

QUALITY ASSURANCE FOR ECONOMY CLASSIFICATION BASED ON DATA MINING TECHNIQUES

Ahmed S. El Rawas¹ and Hamdi A. Mahmoud²

¹Department of Finance , Arab Academy for Science and Technology, Egypt

²Department of Computer Science, Beni Suef, Egypt.

ABSTRACT

Researchers in the quality assurance field used traditional techniques for increasing the organization income and take the most suitable decisions. Today they focus and search for a new intelligent techniques in order to enhance the quality of their decisions. This paper based on applying the most robust trend in computer science field which is data mining in the quality assurance field. The cases study which is discussed in this paper based on detecting and predicting the developed and developing countries based on the indicators. This paper uses three different artificial intelligent techniques namely; Artificial Neural Network (ANN), k-Nearest Neighbor (KNN), and Fuzzy k-Nearest Neighbor (FKNN). The main target of this paper is to merge between the last intelligent techniques applied in the computer science with the quality assurance approaches. The experimental result shows that proposed approaches in this paper achieved the highest accuracy score than the other comparative studies as indicates in the experimental result section.

1. INTRODUCTION

Nowadays, quality assurance focuses on applying new and robust techniques for increasing the quality of decision in the organizations. The researchers in this area aim to merge between quality assurance techniques and computer science. Date mining techniques are the newest area of computer science that used different artificial techniques such as Artificial Neural Network (ANN), Support Vector Machine (SVM), Naïve Bayes tree (NB Tree), k-Nearest Neighbor (KNN), Genetic algorithm and Fuzzy k-Nearest Neighbor (FKNN) etc. Recently, the use of artificial techniques increase gradually in different application specially in quality assurance applications such as detecting if the input indicators related to the developed or developing countries depending on the previous knowledge which the artificial technique learned in the learning phase. Scientists recently replace the traditional methodologies with different robust artificial techniques to increase and improve the result of accuracy rate and automatically determine the accurate decision for the enrolled country. This paper focuses on using three different artificial techniques to identify the type of the countries. These techniques are Artificial Neural Network (ANN), k-Nearest Neighbor (KNN) and Fuzzy k-Nearest Neighbour (FKNN).

2. RELATED WORK

The monetary policy is generally used to increase economic growth, increase quality assurance, decrease unemployment and increase inflation rate. The study will discuss and examine the relation between the monetary policies in different countries; selected countries under study are classified into two groups developed and developing countries.

Monetary policy denotes the actions designed to manipulate the money supply, including bank credit, in order to achieve specified economic objectives and increase the quality assurance by a duly authorized public authority, most commonly a central bank. To understand monetary policy it is necessary to know what money is. Most economists and all politicians take it for granted that

the money supply has important effects on the economic system. Even if they are wrong, belief that it does would make it relevant [1].

The use of monetary policy rules to evaluate and describe central bank policy actions has been growing rapidly. Much of the research on policy rules has focused on economies with highly developed asset markets, especially markets for debt and foreign exchange. Monetary policy rule is understood to be a contingency plan that specifies clearly the cases under which a central bank should change the instruments of monetary policy, the size of the interest rate responses in policy rules matter greatly for economic performance. Changing the interest rate by more than one for one with inflation is a crucial property of a good monetary policy rule. A response that is smaller than one-to-one can result in very poor performance. An example of this is the USA's response of the interest rate to inflation in the late 1960s and the 1970s in comparison with the 1980s and 1990s [2].

In recent years there has been a lot of discussion about the role of stabilization policies. During a recession, it is possible to stimulate the economy through expansionary fiscal or monetary policies. The increased demand is likely, in turn, to stimulate output growth and price inflation and increase the quality assurance decisions. Conversely, during a boom it is possible to curb excess demand through contractionary fiscal or monetary policies. Demand reduction is likely, in turn, to moderate output growth and price inflation [3].

The fundamental objective of quality assurance in the monetary policy area is to assist the economy in achieving a full-employment, non-inflationary level of total output. More specifically, monetary policy entails increasing the money supply during a recession to stimulate spending and, conversely, restricting the money supply during inflation to constrain spending.

The role of monetary policy in macroeconomic stabilization is an inconclusive issue. Besides the development on theoretical grounds, a substantial body of empirical literature has contributed to the ongoing debate by providing significant evidence on how monetary policy affects output growth, domestic prices and exchange rates. No doubt, the adoption of the floating exchange rate system, the slogan of financial reforms, the trade liberalization and relatively more independent central banks have enhanced the significance of monetary policy. Therefore, both academics and policymakers are keen to understand how, when and to what extent the economic aggregates respond to changes in monetary policy [4].

