

## An Early Warning System for Islamic Banks Performance

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**ABSTRACT.** There is increasing demand for predicting the performance of Islamic banks due to the vital importance of any problem that may face these banks before it materializes and negatively affects their performance and their financial status. This will save on the costs of bad performance or failure to depositors, owners and the economy. Thus, a need arises for an early warning system which will identify the possible causes of bad performance, detect potential problem banks, facilitate surveillance of banks as well as reduce its costs and make possible proper timing of examining problem banks as well as scheduling the remedial procedures. This research aims at benefiting from the previous research efforts on the subject to develop a preliminary model for the prediction of the performance level of Islamic banks (i.e. an early warning system), hoping that this will be a cornerstone for further development and improvisation, specially as more information and data become available or accessible. To achieve such objective Discriminant Analysis technique will be utilized, whereby a Discriminant Function will be designed comprising the significant characteristics (financial ratios) as explanatory variables and the profitability rate as dependent variable. Discriminant scores are then extracted and used to distinguish between high performance and low performance groups of banks, thus forming a possible early warning system for the prediction of future performance of the observed banks. The prediction power of such a system is finally tested and conclusions drawn.

### **1. Problem of the Research**

There is increasing demand for predicting the performance of Islamic banks due to the vital importance of prior information on any problem that may face any Islamic bank before it materializes. This will save on the costs of banks bad performance or failure to depositors, owners and the society.

Thus, the rationale for an early warning system comes from the following reasons :

1. Identifying the possible causes of bad performance.
2. Facilitating the surveillance of banks and reducing its costs.
3. Proper timing of examining problem banks and scheduling the remedial procedures.

## 2. Objectives of the Research

1. Using Discriminant Analysis technique to identify the significant characteristics (financial ratios) which distinguish high-performance banks from low-performance ones.
2. Designing a Discriminant Function to classify the performance level of the studied Islamic banks into High performance and Low performance groups based on the Discriminant scores compared to the Cut-off Discriminant Criterion.
3. Testing the prediction powers of the above Early Warning System.
4. Drawing conclusions on the prediction reliability of the above system and the degree of its utilization for future prediction of Islamic Banks performance.

## 3. Review of Literature

Recently an accumulating research on the prediction of business performance and/or failures has evolved. Discriminant Analysis is one of the most utilized statistical techniques for the prediction of the performance of business firms. Originally developed to classify certain variables into two or more pre-specified groups according to the most statistically significant distinguishing characteristics (classifying variables). The discriminant analysis technique usage is extended to the prediction of the status of such a variable in the future, based on the results of the discriminant analysis (discriminant function) several years before, mostly between one and two years prior to the performance or problem or failure occurrence, and the the testing of the classification power of such a function (Altman *et al*; 1981).

Various models are followed in the discriminant analysis, each with its advantages and pitfalls, most prominent among which are the Linear Fisher model and the Logit model (Altman *et al*, 1981; Amemiya, 1981; Johnsen and Melicher, 1994; Scott, 1981).

Discriminant analysis, though not the oldest technique for the evaluation and prediction of business performance, being superseded by the Financial Ratios Analysis, is more preferred to the latter because it gives a summary index of performance, takes into consideration the possible interrelationship among the characterizing variables (independent variables) as they explain the variations in the groupings of the classified variable (dependent variable) and last, but not least, the discriminant analysis can include other non-financial (e.g. managerial, social or political) factors that may affect the behavior of the dependent variable (Altmam *et al*, 1981; Sinkey, 1975).

Lately, discriminant analysis was also applied to the prediction of the performance and/or failure of financial institutions, markets and instruments (e.g. commercial banks and investment companies, bond markets and investment portfolios among others). Although still undergoing fine-tuning improvements, so far the record of such studies were generally impressive. This was evident from the favourable scores they acquired in the statistical testing of their classification results and predictive powers (Altman *et al*, 1981; Haslem and Longbrake, 1971; Sinkey, 1975).

Haslem and Longbrake (1971) used discriminant analysis to distinguish low profitability commercial banks from high profitability banks, members of the Federal Reserve System in the United States, with 46 financial ratios as explanatory variables and 78 banks (observations) for each group of profitability.

This research aims at benefiting from such efforts to develop a preliminary model for the prediction of the performance of Islamic banks (i.e. an early warning system) hoping that this will be a cornerstone for further improvisations and applications.

