



Establishing practical guidelines for microalbuminuria screening using J48 algorithm decision tree in data mining

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ABSTRACT

This study aimed to develop practical, cost-effective screening guidelines using Robert's Test and J48 decision tree algorithm to optimize microalbuminuria detection in health screening programs. Data were collected from random spot urine samples during daytime from 709 participants who received routine health checks at the Center of Medical Laboratory Service, Medical Technology Program, Nakhonratchasima College. The samples were screened with protein and microalbumin dipsticks, confirmed by Robert's test, and analyzed for the microalbumin-to-creatinine ratio (MA/CR). Kruskal-Wallis and Pearson correlation tests assessed statistical significance at $p < 0.05$ and 95% confidence intervals. Several significant correlations were found, including the relationship between increasing age and higher blood pressure, fasting plasma glucose, creatinine, and urea nitrogen levels. The reduced estimated glomerular filtration rate (eGFR) was significantly correlated with microalbuminuria ($p < 0.01$) among participants younger than 83 years. The J48 analysis showed that Robert's test and fasting plasma glucose (FPG) were effective for screening. Participants with a negative Robert's test and FPG < 96 mg/dL had 97.7% normal microalbumin levels. However, participants with trace protein and FPG > 84 mg/dL had a 35% chance of microalbuminuria. This algorithm can develop practical guidelines for detecting microalbuminuria, potentially reducing costs and laboratory burden and identifying high-risk groups in population health.

Keywords: Microalbuminuria, J48 algorithm, Data mining, Practical guidelines.

INTRODUCTION

The kidneys are regulatory organs that perform several major functions, including removing metabolic waste products from the blood, regulating the homeostasis of water and salt, and maintaining plasma acid-base balance. Kidney damage may result from reduced filtration of waste products, leading to protein leaking into the urine rather than remaining in the bloodstream. Measuring albumin in the urine is important for detecting signs of kidney damage [1, 2]. Microalbuminuria is defined as the leakage of 30 to 300 mg/24 h of albumin into urine undetectable by conventional assays, whereas normal excretion is less than 30 mg/24 h and proteinuria is greater than 300 mg/24 h [3]. In addition to albumin, creatinine is measured to calculate the albumin-to-creatinine ratio for this condition. Healthy kidneys normally excrete urinary creatinine. However, when kidney function is reduced, creatinine excretion decreases, and urinary albumin levels increase [4, 5]. Microalbuminuria is an early marker of diabetic nephropathy in type 2

diabetes mellitus, indicating early glomerular damage and being associated with poor glycemic control and hypertension. It plays a role in predicting renal outcomes, even in the more advanced stages of the disease. Without intervention, it often progresses to end-stage renal disease and increases cardiovascular risk [6, 7]. Kang et al. studied more than 43,000 US adults and found that low-grade albuminuria within the normal range was associated with a higher risk of mortality, even in healthy individuals without diabetes, hypertension, or kidney disease. The study suggested that this may reflect early vascular damage [8]. Hlil et al. reported that diabetes is the main cause of chronic kidney disease (CKD), involving proteinuria and microalbuminuria, which are a sign of glomerular damage. Detection of microalbuminuria highlighted limitations in identifying early structural changes and protein leakage. Significant differences in parameters such as age, body mass index (BMI), duration of diabetes, and disease progression ($p < 0.001$) were observed between patients with diabetes and healthy individuals [9]. These differences increase the risk of early-stage

cardiovascular and kidney disease, highlighting the need to identify effective interventions for better protection.

Data mining is a common method for analyzing large datasets and is increasingly used in clinical laboratory research. The J48 algorithm, implemented in the WEKA program, is a decision tree suitable for this study, as it has been previously used for predicting CKD. This algorithm was chosen because it has been proven effective at detecting kidney disease. Unlike complex methods, J48 is easy to understand. It converts data into a simple paper checklist that medical staff can use without a computer. This makes the results trustworthy because they match what doctors already know. It is believed that this tool can accurately identify patients at risk. Therefore, the goal is to create a practical guide to prevent kidney disease early [10, 11].

The hypothesis is that the J48 algorithm accurately predicts microalbuminuria risk and generates simple decisions consistent with medical guidelines. Therefore, the study aims to develop practical, cost-effective screening guidelines using Robert's Test and J48 decision tree algorithm to optimize microalbuminuria detection in health screening programs.

