).

**4.Logistic Regression and Artificial Neural Networks methods**

Logistic Regression and Artificial Neural Networks represent pivotal methodologies in the realm of data analytics and machine learning, offering robust mechanisms for predictive analysis in complex, real-world scenarios. Each method has distinctive characteristics, applicability, and technical prerequisites, shaping modern scientific inquiries and practical applications across various disciplines. This discourse delves into the scientific underpinnings of these techniques, underscored by empirical studies and academic sources, providing a comprehensive scholarly examination.

**4.1. Logistic Regression: Foundations and Applications**

Logistic Regression (LR) stands as a cornerstone in statistical modeling and analysis, particularly suited for circumstances requiring binary classification. Unlike linear regression, LR accommodates categorical dependent variables, fundamentally transforming the analysis landscape for events represented by dichotomies. The crux of LR lies in its utilization of the logistic function, anchoring predicted probabilities within a [0,1] range, thus ensuring coherent interpretations within a probabilistic framework. Essentially, LR computes the probability of a certain class or event existing (e.g., pass/fail, healthy/sick) based on one or multiple independent variables (Hosmer Jr, Lemeshow, & Sturdivant, 2013:18). LR has been instrumental across various scientific fields, demonstrating substantial reliability. Specifically, in medical research, LR has excelled in disease prediction based on diagnostic tests and symptomatology, significantly contributing to prognostic models and treatment strategies (Harrell Jr, Lee, & Mark, 1996:375). At its core, logistic regression is a type of regression analysis used for prediction of outcome of a categorical dependent variable based on one or more predictor variables. The probability of a certain event occurring is represented as a logistic function of a linear combination of the predictor variables. The statement provided discusses logistic regression analysis and highlights certain differences between logistic regression and other regression methods. Here's the translation and some additional context in English:

In logistic regression analysis, the objective is to predict the value of a categorical dependent variable, hence what is attempted is the prediction of 'membership' concerning two or more groups (Mertler & Vannatta, 2005). It is understood that there are several points that distinguish logistic regression when compared with other regression methods. These differences can be listed as follows (Gujarati, 2006:555):

• It is assumed in logistic regression analysis that there is no multicollinearity problem among the independent variables.

• While equality of the variance-covariance matrix is sought in regression models, this equality condition is not sought in the logistic regression model.

• While the condition of the independent variables showing a multivariate normal distribution is sought in regression analysis, and especially the condition of the dependent variables being

The logistic regression model is formulated as follows (Aktaş, 1993:46).

*Linear Equation (Linear Predictor)*

$$z = \beta_0 + \beta_1 x_1 + \beta_0 + \beta_2 x_2 + \cdots + \beta_0 + \beta_n x_n \qquad (1)$$

Here, z represents the linear combination of the independent variables $x_1, x_2, \dots, x_n$ weighted by their respective coefficients $\beta_1, \beta_2, \dots, \beta_n$ plus an intercept $\beta_0$

*Logistic Function (Sigmoid Function)*

$$\pi(x) = \frac{1}{1 + e^{-z}}$$

Here, $\pi(x)$represents the predicted probability that the outcome is 1 (for the binary case, typically representing the "success" or "positive" outcome). The logistic function transforms the linear combination z into a probability by outputting values between 0 and 1.

## *Model Fitting*

The coefficients $\beta_0, \beta_1 \dots . \beta_n$are usually estimated using the method of maximum likelihood estimation (MLE). The goal is to find the set of coefficients that best fits the observed data, by maximizing the likelihood function. In logistic regression, the interpretation of coefficients is essential for understanding the impact of each independent variable on the odds of the predicted outcome. When you interpret the coefficients:

1. For every one-unit increase in the independent variable $x_i$ while holding all other variables constant, the odds of the outcome happening (as opposed to not happening) are multiplied by $e^{\beta i}$. This exponential function of the coefficient $e^{\beta i}$represents the odds ratio (OR) associated with a one-unit change in $x_i$
2. Prediction: Once the logistic regression model has been fitted to the data, it can be utilized to forecast the likelihood of the "success" outcome for new data points. This is typically done by computing the predicted probability π(x) for each observation. If π(x) >0.5π(x)>0.5, the model predicts a "success" (coded as 1); if π(x)≤0.5, the model predicts a "failure" (coded as 0). This 0.5 threshold is common but can be adjusted based on specific needs or domain knowledge to improve model sensitivity or specificity.

