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Original Article

Comparative analysis of QUEST and CHAID decision tree methods in assessing the performance of conventional commercial banks

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Abstract

The performance of conventional banks can be determined based on RGEC analysis (Risk Profile, Good Corporate Governance, Earnings, Capital). This is done to help customers and shareholders understand the stability and capability of the bank in dealing with economic situations. This analysis also supports investment decision-making, banking sector supervision, and maintaining public confidence in the banking industry. The indicators used include Capital Adequacy Ratio (CAR), Return on Assets (ROA), Net Interest Margin (NIM), Non-Performing Loan (NPL), Loan to Deposit Ratio (LDR), Operating Expenses to Operating Income (BOPO), NPL Level, ROA Level, and Bank Rating according to Indonesian Securities Rating Agency (PEFINDO). QUEST and CHAID methods were used to generate binary and non-binary classification trees. The results show that QUEST produces BOPO, ROA, NPL, and Bank Rating indicators while CHAID produces NPL, ROA, LDR, and BOPO indicators as the most significant indicators in assessing the performance of conventional banks.

Keywords: conventional bank, bank performance, QUEST, CHAID, RGEC

1. Introduction

Conventional commercial banks, as key pillars in the financial system, play a central role as catalysts for a country's economic growth (Cipollini, Ielasi, & Querci, 2024). They act as financial intermediaries between providers of funds and individuals or organizations in need of funds (Kazak, ULUYOL, Akcan, & İyibildiren, 2023). Conventional commercial banks provide a variety of financial services, such as lending, depositing, and transferring funds that play a role in driving the economic activity of the community (Boubakri, Mirzaei, & Saad, 2023). Conventional commercial banks support economic development by providing financing to economic sectors that have the potential to grow, including assisting in the financing of infrastructure projects and corporate investment (Ma, Peng, Wu, & Zhu, 2022). The diverse and crucial role played by conventional commercial banks causes banks to have good performance to operate optimally (Shi, Wang, & Emrouznejad, 2023).

The performance of conventional commercial banks is a very important aspect of maintaining the stability and sustainability of a country's financial sector (Athari, Irani, & AIAI Hadood, 2023). Bank performance can be evaluated by various indicators covered in RGEC analysis (Risk Profile, Good corporate governance, Earnings, Capital). A risk profile serves as a central element in evaluating the extent of risk encountered by banks or financial institutions. This component includes credit risk, market risk, operational risk, and liquidity risk that can affect the stability of the bank (García-benau & Zorio-grima, 2018). Assessment of good corporate governance includes aspects of the management of banks or financial institutions in terms of corporate governance, such as operational management and

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transparency in cost management (Aslam & Komath, 2023). Earnings is a component to assess the financial performance of banks, including profitability, net income, and operational performance (Tax *et al.*, 2023). Meanwhile, capital is a component used to assess the level of capital adequacy owned by banks or financial institutions (Ben Salah Mahdi & Boujelbene Abbes, 2018).

Indicators used include Non-Performing Loan, which is a tool to measure credit risk and the quality of bank assets by examining the level of non-performing loans (Benavides-Franco *et al.*, 2023). Loan Deposit Ratio which is a tool to indicating the bank's level of dependence on loans in comparison to the amount of funds received from deposits (Boďa & Zimková, 2021). Operating Expenses to Operating Income is an indicator to measure the efficiency of bank operations and good corporate governance. Return On Assets is an indicator to measure bank profitability by comparing net income with total assets (Liu, Li, Ahmad, & Ren, 2023), while Net Interest Margin measures the income a bank earns from the difference between the interest level received on loans and the interest level paid on deposits (Nguyen, Pham, Nguyen, Nguyen, & Nguyen, 2020). Finally, Capital Adequacy Ratio is a direct measure of the level of capital adequacy held by a bank or financial institution (Andersen & Juelsrud, 2023). RGEC analysis also provides important information in planning and decision-making, so methods are needed that can produce decision trees to identify the most significant indicators of the performance of the bank.

Several decision tree analysis methods have been developed since the 1990s (Du & Gou, 2023). The various developed types of decision trees are widely used in economics, including CHAID (Díaz-Pérez, García-González, & Fyall, 2020), CART (Hu, Quan, & Chong, 2022), C5.0 (Trivedi, 2020), and ID3 (Taamneh, 2018).