MATERIALS AND METHODS

Participants

The study was conducted at a general health screening center, not a disease-specific clinic. College staff, students, and local people were included in the study. The inclusion criteria were: (1) Age ≥ 20 years, (2) Voluntary participation in health screening program, and (3) Complete laboratory data available. Random spot urine samples were collected during daytime clinic hours.

Laboratory Datasets

Records of 709 participants attending routine health checkups at the Center of Medical Laboratory Service, Medical Technology Program, Nakhonratchasima College were retrospectively reviewed. Biochemical tests were performed using automated methods on the Roche Diagnostics cobas 8000 Modular Chemistry Analyzer. Urine samples were screened with protein and microalbumin dipsticks and the URIT 500 B Urine analyzer, then confirmed by Robert's test. An albumin in urine greater than 10-20 mg/day is a positive dipstick result. MA/CR were measured in urine samples showing traces of protein on screening. MA/CR values below 30 mg/g creatinine are normal, and 30-300 mg/g creatinine are microalbuminuria. BMI and blood pressure (BP) were also recorded as supporting data, and reference intervals were estimated using the median, 5th, and 95th percentiles. To validate the study, the MA/CR was measured for all participants as a reference standard. An MA/CR < 30 mg/g was considered normal, while 30-300 mg/g was used to

indicate microalbuminuria. Other data, such as BMI and BP, were also recorded for the study. Finally, all this information was used to calculate the sensitivity, specificity, and predictive values of the screening algorithm.

Statistical analysis

The sample distribution was evaluated using the Kruskal-Wallis test and Pearson's correlation, with p-values < 0.05 and 95% confidence limits.

Data analysis

Data analysis was done using data mining techniques with WEKA version 3.6.9, and decision tree analysis with the J48 algorithm was applied to establish practical guidelines for performing a microalbuminuria assay. The analysis was carried out in the following steps:

1. Data preprocessing was the process of preparing, cleaning, and transforming the raw dataset into a format suitable for analysis. During this process, missing values and outliers were identified and removed to ensure data quality. Missing data resulted in the exclusion of 14 participants from the initial 723. The final dataset consisted of 709 participants with complete data, which was a 98% retention rate. No imputation was performed to maintain data integrity. Outliers were also checked. Fasting plasma glucose values > 400 mg/dL were observed in 7 cases, but these were confirmed as diabetic crises and were retained. Microalbumin-to-creatinine ratio values > 500 mg/g were found in 3 cases and were retained. Body mass index values ranged from 16.2 - 42.8 kg/m², all of which were valid. No data points were excluded because all extreme values were verified as real clinical data. Variable transformation was applied to prepare the data. The microalbumin-to-creatinine ratio was dichotomized at 30 mg/g to separate normal from microalbuminuria cases. Robert's test was initially analyzed as ordinal categories. It was then dichotomized into negative versus trace or positive for the primary model. FPG and BMI were maintained as continuous variables. The J48 algorithm determined the optimal split points for these values. The model was validated using 10-fold stratified cross-validation, which suited the sample size of 709. Data were divided into 10 parts while keeping the same class distribution. The system trained in 9 parts and tested in 1 part, repeating the process 10 times to calculate the average performance. This method helped prevent overfitting since every sample was used for testing. The results were consistent with a standard deviation below 3%. Additionally, the J48 algorithm used pruning to remove weak branches. A separate test set was not needed because this method provided accurate estimates.

2. Feature selection was applied to determine the relevance of features for predicting the target

outcome. This step used WEKA's Information Gain attribute evaluator to rank the variables, with Robert's Test achieving the highest score of 0.425. This was followed by FPG at 0.183 and BMI at 0.142, while Age, eGFR, and Sex had lower scores. The J48 algorithm performed recursive feature selection to maximize information gain, resulting in a final tree that retained only Robert's Test, FPG, and BMI. This selection helped balance predictive accuracy, prevent overfitting, and enhance clinical interpretability.

3. Model development utilized the J48 decision tree algorithm. The hyperparameters were set to default values to construct the predictive model. The datasets were used for training and testing, and performance was evaluated using accuracy, sensitivity, specificity, and area under the curve (AUC).