### 4.2.Artificial Neural Networks: Complex Modeling for Advanced Predictions

Transitioning from traditional statistical methods, Artificial Neural Networks (ANNs) emerge as sophisticated computational systems, mirroring the neural structure of the human brain, designed for pattern recognition, classification, and predictive modeling. ANNs are comprised of interconnected units or nodes (neurons) organized in layers: input, hidden, and output. These structures excel in capturing non-linear relationships, primarily due to their capacity for learning and adaptation, features that traditional models like LR lack (Zhang, Patuwo, & Hu, 1998:44). In finance, ANN models have been revolutionary, particularly in credit scoring, risk management, and stock market predictions, outperforming classical methods by accounting for complex, non-linear interdependencies within the data (Kumar & Ravi, 2006). While LR provides a robust, statistically grounded mechanism for predictive modeling, its application remains confined within the bounds of the relationships it can model, often linear. Conversely, ANNs transcend this limitation, harnessing an advanced algorithmic composition to model non-linear, intricate relationships, though at the expense of the 'black box' critique, owing to their often-opaque decision-making processes. A synergistic approach, therefore, suggests combining LR and ANNs, harnessing LR's statistical robustness and interpretability with ANNs' high-dimensional data processing capacity, optimizing predictive accuracy while mitigating individual methodological constraints.

ANNs are complex computational models inspired by biological neural networks, consisting of multiple layers of interconnected nodes (neurons) designed for pattern recognition and learning from data. An ANN typically consists of three layers:

- Input layer: Where the network receives its input data $(x_i)$
- Hidden layer(s): Composed of neurons that process inputs received from the input layer and forward processed information to the output layer. Each neuron applies an activation function, like the sigmoid function or ReLU, to a weighted sum of its inputs.
- Output layer: Delivers the final output of the network. One of the key mechanisms of learning in ANNs is backpropagation, an algorithm used for minimizing the error between the actual and predicted outcomes. It adjusts the weights of the connections in the network in a way that error is minimized, and the prediction gets closer to the actual outcome.

Mathematically, the update of the weight matrix (W) is represented as:

$$W_{new} = W_{old} - \rho \frac{\vartheta L}{\vartheta W}$$ Where:

- $W_{new} = W_{old}$ are the new and old values of the weight matrix,
- η is the learning rate,
- L is the loss function,
- $\frac{\vartheta L}{\vartheta W}$ is the gradient of the loss function with respect to the weights.

This equation highlights the iterative nature of learning in ANNs, where the weights are updated in the direction that minimizes the loss function. The power of ANNs emanates from their capacity to approximate any non-linear function, as outlined in the universal approximation theorem. However, this complexity comes with challenges in interpreting the model, often described as a "black box" due to the difficulty in intuitively understanding the relationship between the inputs and the response (Goodfellow et al.2016:112).

In summation, both Logistic Regression and Artificial Neural Networks hold imperative scientific and practical significance, each with unique strengths and limitations. Their judicious application, possibly in a complementary manner, is essential for scientific progress and operational efficacy across diverse domains. Future research endeavors necessitating advanced predictive analytics must consider the contextual suitability of each method, potentially integrating both for an enriched analytical outcome.

Artificial neural networks are an information processing system that is inspired by biological neural networks and contains performance characteristics similar to biological neural networks. (Fausett, 1994:78). The applications of artificial neural networks can be listed as:

• Determining whether a company is likely to go bankrupt or not,

• Measuring and analyzing the performance of stocks,

• Predicting the direction of foreign exchange rates,

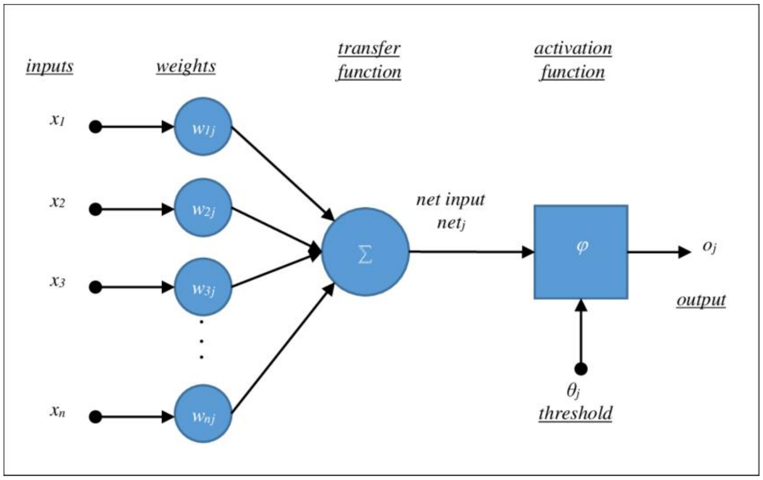
• Determining if there is a bankruptcy risk based on the performance of a business or financial institution,

• Forecasting financial crises as an early warning,

• Making securities trading and predictions, and

• Conducting credit risk analysis for firms.

**Figure 1:** Artificial Neural Cell




**Source: Altunöz, 2013:199.**

In Figure 1, the neurons formed by ANNs (Artificial Neural Networks) can be observed. The inputs represented by 'G' enter the system as indicated by 'A'. The aggregation function, shown as 'NET', calculates the net information coming to the neural cell. Even though this calculation is done using various functions, the commonly accepted equation is as shown in Equation 1.

Artificial neural networks offer certain advantages in terms of usage. These are:

• ANNs, with their learning characteristics based on experiences, can respond instantly to additional data sets.

• They don't require a mathematical model. Starting from the used data, they intelligently and quickly derive relationships. Damage occurring in one or several neurons in ANNs doesn't prevent reaching results or lead to significant errors in the outcomes. In contrast, conventional computer systems are quite sensitive to errors, where minor mistakes can lead to significant changes in the results.

• The networks are non-linear.

• Information is stored throughout the network, and they learn using examples.

• They have the ability to learn and organize autonomously, and they can operate with incomplete information.

However, ANNs also have certain disadvantages. These include:

• There are challenges in interpreting the results from the networks because it's unknown what's inside the system.

• They are not bound by a universally accepted rule in determining the appropriate network structure.

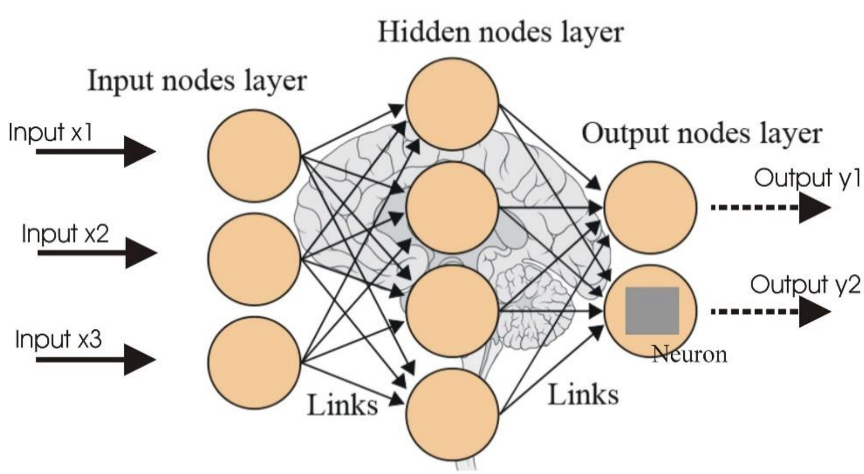
• It's challenging to integrate them into different systems.

• They require a long time for training, resulting in high time and financial costs.

The application of ANNs (Artificial Neural Networks) fundamentally consists of training and testing phases. During the training phase, understanding the structure of the networks, assigning initial values, and using training data to determine weight coefficients are carried out. After completing the training data, the trained network, taking into account the weight values, can predict the outcome of any given data set. In this process, the number of trainings (N) to be applied to the ANN is entered.

