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Analyzing Regional Financial Transparency In Indonesia Through Internet Reporting Using CART Algorithm

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ABSTRACT

The purpose of this study is to analyze the financial transparency of local governments in Indonesia through Internet Financial Reporting (IFR). The approach used is machine learning with the Classification and Regression Trees (CART) algorithm. The data used were secondary data, with 546 local governments in Indonesia as observation units. Data were analyzed using R version 4.5.1. The results of this study indicate 44% or 238 local governments are not transparent in disclosing financial reports through their official websites. The results of the CART analysis show that Audit Opinion is the variable that most influences IFR. Other independent variables also influence IFR, namely Regional Revenue, Financial Independence Ratio, Administrative Age of Local Government, and Per Capita Income. The optimal classification tree produces 7 segments that are able to predict new data with an accuracy of 64.24% and an AUC of 63.83%. The theoretical implications of this research provide a important contribution to the development of public sector accounting theory, particularly within the theoretical framework of transparency, accountability, and good governance. Practical implications include formulating strategies to minimize the number of local governments that are non-transparent in disclosing financial reports on their official websites, the characteristics of which are reflected in segments 5, 6, and 7. The novelty of this research is that it provides new insights into the analytical methods used. The use of machine learning with the CART algorithm has never been used by previous researchers to analyze regional financial transparency through IFR.

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1. INTRODUCTION

In the rapidly evolving digital era, transparency and accountability in public financial management have become increasingly crucial for achieving good governance. One of the efforts to enhance transparency is through Internet Financial Reporting (IFR), which refers to the online disclosure of financial statements by local governments (Budiman and Agustin, 2023). IFR serves as a form of voluntary disclosure, demonstrating accountability to the public regarding the management of local government finances (Nosihana and Yaya, 2016). This reporting mechanism enables the public, investors, and other stakeholders to access financial information easily, promptly, and accurately (Kurniawati, 2018; Soenjoyo and Lindrawati, 2025). Financial transparency can minimize budget misuse and reduce the potential for corruption, which remains a significant challenge in Indonesia (Aprilla et al., 2024). According to the Corruption Perception Index (CPI) 2024, Indonesia scored 37 out of 100, ranking 99th out of 180 countries in terms of corruption (Transparency International, 2025). This score reflects the perception that Indonesia continues to experience a high level of corruption.

The disclosure of IFR by local governments in Indonesia still faces various challenges. Although regulations such as Law No. 14 of 2008 on Public Information Transparency, Government Regulation No. 12 of 2019 on Regional Financial Management, Presidential Instruction No. 3 of 2003 on National e-Government Development Policies and Strategies, and Minister of Home Affairs Instruction No. 188.52/1797/SJ of 2012 on Enhancing Transparency in Regional Budget Management mandate financial transparency, implementation remains uneven. IFR represents a form of transparency carried out by local governments, providing a mechanism for public oversight of financial management and policy decisions. Such transparency can minimize corruption and budget misuse while enhancing public trust (Narulitasari and Zafira, 2021). This can be explained based on Agency Theory, which describes the relationship between the society as the principal and the local government as the agent (Jensen and Meckling, 1976). The local government acts as an agent in the administration of government for the benefit of the principal, namely the society. Transparent financial information can reduce information asymmetry between principals and agents.

The implementation of IFR at the local government level in Indonesia has not been widespread. Several studies indicate that the level of budget transparency is inconsistent. In 2020, only five provinces disclosed complete budget documents, 13 provinces provided partial disclosure, and 16 provinces did not publish their budgets on official websites. This demonstrates that provincial governments have not yet fully optimized the implementation of public information disclosure regulations and local budget transparency (Mutmainnah et al., 2023). Similarly, other studies show that from 2019 to 2021, the average IFR disclosure on official local government websites in Indonesia was only 29.5%, based on a sample of 542 local governments (provinces/regencies/cities) (Suprianto and Salim, 2024). These phenomena and facts provide the basis for this study to identify the factors influencing local government financial transparency through IFR in Indonesia and to formulate appropriate strategies for improvement.

Previous studies on IFR have employed various approaches, including bibliometric analysis (Murdayanti and Khan, 2021), qualitative studies with literature reviews and descriptive analysis (Sharma and Bhardwaj, 2022), quantitative approaches using linear regression models (Hadianto and Murtin, 2020; Wulandari and Sulistyowati, 2024), partial least square models (Putra et al., 2023), and logistic regression models (Nor et al., 2019; Nosihana and Yaya, 2016; Saraswati et al., 2013). The novelty of this study lies in the use of a machine learning approach with the Classification and Regression Trees (CART) algorithm, which has not previously been applied to analyze local government financial transparency through IFR. The CART algorithm offers several advantages: it does not require strict assumptions, provides classification results with low error rates, and can

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handle large datasets (big data) (Lewis, 2000). Moreover, CART generates predictive models in the form of classification trees that are easily interpretable, allowing the identification of characteristics of regions that are not transparent in disclosing financial statements online.