The ineffectiveness of quality assurance of monetary policy is based on uncertainties associated with inverse causal relations from money supply to interest rates, and from interest rates to investment. If in the hypothesized process of monetary policy, increases in money supply do not lead to lower interest rates and thus larger amounts of investment, and then monetary policy will become an effective stabilization policy. In the following sections, we provide logical and empirical evidence in support of the unreliability of the relation from money supply to interest rates [5].

Forni and Gambetti (2010) examine the dynamic exogenous effect of monetary policy by using a standard recursive scheme through a dynamic structural factor model for USA covering the period 1973:3-2007:10 [6]. Their empirical analysis is based on the variables which are used by Stock and Watson (1998). They argue that the factor analysis model is superior to FAVAR proposed by Bernanke *et al.* (1998) because it helps in eliminating the puzzles in monetary policy analysis [7]. They find that a positive shock to Federal Funds Rate (FFR) leads to an appreciation of real exchange rate. This confirms overshooting hypothesis of Dornbusch (1976). Computing impulse response graphs, they show the absence of price puzzle. Further, they argue that industrial production falls, although temporary, to a large extent with a humped-shaped response. Bjørnland (2008) examines the response of macroeconomic economic aggregates to monetary policy by including the exchange rate in the model specification. He uses quarterly data over the period 1993-2004 [8]. Further, he uses Cholesky ordering and the Kim and Roubini's (2000) identification procedures to determine the order of the variables. Bjørnland (2008) shows that

there is a temporary increase in the interest rate, which normally takes four quarters to converge to its normal path. However, his analysis does not provide any statistically significant evidence of the exchange rate puzzle or price puzzle.

Jang and Ogaki (2004) examine the relationship between monetary policy shocks and Dollar/Yen exchange rates, prices and output level for USA. The empirical analysis is carried out, following the model of Jang and Ogaki (2004), through structural VECM and VAR by employing long- and short-run restrictions on the model. They find that an appreciation of exchange rate is the result of a contractionary monetary policy. Furthermore, they find that output in domestic as well as in foreign country significantly declines due to the long-run neutrality restrictions with an exception of USA where a decline in output becomes negligible after four years. Finally, a fall in price is observed as a result of tight monetary policy. While, estimating VECM and VAR with short-run restrictions for variables in their levels, they fail to accept the UIP condition, they find strong evidence in support of the existence of price puzzle [9].

Fullerton *et al.* (2001) apply an error correction model to study the behavior of the exchange rate for Mexican peso over the period 1976-2000. The variables included in the model are nominal exchange rates, consumer price index, liquid international reserves, money supply and real gross domestic product (GDP) as non-policy variables while one-and three-month T-bills rates as policy variables. Their findings based on the balance of payment framework and monetary model of exchange rate do not provide any support to the established theory. However, balance of payment framework with one-month T-bill rate is marginally better than the monetary model of exchange rate [10].

Wong (2000) empirically investigates the impact of monetary policy on macroeconomic variables by applying a time-varying parameter model for USA over the period 1959:1-1994:12. Output and prices are assumed to have lagged effect but FFR and reserves are considered to have only contemporaneous effects. The rolling VAR has been estimated with maximum three lags. The empirical results suggest that output increases in response to a contractionary shock to monetary policy. The output is more responsive to shocks during periods when the central bank adopts inflation controlling policy, whereas, it is less responsive when the central bank aims at promoting economic growth. Overall, the plots of IRF provide the evidence of the presence of price puzzle [11].

Bernanke and Mihov (1998) develop a VAR-based methodology to measure and assess the impact of monetary policy on macroeconomic variables [7]. The measure of MP is derived from an estimated model of Central Bank's operating procedures and the market for commercial bank reserves, which makes it more consistent than the previously used instruments of monetary policy. The model has been estimated for different time periods of post 1965-1996 for USA. The exogenous policy shocks are computed through a standard VAR method by applying generalized methods of moments in which the policy variables are placed last in variable ordering. The IRFs indicate that there is an increase in output in response to an expansionary monetary policy. Further, the plots provide evidence of a slower but a persistent rise in the prices. Yet, their results considerably vary across different measures of monetary policy. Although the study attempts to capture all the possible measures of monetary policy, it fails to notify which of the measure is relatively more effective.

Eichenbaum *et al.* (1995) analyze the exchange rate transmission mechanism of monetary policy for the period 1974:1-1990:5 [12]. They use three measures of monetary policy commonly used in the literature. These measures are FFR, non-borrowed reserves and the narrative measure of Romer and Romer (1989). They estimate a multivariate VAR model by using the ordering of the variables based on the Wold decomposition. The estimates on IRFs reveal that a contractionary monetary policy leads to a significant and continual decline in US interest rate, a sharp and persistent appreciation in US exchange rate, which is contradictory with the overshooting hypothesis of exchange rate.