In the second phase, the Testing phase, using the weight coefficients and other parameters obtained during the Training phase, the system presents to the user the values it produces for data outside the training data (Şeker et al., 2004:81).

**Figure 2:** Artificial Neural Cell Model




**Source:** Kurup ve Dudani

Total function;

$$net = \sum_{i=1}^{n} w_i x_i + b \qquad (1)$$

From Equation (1), we obtain the value from which the output of the processing element is derived. In this process, the mentioned value is passed through a linear or differentiable nonlinear transfer function. This leads us to Equation (2)

$$Y = F(net) = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \qquad (2)$$

In forecasting time series with ANNs (Artificial Neural Networks), a general six-step process is applied (Günay et al., 2007:131).

Step 1:

Data preprocessing is carried out. In this step, the data is transformed into the range (0,1) using the following transformation:

$$x_i' = \frac{x_i - \min(x_i)}{Max(X_i) - \min(X_i)} \qquad (3)$$

Step 2:

A decision is made regarding how much of the series will be allocated for training, how much for validation, and how much for testing.

Step 3:

In this step, the number of inputs in the model, the number of hidden and output layers, how many neurons each layer will contain, the learning algorithm, and the performance criteria are determined.

Step 4:

The best weight value is calculated.

Step 5:

Performance metrics are calculated. The chosen performance metric is determined based on the difference between the forecasts on the test set and the actual data in the test set.

Step 6:

A forecast is made.

### 4.3. Credit Risk Prediction in English Banking Using Artificial Neural Networks and Logistic Regression Method

The dependent variable is defined in the assessment of credit risks for banks. Each quarterly data sample is evaluated to determine if it indicates a high credit risk for the bank. This evaluation is represented by values "0" and "1": a value of "0" is defined as a "negative signal," indicating that the bank has a high credit risk; whereas a value of "1" signifies a "positive signal," indicating that the bank's credit risk is low. In the econometric analysis section of the study, the method selection was influenced by the work of Zhu et al.(2016).

**Table 1: Codes, Description and Category of the Independent Variables**

| Code | Description | Category |
|---|---|---|
| V1 | Current ratio of banks C1 | Liquidity |
| V2 | Quick ratio of banks C2 | Liquidity |
| V3 | Cash ratio of banks C3 | Liquidity |
| V4 | Working capital turnover of banks C4 | Liquidity |
| V5 | Return on equity of banks C5 | Leverage |
| V6 | Profit margin on sales of banks C12 | Profitability |
| V7 | Rate of Return on Total Assets of banks C7 | Leverage |
| V8 | Total Assets Growth Rate of banks C8 | Activity |
| V9 | Accounts receivable collection period of banks C14 | Leverage |
| V10 | Accounts receivable turnover ratio of banks C15 | Leverage |
| V11 | Transaction time and transaction frequency of banks C17 | Non-financial |
| V12 | Credit rating of banks C18 | Non-financial |

The variables were obtained from UK FINANCE and https://www.reportlinker.com. In our study, quarterly data points contained in our data set are used to test the banking credit risk prediction models. Analysis is over the period 2021 to 2023. To process and standardize the data, the Z-score normalization method is utilized in Equation $C_i^* = (C_i - C)/S_i$. This method involves initially calculating the mean and standard deviation of the raw data, which is necessary for the normalization process. The relevant data and these initial calculations can be found in Table 2. This approach ensures that the data is appropriately scaled and standardized for further analysis.

## 1. **Emprical Analysis with** Artificial Neural Networks (ANN)and Logistic Regression **(LR)**

**Table 2: Descriptive statistics of the mean and standard deviation**

| Variable | Mean | Std. Deviation |
|---|---|---|
| V1 | 1.512 | 1.600 |
| V2 | 1.221 | 1.498 |
| V3 | 0.456 | 0.800 |
| V4 | 12.01 | 69.009 |
| V5 | 0.033 | 0.078 |
| V6 | 0.048 | 0.080 |
| V7 | 0.024 | 0.039 |
| V8 | 0.221 | 0.276 |
| V9 | 8.150 | 2.887 |
| V10 | 0.819 | 0.199 |
| V11 | 0.728 | 0.390 |
| V12 | 0.0212 | 0.020 |