Based on the above, the purpose of this study is to analyze the financial transparency of local governments in Indonesia through IFR using machine learning method with the CART algorithm. The theoretical implications of this research provide a important contribution to the development of public sector accounting theory, particularly within the theoretical framework of transparency, accountability, and good governance.

2. METHODS

The data used in this research were secondary data for the year 2024, obtained from various sources. These include the official websites of each local government, the 2024 Local Government Financial Statements (LKPD) audited by the Audit Board of Indonesia (BPK), the BPK representative websites of each province, Statistics Indonesia (BPS) website (https://www.bps.go.id/id) and the Ministry of Finance website (https://djpk.kemenkeu.go.id/). The observation unit consisting of 546 local governments, comprising 38 provinces, 415 regencies, and 93 cities in Indonesia. Data in this research were analyzed using the open-source R software version 4.5.1. The variables used in this study are presented in **Table 1**.

Table 1. Research variables, operational definitions, and data scales

No	Variable	Operational Definition	Scale
1	Internet Financial Reporting (Y)	Disclosure of local government financial statements through official websites. 0: Does not fully disclose financial statements online 1: Fully discloses financial statements online The completeness criteria used refer to the provisions of Minister of Home Affairs Instruction No. 188.52/1797/SJ of 2012, consisting of 12 financial documents.	Nominal
2	Regional Revenue (X1)	Main revenue generated by the local government within its own jurisdiction, (billion rupiah).	Ratio
3	Regional Expenditure (X2)	All expenditures of the local government used to finance government activities, development, and public services, (billion rupiah).	Ratio
4	Audit Opinion (X3)	Type of opinion provided by the Audit Board of Indonesia (BPK) regarding the fairness of the local government's financial statements. 0: Not Unqualified Opinion (Not WTP) 1: Unqualified Opinion (WTP)	Ordinal
5	Type of Local Government (X4)	Classification of the local government. 0: Regency Government 1: City Government 2: Province Government	Nominal
6	Administrative Age of Local Government (X5)	Duration of time a local government has been officially established as an autonomous region, (year).	Ratio
7	Financial Independence Ratio (X6)	The extent to which a local government can finance its own activities without relying on central government assistance, (percent).	Ratio
8	Per Capita Income (X7)	Average revenue received by each resident in a region within one year, (thousand rupiah).	Ratio

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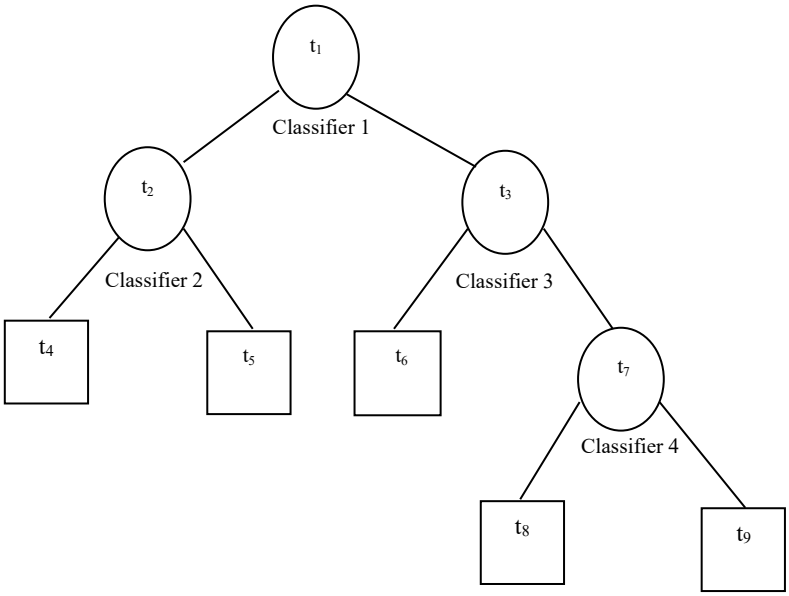
Source: processed by researchers, 2025

The data analysis in this research employed a machine learning method using the Classification and Regression Trees (CART) algorithm. CART is a nonparametric statistical method developed for classification analysis, applicable to both categorical and continuous dependent variables (Wray and Byers, 2020). The primary objective of CART is to generate accurate groupings of data that serve as distinguishing features in a classification process (Otok et al., 2020). In this research, CART was applied to produce segments that characterized regions that fully disclosed financial statements online and those that did not.