#### 4. Discriminant Analysis

Discriminant analysis is a statistical technique used to classify a sample of observations into two or more groups based on a linear composite of input variables. In the two group case, the objective of the discriminant analysis is to create a linear combination of explanatory (discriminant) variables that maximizes the distance between the centers of the two populations under consideration using the pooled within-group covariance matrix. This procedure assumes that the explanatory variables (or predictors) have a multivariate normal distribution with different means but common covariance matrix among the classes. This linear combination is called "discriminant function" and can be written as:

$$z = \sum_i b_i x_i$$

where  $z$  is the value of the discriminant function (score),  $b_i$ 's are the discriminant co-efficients and  $x_i$ 's are the independent (explanatory) variables used to discriminate between the two groups.

Classifying observations into one of the two groups is done by computing the discriminant score for each observation and comparing it to a numerical cut-off value. If the score is above the cut-off value, we assign the observation to group one, and if it is below the cut-off value, we assign the observation to the other group. The cut-off value can be computed as follows:

$$\text{Cut-off value} = (z_1 + z_2) / 2 + \ln [ c(1/2) p_2 / c(2/1) p_1 ]$$

where  $z_1$  and  $z_2$  are the centroids of group one and group two respectively,  $c(i/j)$  is the mis-classification cost and  $P_i$  is the priori probabilities.

For the case of assuming an equal mis-classification cost, as has been in our research, the second part of the cut-off value equation is reduced to the natural logarithm of the priori probabilities ratio. Moreover, if the sample sizes of the two groups are equal, the cut-off value will be reduced to the mean of the two groups centroids (i.e. the first part of the equation only).

Testing the predicting power of the model is usually done on a holdout sample which is not used in the estimation of the discriminant co-efficients. The discriminant score is computed for each observation and compared to the cut-off value computed from the sample used to construct the discriminant function. The percentage of hits in the overall grouping is thereafter calculated to obtain the degree of prediction accuracy. In the absence of a holdout sample, as is the case in our research due to the smallness of the size of sample banks, other methods were suggested in the literature most prominent among them is the Lachenbruch method which will be explained later.

## 5. Data Collection and Organization

Around 40 letters were sent to various Islamic Banks requesting data on balance sheets and income statements during the period 1991-1993. These data was used to formulate performance classification variables and explanatory discriminant variables (income and expense ratios) which are used to predict the performance of the sample banks in the year 1993 (the latest year for which complete data on these variables is available) using data (financial ratios) for each of the previous years 1991 and 1992.

However, only 29 banks responded fully. Out of these, 26 banks with enough operation experience were selected in the sample, namely those which operated before 1989. Such a relatively small number restricted the size of the observations (number of banks) in each group of performance. This had obliged us to compress the number of discriminating (explanatory) variables and aggregate them into block variables which in our belief would at most represent the operational factors affecting the performance levels of the studied banks. Another reason which necessitated aggregating the variables is the unstandardized items in the balance sheets and income (profit and loss) statements of Islamic banks. Only some banks reported fully detailed assets, liabilities and income entries. Worse than that, some banks treated investments belonging to customers (depositors) as off-balance sheet items. Different reporting methods make disaggregate and standardized classification of data difficult. Hopefully in the future, better detailed and standardized data may enable researchers to use more disaggregate variables, thus improving the discriminating performance of such variables.

With regard to the relative lag in the time-period of the data, two clarifications are due:

1. The set of data in this research paper serves the main purpose of testing the reliability and efficiency of the early warning system for Islamic banks and does not incur any conclusions as to the performance of the specific banks covered in the data. Of course, when the system is to be actually applied by the relevant bodies as an early warning system, more updated and comprehensive data is called for.
2. Data on Islamic banks is unfortunately relatively lagging, even from the relevant banks, a problem which should be addressed in order to render the early warning system more efficient and reliable in application.

The available sample of banks is divided into two discrete groups: low performance (problem) banks and high performance (control) banks. The classification (categorization) criteria is based on a summary index of performance to be explained later.

Typically, in discriminant analysis, discrete (dichotomous) variables constitute the categorization basis of the dependent variable. Continuous variables, like the one we are using in this research, pose some problems for discriminant measurement because of the possible arbitrariness in group segmentation, errors in classification tests and low prediction efficiency (Eisenbeis, 1977).