***The Collinearity Diagnosis Method*** utilizes linear regression to analyze collinearity in variables, following the approaches recommended by Way and Goldstein. This method involves using three key indices: the conditional index (CI), tolerance (T), and variance inflation factor (VIF). When a variable exhibits index values of CI greater than 10, T less than 0.2, and VIF greater than 10, it is considered to have strong collinearity and is therefore excluded from the analysis. This threshold-based approach helps in identifying and removing variables that may cause issues due to high collinearity. When independent variables display values such as CI greater than 10, T less than 0.2, and VIF exceeding 10, this suggests a significant level of collinearity. Therefore, any variables meeting or surpassing these thresholds are excluded from our analysis. The linear regression method is employed to assess the threshold values of CI, T, and VIF for every independent variable, leading to the selection of 7 independent variables. In Table 3, we illustrate the collinearity diagnosis index for the original 12 independent variables, alongside the revised index values for the 10 selected independent variables.

**Table 3: Collinearity diagnosis index value**

| Variables | T (Original 12) | VIF (Original 12) | CI (Original 12) | T (Reserved 7) | VIF (Reserved 7) | CI (Reserved 7) |
|---|---|---|---|---|---|---|
| V∗1 | 0.005 | 120.109 | 1.100 | - | - | - |
| V∗2 | 0.006 | 170.700 | 1.019 | - | - | - |

| Variables | T (Original 12) | VIF (Original 12) | CI (Original 12) | T (Reserved 7) | VIF (Reserved 7) | CI (Reserved 7) |
|---|---|---|---|---|---|---|
| V∗3 | 0.054 | 10.909 | 1321 | - | - | - |
| V∗4 | 0.877 | 1.009 | 1.721 | 0.787 | 1.072 | 1.173 |
| V∗5 | 0.133 | 8.134 | 1009 | - | - | - |
| V∗6 | 0.350 | 2.312 | 1.180 | 0.678 | 1.400 | 1.455 |
| V∗7 | 0.100 | 9.222 | 2.080 | - | - | - |
| V∗8 | 0.432 | 1.041 | 2.017 | 0.678 | 1.019 | 1.503 |
| V∗9 | 0.309 | 2.019 | 1.412 | 0.331 | 1.810 | 1.531 |
| V∗10 | 0.590 | 1.700 | 2.031 | 0.617 | 1.573 | 1.321 |
| V∗11 | 0532 | 1.910 | 3.591 | 0.019 | 1.400 | 1.731 |
| V∗12 | 0.617 | 2.001 | 3.000 | 0.500 | 1.915 | 1001 |

Table 3 the term "Tolerance" is abbreviated as "T", while "Variance Inflation" is represented by the acronym "VIF", and "Conditional Index" is denoted by "CI". In the collinearity diagnosis, 7 independent variables have been identified and preserved. These variables are subsequently utilized in the construction of the model for predicting credit risk.

ANOVA (Analysis of Variance) is a statistical method used to evaluate the significance of differences between the means of three or more independent groups (Snedecor & Cochran, 1989). This analysis divides the total variance into two components: within-group variance and between-group variance, thereby determining whether the differences in group means are due to chance or are statistically significant (Fisher, 1925). The basic requirements for using variance analysis include the independence of groups, normal distribution of data, and homogeneity of group variances (Levene, 1960). The results of ANOVA are usually reported along with the F-test statistic, which represents the ratio of between-group variance to within-group variance (Fisher, 1925). If the F-test statistic produces a p-value smaller than the established significance level (usually $p<0.05$), this indicates that there is a statistically significant difference between the group means (Snedecor & Cochran, 1989). This result allows researchers to conclude significant differences between groups and may require the application of post-hoc tests for more detailed analysis (Tukey, 1949). Additionally, the Analysis of Variance (ANOVA) results, as detailed in Table 4, show that collinearity is significant at the 1% level.