The CART algorithm does not require strict assumptions, provides classification results with relatively low error rates, and is capable of handling large volumes of data (big data) (Lewis, 2000). The construction of classification trees in CART operates through a process known as binary recursive partitioning., which follows the structure outlined in **Figure 1**.



Source: (Breiman et al., 1984)

Figure 1. Classification Trees Structure.

The root node of the classification tree, denoted as t_1, contains the entire dataset. The child nodes or internal nodes are represented by t_2, t_3, and t_7. These nodes subsequently undergo further partitioning and become parent nodes. Meanwhile, t_4, t_5, t_6, t_8, and t_9 serve as terminal or end nodes, which are already homogeneous.

Classification using CART involves both training data and testing data. The training dataset is used to build the predictive model, while the testing dataset is employed to evaluate the classification rules generated from the training data. The construction of a classification tree consists of three main stages: selecting a classifier, determining terminal nodes, and assigning class labels (Breiman et al., 1984).

The optimal classification tree can be determined using the V-fold cross-validation estimate. This method is commonly employed to avoid data overlapping. In this process, one partition of the data is used as the testing set while the remaining partitions serve as the learning set, with the procedure repeated *V* times. Subsequently, the average accuracy of the *V* models generated is calculated (Lewis, 2000). The standard value of *V* applied is 10 (i.e., 10-fold cross-validation). A classification tree of excessive size (complex) may lead to overfitting. Therefore, pruning is necessary to obtain an optimal tree. Cost complexity pruning is employed to determine the optimal pruning size, thereby producing a valid classification tree (Breiman et al., 1984).

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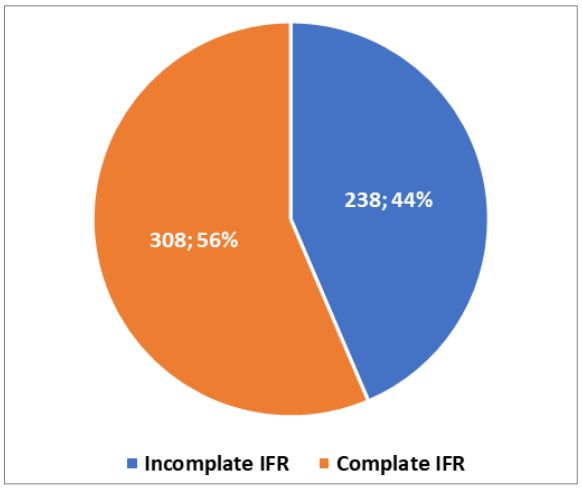
The precision of the classification results can be determined using the values presented in the confusion matrix, which provides information on the actual and predicted classifications generated by the classification system (Otok et al., 2020). Sensitivity is the proportion of positive cases (1) correctly predicted, in this case, the characteristics of regions that fully disclose their financial reports on the internet. Specificity is the proportion of negative cases (0) correctly predicted, referring to the characteristics of regions that do not fully disclose their financial reports on the internet. Overall accuracy represents the proportion of correctly classified observations in the sample.

3. RESULTS AND DISCUSSION

The data in this study were analyzed using descriptive statistics and a machine learning method with the CART algorithm. Descriptive statistical analysis was employed to examine the level of financial transparency of local governments in Indonesia through Internet Financial Reporting and its relationship with the independent variables under investigation. Meanwhile, the CART algorithm was applied to identify the factors influencing the disclosure of local government financial reports via the Internet, to develop a predictive model, and to determine the characteristics of regions that do not disclose financial reports online.

3.1. Descriptive Statistical Analysis

Level of financial transparency of local governments in Indonesia through IFR is shown in **Figure 2**.



Source: processed by researchers (2025)

Figure 2. Level of Financial Report Disclosure through the Official Websites of Local Governments in Indonesia.

Based on **Figure 2**, it can be observed that out of 546 local governments in Indonesia, 44% (or 238) fell into the category of Incomplete IFR. This figure indicates that a considerable proportion of local governments in Indonesia remain non-transparent in disclosing their financial reports through their official websites.

IFR based on the BPK audit opinion on the fairness of the local government's financial statements in Indonesia is shown in **Figure 3**.