In our case, a success/failure categorization will be appropriate, assigning the number zero to failure (or problem) group and the number one to success (or non-problem) group. However, for Islamic banks, data pertaining to failure occurrences is rare because of the rareness of failure cases in the relatively short history of Islamic banks and the absence of a central regulatory body which has the ample authority to decide on failure occurrence. Thus in our research, we restricted our prediction to performance, hoping that in the future more detailed, transparent and standardized information on performance and failure/success occurrences will enable our model to be extended as to function more efficiently as an early warning system for the prediction of failure (or problem) cases in Islamic banks.

## 6. Specification of Variables

Seven financial ratios were used in this research. These ratios were chosen based on the following criteria:

1. Past similar research on the subject (see references and review of literature).
2. Statistical convenience and efficiency, particularly the problem of the number observations versus the number of variables (degrees of freedom) mentioned above, which obliged us to compress explanatory variables to the minimum aggregate (block) variables.
3. Maximum possible representation of the main factors affecting the performance of studied banks, mainly productivity, efficiency, liquidity, risk and leverage. These include only internal factors pertaining to the direct operational income and expense activities of the studied banks, thus excluding any external factors e.g. country-specific political, regulatory and policy factors, which are not directly controllable or predictable by individual banks. These ratios are as follows:

$X_1$  = Total Income/Total Assets, representing productivity of bank resources (resource utilization or asset turnover), where:

Total income includes all income coming from investments (from Islamic financing e.g. *mudarabah*, *murabahah*, *musharakah*, *ijarah* etc., or direct financing), revenues from foreign exchange dealings, revenues from banking services and other sources (unspecified) of income. Total Assets include liquid assets (cash and reserves), short term and long term investments and fixed assets.

$X_2$  = Investment Income/Total Income, representing the level of contribution of income coming from investments, as explained above, to total income. This variable distinguishes those banks relying on investment of funds as the main source of income from those depending on trade (including foreign exchange) transactions and banking services. When detailed and standardized data become, hopefully, available in the future, disaggregating the investment income variable into separate variables (e.g. *mudarabah*, *murabahah*, *musharakah*, *ijarah*) will be fruitful

$X_3$  = Total Income/General and Administrative Expenses, representing the operational efficiency of the bank, where:

General and Administrative Expenses include all operating expenses, staff expenses, depreciation and provisions.

$X_4$  = Provisions for Bad Debts and Investments/Total Assets, representing financing and/or investment risk. Such provisions influence the available funds for financing and investment and the types of financing or investment, thus affecting the level of returns from the utilization of these funds.

$X_5$  = Cash/Total Deposits, representing the liquidity position in the bank which influences the amount of funds free for financing and investment (against the bank's eligible liability) and the level of returns, where: Cash includes cash funds in hand with the bank, balances with other banks (in local and foreign currencies) and reserves (statutory and others). Due to differences in reported items of liquidity among the studied banks, liquidity is limited to the above mentioned common items. Total Deposits include customers current (demand) and investment deposits.

$X_6$  = Customers Investment Deposits/Shareholders Equity, representing the leverage level (debt / equity ratio) in the bank's investment, where:

Shareholders Equity includes paid up capital, reserves and retained profits.

$X_7$  = Net Profit Before Zakat and/or Taxes/Total Assets, representing the profit rate of the bank. Zakat and/or taxes were excluded from the calculation of net profit in order to neutralize the effect of differences in tax and zakat treatment, application and reporting among the studied sample bank.

The profit rate as measured above is chosen as an indicator of profitability for the following reasons:

1. Profitability includes the income and expense activities of the bank, since profit equals income minus expenses. Thus, profitability reflects the main ingredients of cash flow activities in the bank, emanating from the utilization of the bank's resources.

2. The profit rate (net profit/ assets) as a measure of profitability can be decomposed into two ratios as follows:

$$\text{Net profit / Assets} = (\text{Net profit/Capital}) \times (\text{Capital/Assets}),$$
 which mean that the profit rate is influenced by net profit/capital as a measure of the rate of return for the bank's shareholders (owners), and capital/assets as a measure of solvency. Both measures are significant indicators of the success and survival possibilities of the bank.