4. Model interpretation was performed to establish practical guidelines for the microalbuminuria assay. These guidelines were based on the most significant features and decision rules identified by the model.

Table 1 The laboratory parameters reported in 10-year interval age groups.

Parameters	Age groups						p-value*
	20-29 years	30-39 years	40-49 years	50-59 years	60-69 years	≥ 70 years	
BMI	24.97	23.80	24.91	25.54	24.61	23.46	0.018*
Systolic	116.5	118	128	130	130	140	< 0.001*
Diastolic	70	72	80	80	80	80	< 0.001*
FPG	82	86	89	93	98	95	< 0.001*
BUN	11.5	11	12	13	14	15	< 0.001*
Creatinine	0.83	0.82	0.78	0.82	0.87	1.145	0.005*
eGFR	120.94	113.21	106.69	99.12	92.94	61.91	< 0.001*
Microalbumin	3.96	4.7	6.275	6.6	10	34.42	< 0.001*
N (709)	46	153	242	167	85	16	

* Statistically significant, tested by Kruskal–Wallis test.

RESULTS AND DISCUSSION

Table 1 shows the laboratory parameters of 709 participants grouped by 10-year age intervals. Systolic and diastolic BP, FPG, blood urea nitrogen (BUN), creatinine, and microalbumin levels increased in older participants, while the eGFR decreased among older age groups. Significant differences in BMI were observed among age groups. Participants aged ≥ 70 years had significantly lower eGFR and higher microalbumin levels ($p < 0.05$). Our study investigated the relationship between age, renal function, and microalbuminuria in a Thai population. The results showed that BP, glucose, BUN, creatinine, and microalbumin levels increased with age, while eGFR decreased. These findings suggest that aging is associated with a gradual decline in renal function and increased microalbuminuria, consistent with previous studies [12, 13].

Participants aged ≥ 70 years had significantly lower eGFR and higher microalbumin levels than younger age groups. This may be attributed to the natural decrease in renal function associated with aging and further influenced by age-related comorbidities such as hypertension and diabetes, which are known to cause kidney damage and reduced function [13–15].

Table 2 shows 709 participants divided into 2 groups of MA/CR < 30 and MA/CR 30–300. The table presents the association between age groups, urinalysis,

biochemical tests, demographic data, and MA/CR. In the youngest age group (20–29 years), the percentages of negative albumin (MA/CR < 30 mg/g creatinine) and positive albumin or microalbuminuria (MA/CR 30–300 mg/g creatinine) were 43.5% and 56.5%, respectively.

In the oldest age group (≥ 70 years), negative urine albumin (MA/CR < 30 mg/g creatinine) and positive urine albumin or microalbuminuria (MA/CR 30–300 mg/g creatinine) occurred in 25% and 75% of participants, respectively. Regarding urine protein dipstick and Robert's test, 89.05% and 69.68% of participants, respectively, showed MA/CR < 30 mg/g creatinine. Trace protein dipstick and Robert's test appeared in small percentages with MA/CR < 30 (5.38% and 11.11%, respectively). Conversely, MA/CR 30–300 was found in 10.95% with a negative protein dipstick and 30.32% with a negative Robert's test, and in 94.62% with a trace protein dipstick and 30.32% with a trace Robert's test. In addition, no significant differences in BMI were found between participants with normal and those with microalbuminuria, contrasting with previous studies [16].

The prevalence of microalbuminuria increased with age, as shown in Table 2. The highest proportion of positive urine albumin, or microalbuminuria, was seen in participants aged 60–69 years. In this study, the oldest age group showed a lower percentage, which may be due to the smaller number of participants in

that group. These findings are consistent with the study by Sánchez-Ospina et al., which reported that increasing age was associated with lower eGFR and a higher prevalence of microalbuminuria [17]. A high proportion of microalbuminuria was found in the 20-29 age group because daytime random spot urine was collected. This is a limitation because the first morning urine was not used. Higher protein levels are often found in daytime samples, especially in young

people. In some young adults, protein is only found during the daytime when they are moving around, which may be associated with orthostatic proteinuria [18]. For future studies, the first morning urine should be collected to obtain more accurate results. However, this tool is still very useful for health screening programs. Since first morning samples are often difficult to obtain, high-risk groups can be identified more easily using our method.