Based on **Figure 3**, the data reveal that local governments with non-WTP audit opinions were more likely to have incomplete IFR, with 33 out of 43 local governments falling into this category. In contrast, local governments with WTP audit opinions were predominantly associated with complete

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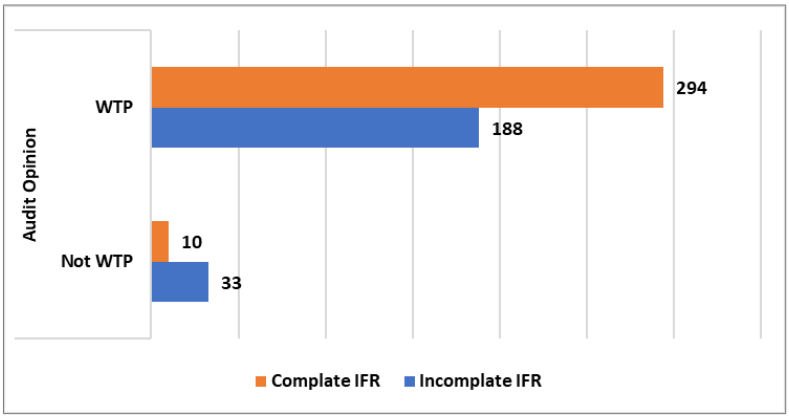
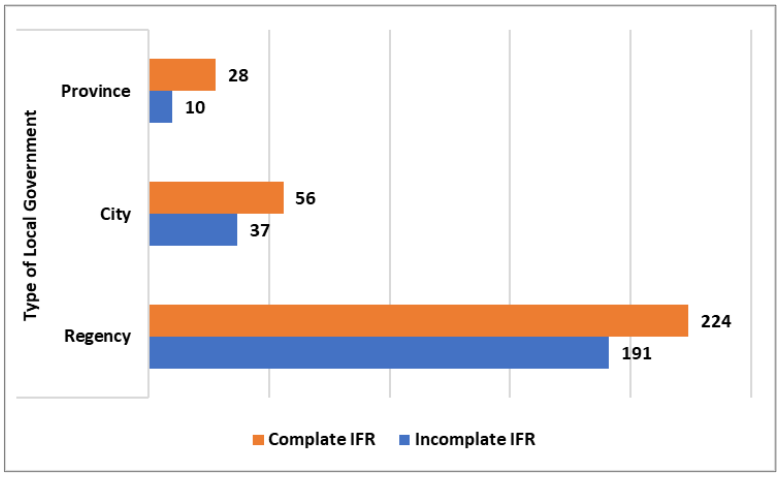
IFR, with 294 out of 482 local governments meeting this criterion. IFR by type of local government in Indonesia is shown in **Figure 4**.



Source: processed by researchers (2025)

Figure 3. IFR by Audit Opinion of Local Governments in Indonesia.



Source: processed by researchers (2025)

Figure 4. IFR by Type of Local Government in Indonesia

Based on **Figure 4**, the data reveal that, overall, local governments with complete IFR consistently outnumber those with incomplete IFR across all levels of government. The largest gap between complete and incomplete IFR occurs at the regency level, which also had the highest total number of observed local governments.

IFR based on other independent variables is shown in **Table 3**.

Table 3. IFR by other independent variables

Variabel		Mean	StDev	Min	Max
Regional Revenue	Incomplete IFR	343.04	1284.19	0.97	17650.92
	Complete IFR	848.39	3499.20	3.91	47538.64
Regional Expenditure	Incomplete IFR	1721.12	2244.12	149.12	27184.46
	Complete IFR	2556.01	4713.05	302.44	62244.59
Age of Local Government	Incomplete IFR	41.22	24.77	2.00	79.00
	Complete IFR	51.28	23.28	2.00	79.00
Financial Independence Ratio	Incomplete IFR	17.20	27.10	0.11	202.85
	Complete IFR	32.56	67.09	0.83	971.93
Per Capita Income	Incomplete IFR	62066.46	60476.16	7077.00	574984.00
	Complete IFR	77286.83	87471.07	8830.00	1003185.00

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Source: processed by researchers (2025)

The results of the analysis in **Table 3** indicate that local governments with incomplete IFR had, on average, regional revenue, regional expenditure, administrative age of local government, financial independence ratio, and per capita income compared to those with complete IFR.

3.2. Classification and Regression Trees (CART) Analysis

In constructing the CART classification tree, the initial step involves splitting the research data into learning and testing datasets. The purpose of dividing the data is to obtain an optimal model. There is no strict rule for the proportion of learning and testing data. However, the learning dataset should be larger than the testing dataset. The classification tree model was built using several alternative proportions of learning data: 70%, 75%, 80%, 85%, and 90% of the total data. The learning data proportion that yields the highest classification accuracy based on the testing data is selected for further analysis. A comparison of the classification accuracy results is presented in **Table 4**.

Table 4. Comparison of classification accuracy on testing data based on learning data models

Learning Data Proportion	Classification Result	
	Accuracy (%)	AUC (%)
70%	**60.61**	**59.64**
75%	51.82	51.07
80%	53.64	52.56
85%	54.22	53.40
90%	49.09	48.25

Source: processed by researchers using R version 4.5.1 (2025)

Table 4 shows that the learning data proportion yielding the highest classification accuracy was 70%, with a total accuracy of 60.61% and an AUC of 59.64% based on the testing data. Therefore, a learning data proportion of 70% was used for further analysis in this study. These data were employed to construct the CART classification tree predictive model, while the remaining 30% served as testing data to evaluate the classification rules generated by the learning dataset.