**Table 4: the Analysis of Variance (ANOVA) results**

| Model | Sum of Squares | df | Mean Square | F | Sig (*) |
|---|---|---|---|---|---|
| Regression | 31.121 | 16 | 2.001 | 11.000 | 0.000 |
| Residual | 120.051 | 501 | 0.180 | - | - |
| Total | 148.141 | 567 | - | - | - |

*****Denotes the signifance level at %1.

Table 4 summarizes the regression analysis. The 'Sum of Squares' column reflects the total variation explained by the model (Regression) and the unexplained variation (Residual). The 'df' column represents degrees of freedom, 'Mean Square' is the sum of squares divided by its respective degrees of freedom, 'F' is the F-statistic, and 'Sig (a)' is the significance level of the F-statistic. A significant 'Sig (*)' value, like 0.000 here, often indicates that the model significantly predicts the dependent variable.

The Wald-forward method in logistic regression is a stepwise selection technique used to determine the best model by adding variables based on statistical criteria. Here's how it works in the context of logistic regression: Logistic regression is used when the dependent variable is binary (i.e., it has two possible outcomes). It models the probability of a particular outcome based on one or more predictor variables. The Wald-forward method is a type of stepwise regression, which is a way of selecting variables in a regression model. Stepwise methods can be forward, backward, or both. The Wald-forward method uses the Wald statistic to decide which variables to include in the model. The Wald statistic is used to test the significance of individual coefficients in the model.

### Experimental Results of Cross Validation and Wald- Forward Analysis

Samples were divided instances randomly into five separate sections with comparable dimensions and patterns: namely, groups 1 through 5. We allocate four of these sections for training purposes and assign the fifth one as the evaluation set. This cycle is conducted five times to guarantee that each section undergoes testing. In our study, the selection of key independent variables for developing the Banking credit risk prediction model is conducted using the Wald-forward approach in logistic regression (LR). This paper outlines a criterion for exclusion of variables from the model: those with significance values exceeding 0.01 are not considered.

*Start with No Variables:* Initially, the model contains no predictor variables.

*Add Variables One by One:* In each step, each variable not in the model is tested for inclusion using the Wald statistic.

*Inclusion Criterion:* A variable is added if its associated Wald statistic is significant, typically based on a predefined p-value threshold (e.g., $p < 0.05$).

*Iterative Process:* This process continues iteratively, adding one variable at a time until no more variables meet the criterion for inclusion.

*Model Evaluation:* After the selection process, the final model is evaluated for its goodness of fit, typically using measures like the Akaike Information Criterion (AIC), likelihood ratio tests, or examining the model's classification accuracy. In summary, the Wald-forward method in logistic regression is a systematic approach to building a logistic model by adding variables based on the significance of their Wald statistics. This method aims to identify a parsimonious model that adequately explains the relationship between the predictors and the binary outcome.

The practical outcomes from the LR analysis reveal that the variables V4, V9,V11 and V12 consistently remain in the logistic regression model, as detailed in Table 5.

**Table 5. Significance values of independent variables**

| Independent Variables | Coefficient | Significance | Situation* |
|---|---|---|---|
| V4 | -0,155 | 0,000 | reserved |
| V6 | 0,242 | 0,798 | excluded |
| V8 | 0,211 | 0,333 | excluded |
| V9 | -0,106 | 0,007 | reserved |
| V10 | 1,089 | 0,675 | excluded |
| V11 | 1,718 | 0,000 | reserved |
| V12 | 1,342 | 0,002 | reserved |
| Constant | -0,171 | 0,000 | reserved |

Note: * shows the independent variables are excluded when their significance values are greater than 0.01

Referencing Table 5, we initially present the equation(4) for the LR model as follows:

$$ln\left[\frac{p}{1-p}\right]=-0,171-0,155V_4-0,106V_9+1,718V_{11}+1,342V_{12} \quad (4)$$