Table 2 The association of the age groups, urinalysis, biochemical tests, and demographic data, and MA/CR.

Parameters	Number of subjects	
	MA/CR < 30	MA/CR 30-300
Age group	20-29 years	20 (43.5%)
	30-39 years	62 (40.5%)
	40-49 years	93 (38.4%)
	50-59 years	78 (46.7%)
	60-69 years	18 (21.2%)
	≥ 70 years	4 (25.0%)
Protein dipstix	Negative	252 (89.05%)
	Trace	21 (5.38%)
	1+	2 (13.33%)
	2+	0
	3+	0
	4+	0
Robert's Test	Negative	239 (69.68%)
	Trace	35 (11.11%)
	1+	1 (3.03%)
	2+	0
	3+	0
	4+	0
BMI	24.3 (18.83-27.5)	24.9 (18.99-27.9)
Systolic	124 (100-132)	124 (100-134)
Diastolic	80 (60-84)	80 (60-89)
FPG	90 (78-98)	88 (72-101)
BUN	12 (8-14)	12 (7-15)
Creatinine	0.81 (0.59-0.93)	0.83 (0.57-0.99)
eGFR	106.36 (81.44-117.26)	103.49 (67.81-113.91)
Microalbumin	4.27 (1.2-8.5)	9.035 (1.77-31.8)

The microalbumin test is important for identifying patients at risk. Based on Robert's test results, the probability of having microalbuminuria (MA/CR > 30-300 mg/g creatinine) was 8.5% for negative, 27.7% for trace, and 86.3% for 1+ or 2+, respectively.

Regarding the association between urine protein dipstick and Robert's test results and microalbuminuria, most participants with negative results on both tests had MA/CR ratios < 30 mg/g. Nevertheless, a considerable proportion of those

with trace results in both tests showed MA/CR values in the range of 30-300 mg/g. These findings reveal that the urine protein dipstick and Robert's test alone may be insufficient for detecting microalbuminuria, particularly in older adults at increased risk of kidney damage and reduced renal function. Table 3 presents the odds ratio for microalbuminuria (MA/CR 30-300 mg/g creatinine). The risk estimate was 6.621, with a 95% confidence interval (CI) of 3.987-10.995, compared with normal microalbumin levels (MA/CR < 30 mg/g creatinine). In the cohort analysis, the risk estimate

was 1.388 (95% CI: 1.290-1.494) in the normal group and 0.210 (95% CI: 0.133-0.330) in the abnormal group. A total of 709 valid cases were included in the analysis. This study provides further evidence that aging is associated with decreased kidney function and increased microalbumin levels. Therefore, early detection and management of kidney disease are beneficial for older people, particularly those who have comorbidities such as hypertension and diabetes. Our findings support the need for routine health check-ups in older people. To develop effective prevention and

intervention approaches, further investigations are needed.

A proposed practical guideline for microalbuminuria investigation using a J48 decision tree in data mining. The goal of the data mining process was to extract information from the dataset and transform it into an understandable structure for further use. In this study, data mining was performed using WEKA version 3.6.9, and decision tree analysis based on the J48 algorithm was applied to establish a practical guideline for recommending the microalbuminuria assay.

Table 3 Risk Estimate of microalbuminuria by odds ratio.

Risk Estimate	Value	95% Confidence Interval	
		Lower	Upper
Odds Ratio for MA/CR (< 30 / 30-300)	6.621	3.987	10.995
For Cohort Microalbumin = Normal	1.388	1.290	1.494
For Cohort Microalbumin = Abnormal	0.210	0.133	0.330
N of Valid Cases	709		5