The construction of the maximal classification tree used 70% of the learning data, comprising 381 observations. The process began by building the classification tree with a complexity parameter (cp) set to 0 and a 10-fold cross-validation (V = 10) estimate. The results of building a maximum classification tree using learning data are shown in **Figure 5**.

The maximal classification tree produced 20 terminal nodes, and all independent variables—Audit Opinion (X3), Regional Revenue (X1), Administrative Age of Local Government (X5), Financial Independence Ratio (X6), Per Capita Income (X7), Type of Local Government (X4), and Regional Expenditure (X2)—were included in the tree. The resulting maximal tree was large and complex, making it difficult to interpret. Therefore, pruning was necessary to obtain an optimal classification tree.

Pruning of the tree was performed to avoid overfitting and underfitting. Overfitting occurs when the obtained accuracy exceeds or does not reflect the true value, whereas underfitting occurs when the obtained accuracy is lower than the true value. The optimal classification tree can be obtained by pruning based on the complexity parameter (cp) that produces the smallest relative error. The resulting cp values are presented in **Table 5**.

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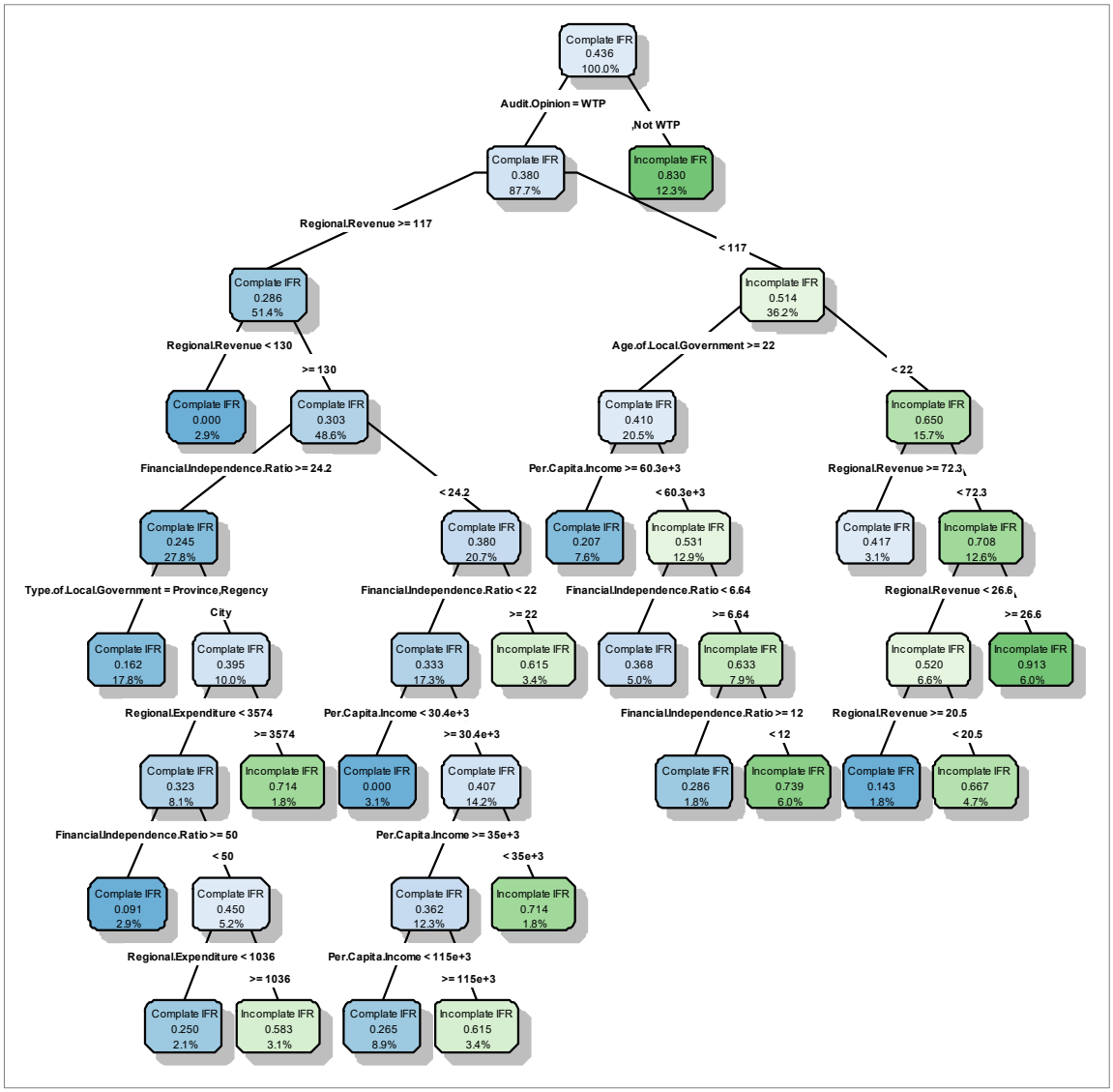
Table 5. Complexity parameter value