This research uses QUEST (Quick, Unbiased, Efficient, and Statistical Tree) and CHAID (Chi-squared Automatic Interaction Detection) methods to determine the comparison of key indicators in the performance assessment of conventional commercial banks (Inoue, Imura, Tanaka, Matsuba, & Harada, 2022). With a robust statistical approach, the QUEST method helps in extracting significant relationships between various indicators such as CAR (Capital Adequacy Ratio), ROA (Return on Assets), NPL (Non-Performing Loan), NIM (Net Interest Margin), BOPO (Operating Expenses to Operating Income), LDR (Loan to Deposit Ratio), NPL Level, ROA Level, and Bank Rating. CHAID is used to understand the interactions between variables in the context of bank performance analysis. With a chi-squared approach, CHAID allows the identification of more complex patterns in data and describes how those variables relate to each other (Muñoz-Rodríguez, Patino Alonso, Pessoa, & Martín-Lucas, 2023). The result is a key indicator that influences bank performance, enabling decision-makers to devise more effective strategies to manage risk and increase profitability.

2. Materials and Methods

The analysis is conducted with data taken from the financial statements of 72 conventional commercial banks in 2022 listed on the Indonesia Stock Exchange (IDX). The data collected involves several crucial performance indicators, including CAR, ROA, NIM, NPL, LDR, BOPO, NPL Level, ROA Level, and Bank Rating.

2.1 Quick, unbiased, and efficient statistical tree (QUEST)

QUEST method introduced by Loh and Shih in 1997 (Darabi *et al.*, 2019) is a tree-structured classification algorithm that produces binary decision trees. The QUEST algorithm is divided into three parts, namely, variable selection algorithm, determination of baffle points, and termination of tree formation (Loh & Shin, 1997).

In the initial stage, the Variable Selection Algorithm operates with a predetermined significance level (α) and a set of ordered ($X_1, \ldots, X_{k1}$) and categorical ($X_{k1+1}, \ldots, X_k$) variables. For each node t, ANOVA F-tests and chi-squared tests are conducted to identify the variable X'_k with the highest p-value. If the minimum p-value falls below a threshold of α/K, X'_k is selected to block the node; otherwise, the algorithm proceeds to calculate ANOVA statistics for ordered data. Table 1 is used to obtain the calculated statistic, namely: f_h In decision making, H_0 is rejected at the level α, if the value $f_h >$ f_h $f_{\alpha[(k-1,(n-k)]}$ The Sealing Point Determination Algorithm for Numeric Variables follows, focusing on the chosen variable X for node separation. It employs the 2-means clustering algorithm, computes means, variances, and superclass prior probabilities, and determines the sealing point using quadratic equations. For categorical variables, a transformation to dummy vectors and dimensionality reduction through SVD is executed.

The iterative process continues until the Tree Termination Algorithm halts the tree construction under certain conditions. This includes the absence of significant differences between independent variables and the response variable, reaching the predefined maximum tree depth, or blocking a node resulting in parent and child nodes falling below a specified minimum size.

In essence, the QUEST method systematically constructs binary decision trees, iteratively selecting variables based on statistical significance, determining cutoff points, and terminating tree growth under specific conditions.

2.2 Chi-squared automatic interaction detection (CHAID)

The CHAID technique, which was presented by Kass in 1975 (Díaz-Pérez & Bethencourt-Cejas, 2016), is an algorithm for creating a classification tree with a non-binary structure. The CHAID algorithm is divided into three stages, namely merging, splitting, and stopping algorithms (Kass, 1980).

To determine the split predictor for a node, the algorithm follows a set of steps. Firstly, for each estimator X, it identifies the category pair with the largest p-value based on the response variable class Y. If Y is continuous, an ANOVA test F is employed, setting up hypotheses to compare group averages. The decision to reject the null hypothesis is made based on a significance level α. In the case of a nominal response variable Y, a bidirectional cross-tabulation is performed with categories from X and Y. The chi-squared test is then applied, and if the calculated statistic exceeds the critical value or the p-value is below α, H_0 is rejected,

Table 1. Analysis of variance of one-way classification

Source of variation	Sum of squares	Df	Calculate mean	f count
Group	JKK	k - 1	$s_1^2 = \frac{JKK}{k-1}$	$f_h = \frac{s_1^2}{s^2}$
Error	JKG	n – k	$s^2 = \frac{JKG}{n-k}$	
Total	JKT	n -1		

indicating a relationship between the independent and response variables.

The algorithm further compares category pairs with the largest p-value to a predetermined significance level (α_{merge}). If the p-value is greater, merging these pairs into a new category is recommended; otherwise, the algorithm repeats the process. To enhance precision, corrected p-values for categories X and Y are computed using Bonferroni correction. The X estimator with the smallest corrected p-value is then chosen. If this value is below a predefined significance level (α_{split}), nodes are partitioned based on category X. If the corrected p-value exceeds α_{split}, the node remains unsplit.