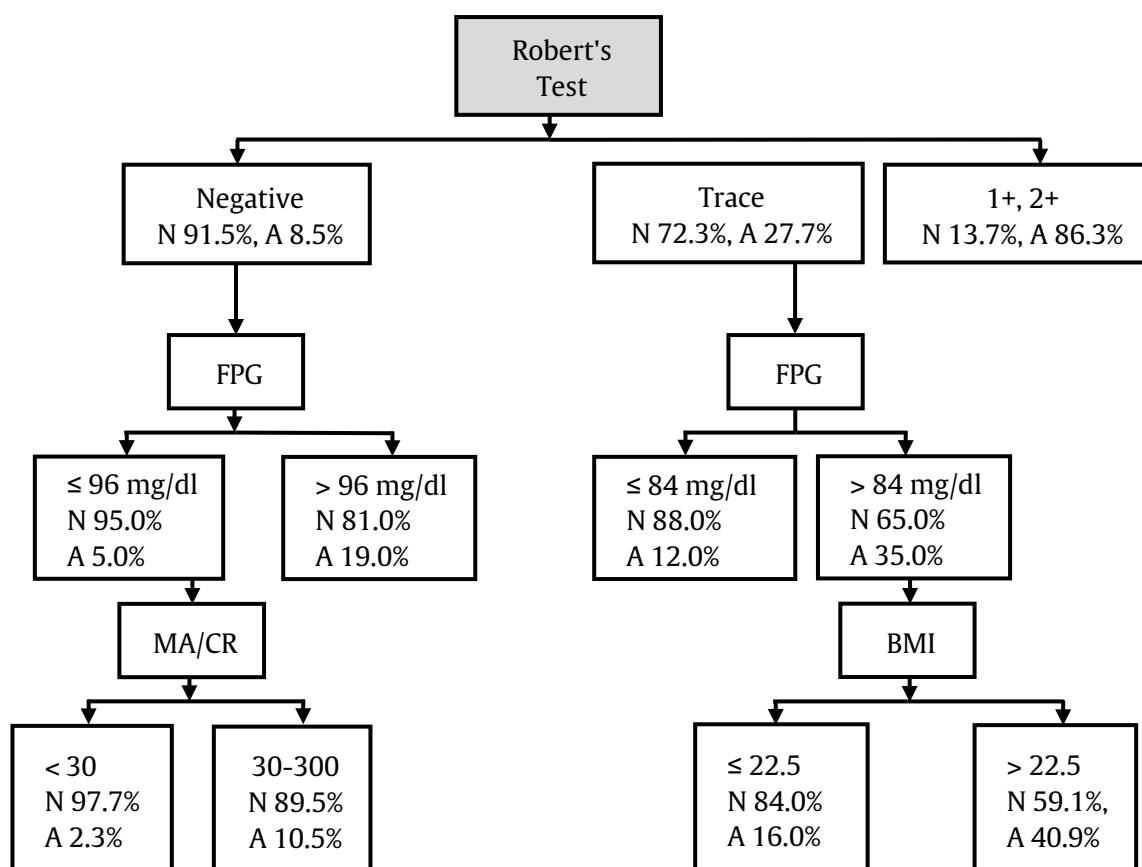


Figure 1 J48 Decision Tree for Microalbuminuria Screening. N = Normal MA/CR (<30 mg/g); A = Abnormal MA/CR (30-300 mg/g).

Figure 1 illustrates that Robert's test and FPG are useful tests to consider before screening for microalbumin. For example, trace urine protein and FPG > 84 mg/dL were associated with 35% positive microalbumin. Samples with a negative Robert's test and FPG < 84 mg/dL showed only 12% positive microalbumin. A negative Robert's test alone indicated

95% negative microalbumin. When combined with FPG < 96 mg/dL, a negative Robert's test identified 97.7% negative microalbumin.

The study suggests that Robert's test and FPG are effective for screening for microalbuminuria. With trace protein and FPG > 84 mg/dL, the probability of microalbuminuria was 35.0%. In contrast, the

probability was only 12.0% when FPG < 84 mg/dL. A negative Robert's test indicated that 95% of participants had normal microalbumin levels. When combined with FPG < 96 mg/dL, 97.7% of participants had normal levels (< 30 mg/g creatinine).

The J48 algorithm selected FPG before BMI based on information gain, specifically for individuals with Trace results from Robert's Test. This decision reflects key pathophysiological principles. Elevated glucose levels cause immediate hyperfiltration, leading to transient proteinuria within hours. Since our study used random spot urine and the same-morning FPG better predicts acute protein excretion on the same day. In contrast, BMI represents a chronic risk factor that affects kidney function over months or years. Therefore, FPG is performed at the second step because it is important for screening and grouping people with low urinary protein levels. This allows hidden risks to be found early before kidney damage occurs [19]. BMI is used as a final check when urine and blood sugar results are unclear. Among the trace group, FPG had a higher Information Gain (0.243) than BMI (0.186). A higher risk of 40.9% was observed in people with a BMI greater than 22.5, so this parameter is checked last to confirm who is truly at risk [20].