cp	nsplit	rel error	xerror	xstd
0.18674699	0	1.0000000	1.0000000	0.05830458
0.05421687	1	0.8132530	0.9096386	0.05751509
0.02409639	3	0.7048193	0.9277108	0.05770357
0.01807229	5	0.6566265	0.9036145	0.05744881
0.01405622	6	0.6385542	0.8614458	0.05693586

Source: processed by researchers using R version 4.5.1 (2025)

Table 5 presents several alternative cp values along with their corresponding error rates. The optimal cp value was 0.0140562, which yielded the smallest relative error (xerror) of 0.8614458. This cp value was used to prune the tree, resulting in the following optimal classification tree model.



Source: processed by researchers using R version 4.5.1 (2025)

Figure 5. Maximal Classification Tree.

Figure 6 presents the CART classification tree model for IFR. Several variables were suspected to influence the disclosure of local government financial reports via the Internet, including Audit Opinion (X3), Regional Revenue (X1), Financial Independence Ratio (X6), Administrative Age of Local

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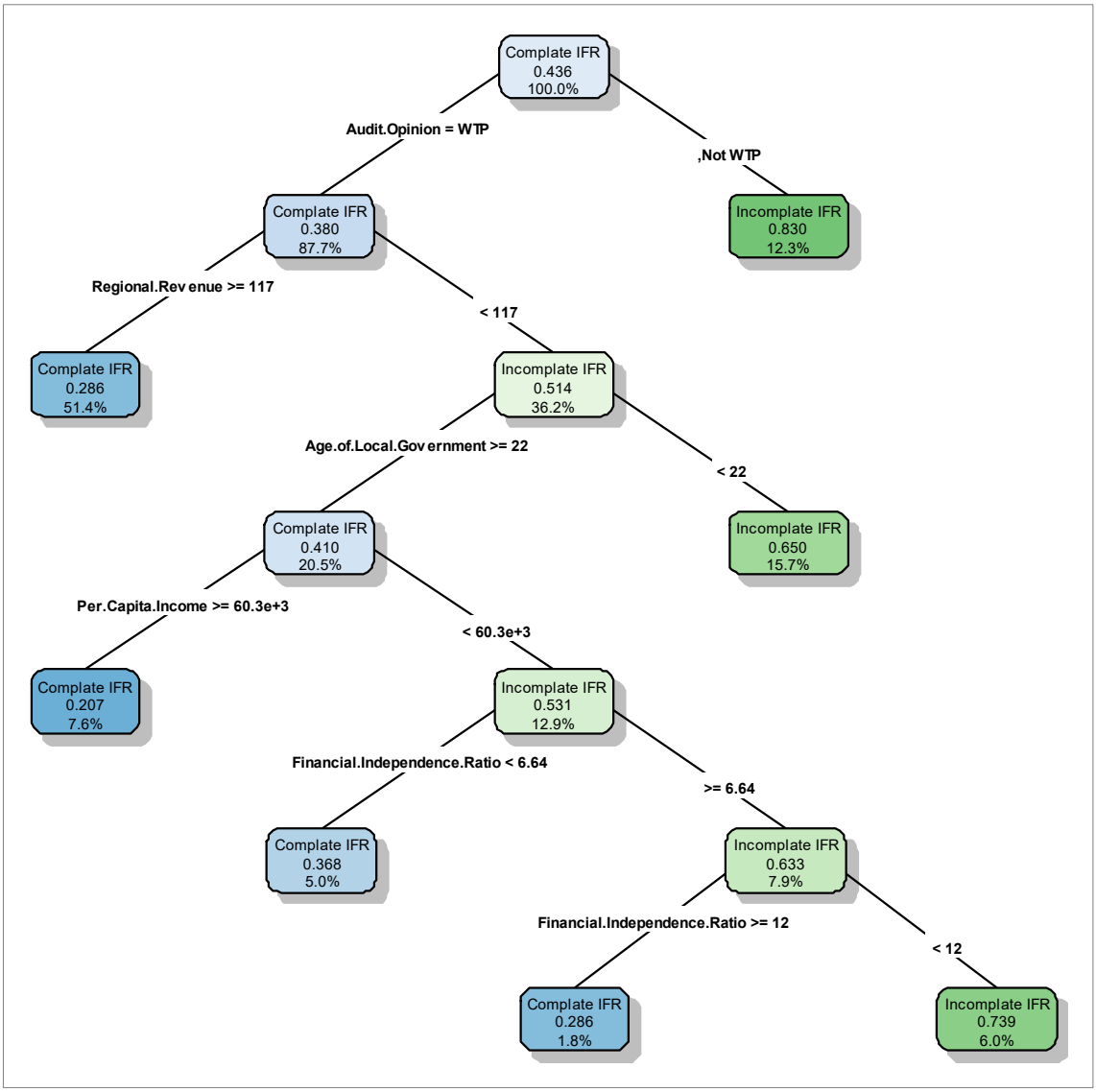
Government (X5), and Per Capita Income (X7). Among these variables, Audit Opinion was the most influential factor, as it served as the primary splitter in the optimal classification tree. The influence of all independent variables on IFR in the classification tree is fully illustrated in **Figure 7**.