3. Dividing net profit by assets serves the extra significant purpose of neutralizing the effect on performance of differences in size among the sample banks, thus diluting the possible bias in discriminating low performance banks from high performance ones due to share size. The technique of matching (pairing) each group of performance banks according to size utilizing the absolute value of assets, used in many similar studies, will not be efficient in our sample banks due to the fact that assets are reported in different currencies.

The dependent variable i.e. the performance level, is classified into two groups: low performance group and high performance group. Performance is measured in the form of a summary index composed of the following four financial ratios:

Profitability = Net Profit / Total Assets.

Productivity = Total Income / Total Assets.

Efficiency = Total Income / General and Administrative Expenses

Leverage = Customers Deposits / Shareholders Equity

Classification of the 26 sample banks between the two performance groups is based on the ranking of each bank according to each of the above four financial ratios, summing up the ranking scores of each bank for the four financial ratios and calculating the average score. Those banks with 14 points or less were classified into the high performance group, while those scoring above 14 points are classified into the low performance group. Twelve banks were thus classified into the high performance group and fourteen banks were classified into the low performance group.

## 7. Empirical Results

Discriminant analysis was run using the SPSS Discriminant program on the initial seven financial ratios defined above ( $X_1$ - $X_7$ ) as explanatory (discriminant) variables, for the 26 sample of Islamic banks to distinguish high performance banks from low performance ones. The statistics of these ratios for one and two years prior to the performance year (1993) are presented in Table 1.

**Table 1:** Univariate Statistics for the Explanatory Variables

Ratio	High Performance Group		Low Performance Group	
	Mean	St. Dev.	Mean	St. Dev.
One Year Prior (1992)				
x <sub>1</sub>	0.125	0.130	0.055	0.028
x <sub>2</sub>	0.103	0.113	0.045	0.023
x <sub>3</sub>	5.047	2.696	2.584	0.996
x <sub>4</sub>	0.047	0.093	0.012	0.013
x <sub>5</sub>	0.254	0.211	0.285	0.205
x <sub>6</sub>	11.706	6.059	7.539	6.900
x <sub>7</sub>	0.024	0.022	0.008	0.009
Two Year Prior (1991)				
x <sub>1</sub>	0.095	0.058	0.064	0.030
x <sub>2</sub>	0.081	0.065	0.053	0.026
x <sub>3</sub>	4.629	2.614	3.124	1.569
x <sub>4</sub>	0.017	0.028	0.012	0.014
x <sub>5</sub>	0.266	0.177	0.323	0.264
x <sub>6</sub>	9.118	7.363	9.003	10.933
x <sub>7</sub>	0.029	0.020	0.015	0.017

Two separate runs were conducted for the one year prior to the performance year data and the two years prior to the performance year data, using the linear discriminant analysis to classify Islamic banks performance. The two years prior model did not pass the statistical significance test of the inequality of the group means (1), and so was dropped from the analysis. The one year prior model gave impressive results and passed the significance test of the mean group inequality at 0.05 level of significance,

indicating that the two groups (high and low performance groups) came from two different populations. The one year prior model also passed the statistical test of the equality of the two dispersion matrices at 0.01 level of significance, allowing the use of linear classification rule. The classification results for the one year prior to the performance year is given in Table 2.

**Table 2:** Classification Results for the One Year Prior to the Performance Year

Performance Group	No. of Cases	Correct Classification		Mis-classification	
			%		%
High	12	10	83.3	2	16.7
Low	14	13	92.9	1	7.1
Total	26	23	88.5	3	11.5

The results indicate that out of 12 high performance banks, the model correctly classified 10 banks. The classification accuracy for the high performance group of banks is 83.3%, while the mis-classification rate, the type I error i.e. classifying a high performance as low performance, is 16.7%. For the low performance group of banks, out of the 14 banks the model correctly classified 13 banks. The classification accuracy for the low performance group of banks is 92.9%, while the mis-classification rate, the type II error i.e. classifying a low performance as high performance, is only 7.1%. The overall accuracy of the model is 88.5%, which is comparable to most of the studies that used discriminant analysis.

The relative importance of the explanatory variables used to discriminate between high and low performance banks will be determined first by applying univariate statistics to individual variables. Table 3 presents the relative importance of the individual variables and their ranks.