This situation indicates that the independent variables V4, V8, V9, V11, and V12 have a significant impact on predicting the credit risk signals of banks. The relationship between working capital turnover of banks (V4) and credit risk involves how efficiently a bank manages its working capital in relation to the credit risk it bears. Working capital turnover, a measure of operational efficiency, indicates how effectively a bank uses its working capital to generate sales or revenue. This ratio is typically calculated by dividing the bank's annual revenues by its average working capital. A higher working capital turnover ratio suggests that the bank is efficiently using its working capital to generate more sales or revenue, which could imply lower liquidity risk and potentially lower credit risk since the bank may be in a better position to meet its short-term obligations. Conversely, a lower working capital turnover ratio indicates that the bank is less efficient in using its working capital, which could result in higher liquidity risk and potentially increase the bank's credit risk. This is because a bank with poor working capital management may face difficulties in covering its short-term liabilities, impacting its overall financial stability and ability to lend. Therefore, the relationship between working capital turnover and credit risk in banks is crucial. Banks with efficient working capital management and higher turnover ratios are generally perceived as having lower credit risk, whereas banks with poor working capital management and lower turnover ratios may be viewed as having higher credit risk. In this context, the result obtained is significant, and an increase in the coefficient reduces the credit risk of banks.

The relationship between the accounts receivable collection period of banks (V9) and bank credit risk refers to how the time it takes for a bank to collect its outstanding receivables impacts its exposure to credit risk. The accounts receivable collection period, often measured in days, indicates the efficiency and effectiveness of a bank's credit and collections policies. Therefore, the accounts receivable collection period is an important indicator for assessing a bank's credit risk. Banks with effective credit management practices that result in shorter collection periods are typically exposed to less credit risk, whereas banks with longer collection periods may face higher credit risk due to potential liquidity constraints and credit management issues. In this context, the result obtained is significant, and an increase in the coefficient reduces the credit risk of banks as a parallel of expectations.

In this section of the study, the "Hosmer-Lemeshow test" will be used to assess the "Goodness of Fit" of the LR model. According to Hosmer et al. (2013), the significance level is set at 5% for the LR model. In the study, we calculate the degrees of freedom (DF) value using the Hosmer-Lemeshow function..

**Table 6: Hosmer–Lemeshow test of a logistic regression model**

| | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 |
|---|---|---|---|---|---|
| **Pearson chi-square** | 8.808 | 8.810 | 10.830 | 11.199 | 3.068 |
| **Degrees of freedom** | 8.000 | 8.000 | 8.000 | 8.000 | 8.000 |
| **p-value** | 0.160 | 0.359 | 0.212 | 0.191 | 0.930 |
| **Critical value** | 12.301 | 12.301 | 12.301 | 12.301 | 12.301 |

Based on the significance level and DF, we calculate the critical value of the LR model as 12.301 through the “CHINV” statistical method as seen in Table 6. For each group test shown in Table 6, the p-value is greater than 0.05, and the Pearson chi-square value is less than 12.301, suggesting that the LR model has a good fitting ability.

The optimal cutoff point for the prediction accuracy ratio of the logistic regression model typically refers to the threshold value used to classify the predicted probabilities into different categories, such as "success" or "failure", "yes" or "no", etc. In logistic regression, predictions are made in terms of probabilities, with the default threshold often being 0.5. This means if the predicted probability of an event is greater than or equal to 0.5, the event is predicted to occur; otherwise, it is predicted not to occur.

However, this default cutoff of 0.5 might not always be optimal, especially in cases where the cost of false positives differs significantly from the cost of false negatives, or the dataset is imbalanced. The optimal cutoff point should maximize the model's effectiveness based on the specific context and objectives, such as maximizing overall accuracy, sensitivity (true positive rate), specificity (true negative rate), or the area under the Receiver Operating Characteristic (ROC) curve.

**Table 7: Optimal cutoff point for the prediction accuracy ratio of the LR**

| | **Group 1** | **Group 2** | **Group 3** | **Group 4** | **Group 5** | **Mean (SD)** |
|---|---|---|---|---|---|---|
| Optimal cutoff point | 0,388 | 0,432 | 0,597 | 0,501 | 0,523 | 0,488 |
| Positive signal | 55,50% | 85% | 80,10% | 86,10% | 70,40% | 75,42% |
| negative signal | 57.4% | 44,80% | 46,80% | 50,10% | 54,70% | 50,75% |
| Overall | 56,30% | 70,40% | 64,60% | 75,20% | 60,90% | 65,48% |

In Table 7, we display the optimal cutoff point for the prediction accuracy ratio of the Logistic Regression (LR) model. The empirical findings indicate that the average prediction accuracy ratio for "positive signal" stands at 75.42%, while the average for the "negative signal" prediction accuracy ratio is considerably lower at 50.75%.