Figure 7 shows that Audit Opinion was the most important variable, having the greatest influence on IFR, with a relative importance of 16.65% of the total value in the classification data of local governments in Indonesia. This is supported by research conducted by (Nor et al., 2019; Putra et al., 2023; Rahayu and Khasanah, 2022), which found that audit opinions significantly influence the IFR. Local governments that receive an WTP audit opinion are more likely to publish their complate financial reports so the public can understand their performance. These findings strengthen the theoretical basis that the quality of public financial governance is reflected through reporting transparency, as explained in Agency Theory. The government will be accountable to the public by providing financial reports that comply with government accounting standards, provide adequate disclosure, and comply with laws and regulations as a form of accountability for its financial performance.



Source: processed by researchers using R version 4.5.1 (2025)

Figure 6. Optimal Classification Tree.

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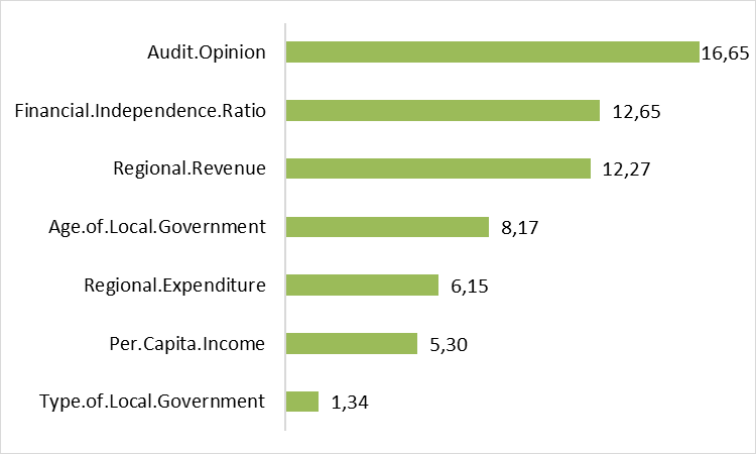

Source: processed by researchers using R version 4.5.1 (2025)

Figure 7. Variable Importance.

The financial independence ratio is a variable that influences the IFR, with a relative importance of 12.65%. This is consistent with research conducted by (Indaryani and Rahayu, 2023), which states that the financial independence ratio has a positive and significant effect on the IFR. The higher the level of financial independence of a local government, the more open it tends to be in disclosing information to the public via the internet as a means of strengthening accountability. Public disclosure is intended to ensure public awareness and confidence in the local government's ability to carry out its duties effectively and minimize conflicts of interest between agents and principals, in accordance with the main principles of Agency Theory.

High regional revenue reflects the region's ability to manage and exploit local resources independently, which demands greater accountability to the public for the use of these funds. Regional revenue is a variable that influences the IFR with a importance level of 12.27%. This is supported by research conducted by (Fawziah and Arza, 2020; Wulandari and Sulistyowati, 2024), which states that regional revenue has a positive and significant effect on IFR. Local governments with high regional revenue also have a high desire to disclose financial reports online. This is because regional revenue is one indicator of good performance of local governments. Disclosure through the official website is a form of local government accountability, which allows the public to access financial information openly and in real time. This is a form of public responsibility and is in line with the basic principles of Agency Theory.

The administrative age of local government is a variable that influences IFR, with a relative importance of 8.17%. This is consistent with research conducted by (Narulitasari and Zafira, 2021), which found that the administrative age of local government has a positive and significant effect on IFR. The longer a local government has been established, the better its IFR disclosures will be. As the administration ages, local governments tend to have better bureaucratic systems, human resources, and infrastructure in managing finances and presenting information transparently in accordance with government accounting standards. This is a form of local government responsibility towards the public in accordance with the principles of Agency Theory.