**Table 3:** Relative Contributions and Ranks of the Individual Variables

Variables	Univariate F		Wilks' Lambda		Standardized Coefficient	
	Value	Rank	Value	Rank	Value	Rank
x <sub>1</sub>	3.88	3	0.86	3	1.35	2
x <sub>2</sub>	3.45	4	0.87	4	-1.51	1
x <sub>3</sub>	10.14	1	0.70	1	0.51	6
x <sub>4</sub>	1.97	6	0.92	6	0.82	4
x <sub>5</sub>	0.15	7	0.99	7	0.11	7
x <sub>6</sub>	2.63	5	0.90	5	0.80	5
x <sub>7</sub>	6.39	2	0.79	2	1.01	3

The results show that the efficiency variable (x<sub>3</sub>) and the profitability variable (x<sub>7</sub>) ranked first and second respectively and were significant at 0.05 level in the univariate F-test. The productivity variable (x<sub>1</sub>) and the investment contribution variable (x<sub>2</sub>) ranked third and fourth respectively and were significant at 0.01 level in the univariate F-test. The rest of the variables were significant at 0.25 level.

Determining the relative importance of the variables by the univariate F-test on individual variables has a great appeal in the discriminant analysis literature (Eisenbeis, 1977, pp. 882-884). This is because variables may show little or insignificant discriminant contribution based on an individual univariate test, but when combined with other variables they may show high significance. A backward stepwise method based on the contributions to the multivariate F-test has been proposed. The results of the backward stepwise method is presented in Table 4. They show that the risk variable ( $x_4$ ) and the liquidity variable ( $x_5$ ) were removed. This indicates that these two variables have no significant power in distinguishing between high and low performance groups of Islamic banks i.e. high risk and liquidity are common characteristics of both groups. The other five variables were included by the procedure and they were significant in the multivariate F- test at 0.01 level. The efficiency variable ( $x_3$ ) and profitability variable ( $x_7$ ) were the most important ones to discriminate between the high and low performance groups.

Table 4: Variable Ranks as they were included in the Backward Stepwise Method

Variable	$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$
Rank	5	4	1	r	r	3	2

r = removed; Multivariate F-Test = 6.21; significant at 0.01

The classification results based on the five variables selected by the backward stepwise procedure is presented in Table 5. They show that the type I error was eliminated, but type II error was increased. The five variables correctly identified the whole set of the low performance banks but mis-classified three high performance banks. The results also show that the removal of variables by the backward stepwise method does not change the overall classification accuracy of the model (88.5%).

Table 5: Classification Results of Islamic Bank Performance for One Year Prior to the Performance Year

Performance Group	No. of Cases	Correct Classification	%	Mis- classification	%
High	12	9	75.0	3	25.0
Low	14	14	100	0	0
Overall	26	23	88.5	3	11.5

The discriminant function used to derive the classification results in table 5 is:

$$z = 23.05 x_1 - 23.41 x_2 + 0.33 x_3 + 0.09 x_6 + 45.66 x_7$$

where  $z$  is the discriminant score for each Islamic bank. The classification rule is to assign an Islamic bank whose score is above 3.14 (the cut-off point) to the high performance group and that whose score is below the cut-off point to the low performance group.

## 8. Reliability Test

Applying the above discriminant function to data on the five explanatory variables for an Islamic bank one year prior to the performance year and computing the  $Z$  - score enables the model to function as a predictor of performance of the bank for the following year.

Testing the predicting accuracy of the model is usually done by using a holdout sample that has not been used in deriving the discriminant function. In the absence of a holdout sample, as in our case, various methods have been proposed in the discriminant analysis literature (Altman *et al*, 1981: 153-158 ). The most powerful test, specially for small samples as in our case, is the Lachenbruch method. This method uses the original sample as a holdout sample. The procedure of this method is to holdout one observation from the original sample each time and use the remaining observations to derive a function to classify the holdout observation. This procedure is repeated until all observations are classified and then the classification accuracy of the holdout sample is computed. Applying this method to our observations produced results similar to those shown in table 5, with 88.5% classification accuracy and 11.5% expected overall errors .