3. Results and Discussion

There are two hypotheses in the selection of the baffling variables as follows:

H_0 = No noteworthy correlation exists between the independent variables and dependent variables.

H_1 = A meaningful correlation exists between the independent variables and dependent variables.

3.1 Application of QUEST in assessing the performance of conventional commercial banks

Initial node t_0 consists of 72 commercial banks from two categories, namely banks with good performance (60 banks) and banks with poor performance (12 banks). The selection of baffling variables is done by conducting ANOVA F test on numerical variables and Chi-Squared test on categorical variables. Furthermore, variables with *p - value* which is smaller than α are selected to partition the previous node into two new vertices with partitioning points through a quadratic equation $\alpha x^2 + bx + c = 0$ (Loh & Shin, 1997) for numeric variables. The QUEST method uses only one of the two roots as a partitioning point, which is a root whose value is close to the sample mean of each class. For categorical variables, the partition point is identified by converting these variables into numerical representations for each class.

Each performance indicator as an independent variable is calculated and the p-value is shown in Table 2. Then a decision tree will be formed based on variables that are significant to the performance of conventional commercial banks. The significant variables obtained are BOPO, ROA, NPL and Bank Rating.

In determining the partition point value, the variable is selected with p-value smaller than 0.0055 and in the first iteration that is BOPO**.** The BOPO variable is a numerical variable so a quadratic discriminant analysis is required to obtain the baffle point value. In the fourth iteration, the ranking variable is the variable selected with p-value of 0.002. Rank is a categorical variable so the transformation of categorical variables into numerical variables is carried out. The fifth iteration showed that no variable had a p-value smaller than the predetermined p-value α, so the blocking process was stopped. The resulting classification tree from the QUEST approach is depicted in Figure 1.

From the results of the classification above, it can be seen that the factors that affect bank performance are BOPO, ROA, NPL and Bank Ratings. There are nine nodes consisting of one parent node (performance node), three inner nodes and five end nodes. In guessing the final node response, the response modifier whose presentation is largest is selected. There are five classes with groupings shown in Table 3. It can be concluded that BOPO is the most significant factor affecting the performance of a conventional commercial bank, superior to ROA, NPL and Rating Bank.

Processing with CHAID begins with chi-squared testing to identify the most significant independent variables. An insulating variable is selected if it has the largest statistical test value or a p-value smaller than predetermined α (α = 0,05). After the insulating variable is selected, the independent variable is again subjected to statistical tests according to the type of data. Then the variable that has the smallest p-value will be re-identified. The step is repeated until there are no more significant variables to partition the previous node. The acquisition of the test statistical value and p-value of each variable is shown in Table 4.

Table 2. Statistical test values and p-value of QUEST method

Variable	I		II		III		IV		V	
	Stat	Sig.	Stat	Sig.	Stat	Sig.	Stat	Sig.	Stat	Sig.
CAR	2,936	0,091	0,408	0,525	2,936	0,091	2.936	0,091	0,660	0,462
ROA	26,95	0,000	8,917	0,004			4,586	0,020	24,45	0,008
NPL	18,63	0,000	3,850	0,054	14,18	0,000			0,977	0,379
LDR	6,085	0,016	1,517	0,223	10,96	0,236	1,042	0,669	1,197	0,335
BOPO	52,93	0,000			3,909	0,096	2,793	0,139	2,349	0,200
NIM	0,200	0,656	0,693	0,408	77,43	0,090	0,187	0,976	0,535	0,505
T.ROA	5,236	0,022	1,719	0,190	66,50	0,391	67,28	0,333	0,000	1,000
T.NPL	0,048	0,826	0,026	0,871	66,94	0,376	67,66	0,321	3,000	0,083
Rank	3,234	0,357	4,471	0,215	204,8	0,249	192,4	0,002		