Per capita income is also a variable that influences IFR with a relative importance of 5.30%. According to Agency Theory, the higher the level of societal welfare, as reflected in per capita income, the greater the public demand for transparency and efficiency in regional financial management. People with better economic status generally have higher levels of literacy and public participation, making them more critical of government performance and demanding open access to information. This is consistent with research conducted by (Masra and Sari, 2020), which states that per capita income has a positive and significant effect on IFR. High per capita income indicates a better level of community welfare, which can encourage local governments to implement IFR as a

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way to increase transparency and accountability to stakeholders. This may be due to political monitoring by the public, which can increase demand for information on local government performance through IFR.

The characteristics of local governments can be divided into seven segments based on the number of terminal nodes produced by the optimal classification tree (**Figure 6**), as presented in **Table 6**.

Table 6. Segmentation of regional characteristics

Segment *k*	Characteristic
1	Local governments with regional revenue of at least 117.44 billion rupiah and a WTP audit opinion
2	Local governments with per capita income of at least 60342.5 thousand rupiah, administrative age of at least 22 years, regional revenue below 117.44 billion rupiah, and a WTP audit opinion
3	Local governments with an financial independence ratio below 6.64%, per capita income below 60342.5 thousand rupiah, administrative age of at least 22 years, regional revenue below 117.44 billion rupiah, and a WTP audit opinion
4	Local governments with an financial independence ratio of at least 12.045%, per capita income below 60342.5 thousand rupiah, administrative age of at least 22 years, regional revenue below 117.44 billion rupiah, and a WTP audit opinion
5	Local governments with an financial independence ratio between 6.64% and less than 12.045%, per capita income below 60342.5 thousand rupiah, administrative age of at least 22 years, regional revenue below 117.44 billion rupiah, and a WTP audit opinion
6	Local governments with an administrative age of less than 22 years, regional revenue below 117.44 billion rupiah, and a WTP audit opinion
7	Local governments with a non-WTP audit opinion

Source: processed by researchers (2025)

The segmentation results in **Table 6** can be tabulated based on the number and proportion of regions that disclose their financial statements on the internet either completely or incompletely. The proportion values at the terminal nodes represented the classification tree model, as presented in **Table 7**.

Table 7. Distribution of local governments based on the disclosure of financial report information through official websites in each segment

Segment *k*	Disclosure of Local Government Financial Report Information			
	Incomplete IFR		Complete IFR	
	Number	Proportion	Number	Proportion
1	56	0.29	140	0.71
2	6	0.21	23	0.79
3	7	0.37	12	0.63
4	2	0.29	5	0.71
5	17	0.74	6	0.26
6	39	0.65	21	0.35
7	39	0.83	8	0.17
Total	166	0.44	215	0.56

Source: processed by researchers using R version 4.5.1 (2025)

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The characteristics of regions that tended not to disclose local government financial reports completely are reflected in segments 5, 6, and 7.

3.3. Evaluation of the CART Classification Tree Results

The classification accuracy of the CART method based on both learning data and testing data, is presented in **Table 8**.

Table 8. Classification Accuracy of the CART Method

Classification Result	Accuracy (%)	AUC (%)
Learning Data	72.18	72.40
Testing Data	64.24	63.83

Source: processed by researchers using R version 4.5.1 (2025)

Table 8 shows that the optimal classification tree, obtained using the CART method, achieved an accuracy of 72.18% with an AUC of 72.40% on the learning data. It was also able to correctly predict new data (testing data) with an accuracy of 64.24% and an AUC of 63.83%.

4. CONCLUSION

The findings of this study show that of the 546 local governments in Indonesia, 44% (or 238) local governments are not yet transparent in disclosing their financial reports through their official websites. Audit opinion was the most important and influential variable for IFR, with an importance value of 16.65%. Other independent variables that also affect IFR are regional revenue, financial independence ratio, administrative age of local government, and per capita income. The optimal CART classification tree produced seven segments and is able to predict new data with an accuracy of 64.24% and an AUC of 63.83%. Local governments that tended to be less transparent in disclosing financial reports on their official websites are characterized as follows: (a) Segment 5, governments with an financial independence ratio between 6.64% and less than 12.045%, per capita income below 60342.5 thousand rupiah, administrative age of at least 22 years, regional revenue below 117.44 billion rupiah, and a WTP audit opinion; (b) Segment 6, governments with an administrative age of less than 22 years, regional revenue below 117.44 billion rupiah, and a WTP audit opinion; and (c) Segment 7, governments with a non-WTP audit opinion.

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