## 9. Conclusions

1. The model used in this research proved to be highly efficient in discriminating between high and low performance Islamic banks groups in spite of the fact that only 26 sample banks and seven initial aggregate financial ratios ( discriminant variables ) were included in the analysis. Five of these variables turned to be significant in the discriminant function utilized to test the classification accuracy and prediction reliability of the model.

2. Reliability of the model as a predictor or as an early warning system of performance of Islamic banks is expected to improve when more detailed and standardized data become available, allowing for larger disaggregate number of explanatory (discriminant) variables to be included. Bank- specific and/or external variables i.e. managerial, organizational, market, political variables can also be added.

3. The model can also be utilized as an early warning system for various types of performance including bankruptcy, insolvency and failure, when data on such types become available and/or accessible.

### Notes:

1. The group centroid can be computed by substituting the mean value of the predictor variables in the discriminant function. This can be written as:

$$z_i = b_1 x_{1i} + b_2 x_{2i} + \dots + b_m x_{mi} \quad i= 1, 2$$

where  $z_i$  is the centroid of group  $i$  and  $X_{mi}$  is the mean value of the  $m$ th predictor of group  $i$ .

2. Testing the inequality of a group mean is the same as testing the significance of the discriminant function . The null hypothesis is:

$$H_0 : u_1 = u_2 \text{ or equivalently Wilks' Lambda} = 1$$

This hypothesis can be tested by an F-test or chi-square test as follows:

$$F_p, N-m-1 = N-M-1 / m \cdot 1^{-\wedge / \wedge}, \text{ or } x_{2 m} = - [ (n-1) - (m+1/2) ] \ln^{\wedge}$$

The null hypothesis is rejected if the computed  $F$  or  $x_2$  is bigger than the table value at 5% level of significance. The computed  $F$  is 4.42 and  $x_2$  is 20.5. These values are bigger than the table values of 2.66 and 14.07 respectively. which leads to rejecting the null hypothesis.

3. The test for equality of group covariance matrices (dispersion matrices) is done using the method of Box's  $m$  and approximate  $F$  (Altman *et al*, 1981: 45 ). The null hypothesis is:

$$H_0 : s_1 = s_2$$

where  $s_i$  is the dispersion matrix of group  $i$   $i=1,2$ .

The computed approximate  $F$  is 1.67, which is less than the table value of

This leads to accepting the null hypothesis .

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## نظام الإنذار المبكر لأداء البنوك الإسلامية

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**المستخلص:** تزايدت الحاجة إلى التوقع المبكر لأداء البنوك الإسلامية بسبب الأهمية المتنامية لمعالجة المشاكل أو الصعوبات التي يمكن أن تواجه هذه البنوك قبل أن تؤثر سلباً على مركزها المالي، حيث ستؤدي المعالجة المبكرة إلى تفادي (أو على الأقل تخفيض) تكلفة الأداء المتدني أو الفشل سواء للمودعين أو المالكين (المساهمين) أو للنظام المصرفي والاقتصاد الوطني. لذا تنشأ الحاجة إلى نظام إنذار مبكر يمكنه التعرف مسبقاً على المسببات المحتملة للأداء المتدني وتسهيل عملية مراقبة البنوك المتعثرة وتخفيض تكاليف هذه المراقبة وتحسين توقيت فحص ومن ثم معالجة مشاكل البنوك التي تواجه صعوبات في أدائها.

يهدف هذا البحث إلى تصميم نموذج مبدئي للتوقع المبكر لأداء البنوك الإسلامية (نظام إنذار مبكر) بالاستفادة من الأبحاث والدراسات السابقة التي استخدمت هذا المنهج في توقع أداء المنشآت المالية، أملاً في تطوير هذا النموذج في المستقبل خاصة عندما تتوفر معلومات وبيانات أشمل.

لتحقيق هدف البحث ينوي الباحثان استخدام منهج "التحليل التمييزي"، حيث سيجري تصميم دالة تمييزية تشكل الخصائص المالية المؤثرة في مستوى أداء البنوك المدروسة، واستخدام أداء البيانات المجمعة عن هذه المتغيرات في استخراج نقاط التمييز التي تستخدم للتمييز بين مجموعتي البنوك عالية الأداء ومنخفضة الأداء.

أخيراً سيتم اختبار القدرة التوقعية للدوال المستخرجة وتحليل نتائج الاختبار وصياغة النتائج العامة للبحث.