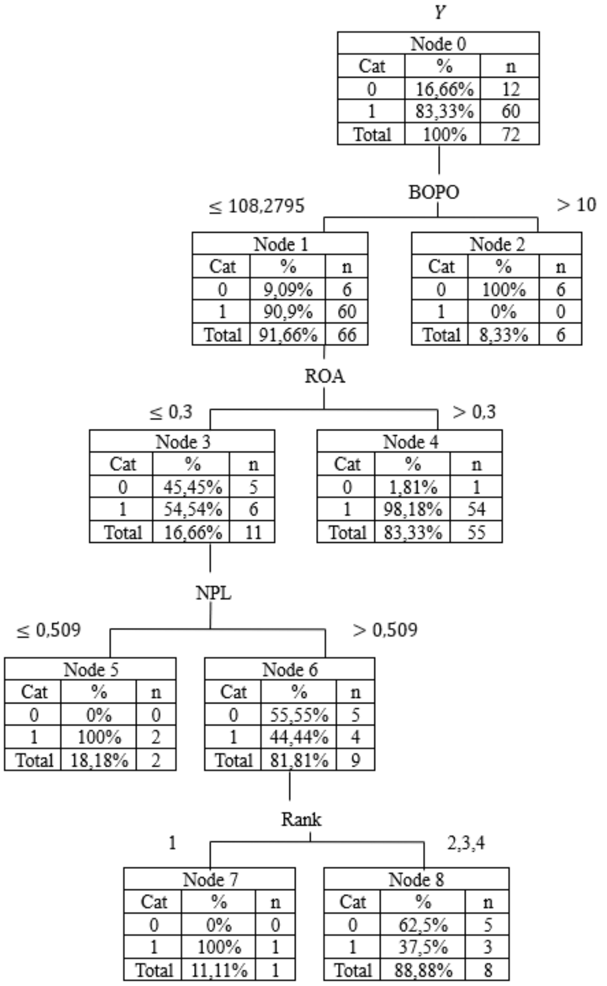

Figure 1. QUEST classification tree on conventional bank performance indicators

3.2 Application of CHAID in assessing the performance of conventional commercial banks

The result of model building is a classification tree shown in Figure 2 with nine nodes consisting of one parent node (performance node), three inner nodes and five end nodes. From the classification tree of CHAID analysis results, it can be seen that the most significant factors are NPL, ROA, LDR and BOPO. There are five classes with groupings shown in Table 3. It can be concluded that NPL is the most significant factor affecting the performance of a conventional commercial bank, superior to ROA, LDR and BOPO.

3.3 Comparison between QUEST and CHAID

3.3.1 Classification tree

The resulting trees from QUEST and CHAID methods have the same depth of 4, and have the same number of vertices and final nodes. The QUEST and CHAID methods gave 9 nodes with 1 parent node, 3 inner nodes and 5 end nodes. The tree gene level from the QUEST method is a binary tree, because QUEST only levels two new categories in each partition. The CHAID method also levels binary trees, but for different reasons. This is because the p-value of the independent variable category pairs is always greater than α = 0.05, so in the end only two new categories are left in each partition.

Table 3. Assessment of bank performance results using QUEST and CHAID methods

Model	Node	Level indicators
QUEST	2	BOPO > 108, 2795
	4	BOPO ≤ 108, 2795 and ROA > 0, 3
	5	BOPO ≤ 108, 2795, ROA ≤ 0, 3 and NPL ≤ 0, 509
	7	BOPO ≤ 108, 2795, ROA ≤ 0, 3, NPL > 0, 509 and have a rating of 1
	8	BOPO ≤ 108, 2795, ROA ≤ 0, 3, NPL > 0, 509 and have a rating of 2,3,4
CHAID	1	Poor NPLs > 5%
	3	Good NPLs ≤ 5%; poor ROA < 0, 5%
	5	Good NPL ≤ 5%, good ROA ≥ 0, 5%; poor LDR > 100%
	7	Good NPL ≤ 5%, good ROA ≥ 0, 5%, good LDR 50-100%; poor BOPO > 85%
	8	Good NPL ≤ 5%, good ROA ≥ 0, 5%, good LDR 5-100%; good BOPO ≤ 85%

3.3.2 Processing time

The time it takes for QUEST to process data into a classification tree tends to be longer compared to CHAID. The implementation of QUEST takes longer because in the selection of split points QUEST applies quadratic discriminant analysis while CHAID has a simpler algorithm.

3.3.3 Significant variables

The decision tree produced by the QUEST method defines BOPO which measures the operational efficiency of the bank, ROA which measures the profitability of the bank, NPL which measures the quality of the bank's credit portfolio and Rating which reflects an external assessment of the credibility and quality of the bank. These variables are the main variables that allow assessing the performance of conventional commercial banks. In the CHAID method, NPL, ROA, LDR which indicates liquidity risk, and BOPO are the main variables in assessing the performance of conventional commercial banks. The variables obtained with these two methods have overlap, namely they share NPL, ROA, and BOPO.

The application of QUEST produces the highest accuracy of 85.17% while CHAID gave 72.97% in cross-validation. Comparison of accuracy, precision, recall, f1 score values in QUEST ranged from 94-98% and CHAID ranged from 29-100% with the smallest recall of 29.7%. The classification results show that QUEST method is good enough to be used to classify and determine the main variables that are most influential in assessing the performance of conventional commercial banks. These methods have different levels of accuracy as seen in Table 5.