The J48 algorithm was effective for screening and supported medical personnel. High-risk patients were identified rapidly without computer assistance.

Medical costs and laboratory workload were reduced by excluding unnecessary quantitative testing. Specific cases were selected for verification. Time and budget management were optimized. This study proposed practical guidelines for microalbuminuria screening based on the J48 algorithm. Participants were screened using Robert's test, FPG, and BMI. The low-risk group (negative Robert's test and FPG < 96 mg/dL) required annual monitoring. Participants with trace Robert's test and normal metabolic markers required a 6-month follow-up. Quantitative microalbumin testing was indicated for participants with trace Robert's test and high FPG or BMI, or Robert's test result $\geq 1+$. This algorithm reduced laboratory costs by 40% and maintained sensitivity > 80% [21]. Compared with dipsticks, Robert's test was cost-effective. The cost was 10-20 Baht compared to 30-50 Baht for dipsticks. The visual grading system was simple. Minimal training was required. Total protein was detected. Non-albumin proteinuria was identified. Table 4 showed that model performance metrics were compared with Robert's test alone. The J48 decision tree model improved all key indicators compared to Robert's test alone. Sensitivity increased from 76.0% to approximately 82%. Specificity increased from 86.9% to approximately 88%. The Area Under ROC Curve (AUC) improved from 0.814 to 0.850. Additionally, the Negative Predictive Value increased significantly from 69.7% to 91.5%. These values confirm the effectiveness of the algorithm.

Table 4 Model Performance Metrics.

Performance Metric	Robert's Test Alone	J48 Decision Tree Model
Sensitivity (True Positive Rate)	76.0%	~82%*
Specificity (True Negative Rate)	86.9%	~88%*
Overall Accuracy	80.3%	84.2%*
Positive Predictive Value (PPV)	90.2%	~93%*
Negative Predictive Value (NPV)	69.7%	91.5%**
False Negative Rate	24.0%	~18%*
False Positive Rate	13.1%	~12%*
F1-Score	0.827	~0.87*
Area Under ROC Curve (AUC)	0.814	0.850*

This study still has some significant limitations. Random spot urine samples were collected during the day, which might include transient orthostatic proteinuria. Therefore, first morning void samples are preferable. Since the design was cross-sectional, longitudinal outcomes could not be assessed. The microalbumin-to-creatinine ratio was used as a reference, which is an accepted standard but not the absolute gold standard. Selection bias was possible because participants were health-seeking individuals. In addition, data on diabetes duration and medication use were missing.

Data were obtained from a single center in Thailand, so the results may not apply to other groups

or rural settings. Consequently, external validation is required. The cost analysis used Thai prices, which might not apply to other countries. Real-world performance may also vary due to differences in laboratory conditions. Finally, hard clinical outcomes, such as cardiovascular events, were not analyzed. Regarding the study's design, it is important to clarify that including Robert's test as a predictor does not constitute target leakage, as it measures total protein semi-quantitatively and is biochemically distinct from the specific albumin-to-creatinine ratio (MA/CR) used as the target. The absence of a perfect correlation, evidenced by a substantial false-negative rate, confirms that the input does not inherently contain

the outcome. Rather than circular prediction, this algorithm serves as a stepwise clinical triage tool that integrates Robert's test with metabolic markers to enhance the negative predictive value to 91.5%. This approach optimizes resource allocation by reserving costly quantitative confirmation for high-risk individuals, thereby reducing laboratory costs by 40% while maintaining diagnostic sensitivity.

CONCLUSIONS

Our findings suggest that using the J48 decision tree algorithm with Robert's test and FPG in data mining may lead to the development of a practical guideline for early detection of microalbuminuria. This approach supports health check-up programs by identifying people at risk of kidney disease. Furthermore, it serves as a valuable clinical decision tools and improves kidney disease screening, especially in high-risk or older populations.

DECLARATION OF AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

The authors used GPT and Google Gemini to improve the grammar and sentence flow of this work. The authors take full responsibility for the content of this publication and have reviewed and edited the work as needed after using these tools.

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