A Radial Basis Function (RBF) network represents a form of forward-propagating neural network that consists of three distinct layers: the entrance layer, the concealed layer, and the terminus layer. Every layer is assigned unique functions and responsibilities (Haykin, 1999) In this article, we implement a Radial Basis Function (RBF) network structure into the ANN model. Following the diagnosis of collinearity, we utilize independent variables as input layer variables for the RBF network model.

**Table 8:Optimal cutoff point for the prediction accuracy ratio of the ANN**

| | **Group 1** | Group 2 | **Group 3** | Group 4 | **Group 5** | Mean (SD) |
|---|---|---|---|---|---|---|
| Optimal cutoff point | 0,221 | 0,345 | 0,444 | 0,423 | 0,523 | 0,391 |
| Positive signal | **0,655%** | 0,89% | **0,823%** | 0,871% | **0,734%** | 79% |
| negative signal | 58.8% | 4,78% | 0,499% | 0,541% | 0,603% | 53% |
| Overall | **0,603%** | 0,712% | **0,669%** | 0,788% | **0,679%** | 69% |

Table 8 indicates that the average value of the "positive signal" prediction accuracy ratio has increased from 75.42% in the previous model to 79.8%. Additionally, the average value of the "negative signal" prediction accuracy ratio has clearly increased. Furthermore, the overall prediction accuracy ratio has also risen from 65% in the LR model to 69%.

## Comparing the Banking Credit Risk Estimation Accuracies of the LR and ANN Models

Hosmer and colleagues suggest that the area under the Receiver Operating Characteristic (ROC) curve provides a comprehensive measure of classification accuracy, with guidelines as follows: a ROC of 0.5 indicates no ability to discriminate, values between 0.5 and 0.7 suggest poor discrimination, values between 0.7 and 0.8 imply acceptable discrimination, values between 0.8 and 0.9 reflect excellent discrimination, and values at or above 0.9 represent outstanding discrimination (Zhu et al.2016).

**Table 9: Discrimination Accuracies of the ANN and LR models**

| Models | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Mean (SD) | Discrimination Accuracy |
|---|---|---|---|---|---|---|---|
| LR | 0.701 | 0.712 | 0..736 | 0.744 | 0.751 | 0.720 (0.015) | No |
| ANN | 0.819 | 0.841 | 0.798 | 0.816 | 0.830 | 0.833 (0.010) | Excellent |

When comparing the two models according the esitimations in Table 9, it can be said that artificial neural networks are superior to logistic regression.

## Conclusion

In this study, we analyzed the quarterly financial and non-financial data of British banks covering the period from 2021 to 2023. The research highlights the strategic necessity of accurately predicting credit risk for the success and financial stability of the banking sector. In this context, the application and comparison of two sophisticated predictive modeling methods, Logistic Regression (LR) and Artificial Neural Networks (ANN), were undertaken. The results demonstrate that both LR and ANN models are effective tools for credit risk prediction, yet their performance varies depending on the context and the data set utilized. ANN models, in particular, have shown superior results in predicting credit risk due to their ability to decipher hidden patterns and relationships in complex and multidimensional data sets. However, this study reveals that both ANN and LR models can make valuable contributions to credit risk management in the banking sector. While ANN models stand out for their exceptional ability to model the complexities and interrelationships in data sets, LR models are highlighted for their transparency and interpretability of results.

Future research should focus on enhancing the predictive performance of these models using broader and more diverse data sets. Additionally, testing the applicability of the model for banks in different geographical locations and under various economic conditions is also vital. This will validate the universal applicability of the models and their effectiveness under different market conditions.In conclusion, this study provides significant findings on predicting credit risk in British banks and offers valuable insights for improving credit risk management practices. It also underscores the need for increased application of advanced technology-based predictive models in the banking sector and the development of credit risk management strategies.

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