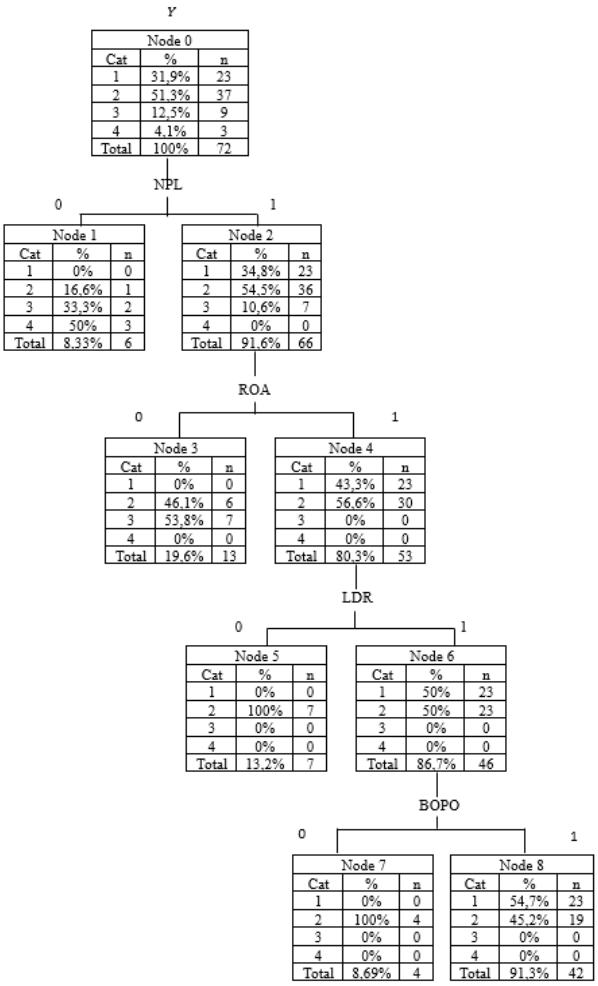

Figure 2. CHAID classification tree on conventional bank performance

4. Conclusions

The performance analysis of conventional commercial banks using the QUEST and CHAID methods indicates some differences, although not very significant. The QUEST method produces BOPO, ROA, NPL, and Bank Ranking as the main indicators in determining bank performance. This is because QUEST employs a nonparametric approach to identify and split nodes based on differences in response distributions. This approach allows QUEST to capture more complex patterns in the data. CHAID produces NPL, ROA, LDR, and BOPO as the primary indicators. CHAID uses chi-square tests to split nodes in the decision tree, enabling it to identify statistically significant relationships between variable categories. This method is more suitable for data with clear and well-defined structures, especially when the observed variables are categorical.

Thus, both of these decision tree methods have extensive uses in various sectors and business applications due to their capabilities in segmentation, risk analysis, easy interpretation, flexibility, and efficiency in describing patterns in data. This analysis can help conventional commercial banks to design effective strategies in improving bank performance based on the significant indicators obtained.

Analysis of conventional commercial bank performance using QUEST and CHAID methods shows that both methods have their own advantages and disadvantages. The selection of the appropriate method depends on the characteristics of the data, the complexity of relationships between variables, and the preference for the results of the decision tree. This research can be pursued further by integrating the decision tree method with ensemble learning to obtain higher accuracy.

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Table 4. Statistical test values and p-value for CHAID method

Variable	I		II		III		IV	
	Stat	Sig.	Stat	Sig.	Stat	Sig.	Stat	Sig.
CAR	7,099	0,069	8,558	0,014				
ROA	33,91	0,000	34,38	0,000				
NPL	38,89	0,000						
LDR	14,11	0,003	8,803	0,012	6,183	0,013		
BOPO	32,37	0,000	29,24	0,000	3,317	0,069	4,381	0,036
NIM	14,40	0,002	8,558	0,014				
T. ROA	9,028	0,029	1,436	0,488	0,766	0,382	1,075	0,300
T. NPL	0,146	0,986	0,346	0,841	1,542	0,214	2,681	0,102
Rank	9,534	0,390	7,530	0,275	4,289	0,232	2,555	0,465

Table 5. Comparison of the model performances

Model	Accuracy Rate (%)					
	Cross Validation	AUC-ROC	Accuracy	Precision	Recall	F1 Score
QUEST	85,17	26,8	94,4	95	98,2	96,6
CHAID	72,97	50	63,8	100	29,7	45,8

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