3. PRELIMINARIES

A. Economy Database

This study examines the impact of monetary policy on quality assurance of the economic growth in-group of countries. The study uses panel data covering the range from 1990 to 2014, selected countries under study are classified into two groups; developed and developing countries. Definitions and sources of used indicators are used in the table below;

Indicator Name	Long definition	Source
GDP per capita (constant 2005 US\$)	GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in constant 2005 U.S. dollars.	World Bank national accounts data, and OECD National Accounts data files.
Real interest rate (%)	Real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator. The terms and conditions attached to lending rates differ by country, however, limiting their comparability.	International Monetary Fund, International Financial Statistics and data files using World Bank data on the GDP deflator.
Official exchange rate (LCU per US\$, period average)	Official exchange rate refers to the exchange rate determined by national authorities or to the rate determined in the legally sanctioned exchange market. It is calculated as an annual average based on monthly averages (local currency units relative to the U.S. dollar).	International Monetary Fund, International Financial Statistics.
Money and quasi money (M2) as % of GDP	Money and quasi money comprise the sum of currency outside banks, demand deposits other than those of the central government, and the time, savings, and foreign currency deposits of resident sectors other than the central government. This definition of money supply is frequently called M2; it corresponds to lines 34 and 35 in the International Monetary Fund's (IMF) International Financial Statistics (IFS).	International Monetary Fund, International Financial Statistics and data files, and World Bank and OECD GDP estimates.
Exports of goods and services (% of GDP)	Exports of goods and services represent the value of all goods and other market services provided to the rest of the world. They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communication, construction, financial, information, business, personal, and government services. They exclude compensation of employees and investment income (formerly called factor	World Bank national accounts data, and OECD National Accounts data files.

	services) and transfer payments.	
Imports of goods and services (% of GDP)	Imports of goods and services represent the value of all goods and other market services received from the rest of the world. They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communication, construction, financial, information, business, personal, and government services. They exclude compensation of employees and investment income (formerly called factor services) and transfer payments.	World Bank national accounts data, and OECD National Accounts data files.
Consumer price index (2010 = 100)	Consumer price index reflects changes in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. The Laspeyres formula is generally used. Data are period averages.	International Monetary Fund, International Financial Statistics and data files.
Gross capital formation (current US\$)	Gross capital formation (formerly gross domestic investment) consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories. Fixed assets include land improvements (fences, ditches, drains, and so on); plant, machinery, and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings. Inventories are stocks of goods held by firms to meet temporary or unexpected fluctuations in production or sales, and "work in progress." According to the 1993 SNA, net acquisitions of valuables are also considered capital formation. Data are in current U.S. dollars.	World Bank national accounts data, and OECD National Accounts data files.

B. Artificial Neural Network (Ann)

Artificial neural network (ANN) has been used in many real word identification problem. The main applications that ANN applied on it are face bioinformatics, detections, hand written recognition, supervised and unsupervised learning, pattern recognition etc. in this paper we used it in identifying and classify the countries in to two types developed or developing. The mechanism that the artificial neural network uses like the human brain; it takes the structure of biological neural system. After the network train using supervised learning technique, it can use to identify the test cases use to predict or determine the type of the country [13].

Due to the characteristics of artificial neural networks (ANN), such as high speed because of the parallel processing, the ability to model systems with complex and nonlinear input and output and learning capability generalize capability it uses in the various sciences applications. Multi-Layer Perceptron neural networks is one of the most widely used artificial neural network [14].

Artificial neural networks consist of an input layer, the hidden layers and an output layer. Adjustment of neural network parameters such as number of neurons of each layers and the

number of middle layers plays an important role in the performance of the network and achieving the best solution [15]. There are no accurate criteria to determine the number of neurons in the middle layers, but it should be noted that the increasing of number of neurons in the middle layer reduces the speed of the algorithm. While the reduction in number of neurons, decrease also ability of the network analysis [16].

C. k-Nearest Neighbor (KNN)

K-Nearest Neighbor identifier (KNN) is one of the simplest identification techniques. If there is no prior knowledge about the distribution of country data KNN is one of the first choices for these identification problems. KNN classifier has been both a benchmark classifier algorithm [17]. KNN classifier performance determined by choice of K as well as the distance metric applied [18]. In 2002 the predetermining of the K value difficult when the points are uniformly distributed [19].

The k-Nearest Neighbor (KNN) identifier is one of the common artificial techniques that used in machine learning [20-22]. KNN relay on cases that does not need a learning phase. The training cases related with a distance function and the selection of the function class based on the classes in the nearest neighbors is the used application. Before identifying a new object, it must compare with the other training objects using a similarity ration. The nearest neighbor object that considered as the accurate object for the test object is the object that appears mostly between the neighbors be classified. The neighborhoods are weighted by using the distance that separates object from the new elements to identify. The appropriate function in this technique relay on the selection of parameters like the parameter k. K is used to represents the number of neighbors selected to allocate the object to the new element and the used distance.

Algorithm 1 " K-Nearest Neighbor Classifier (KNN) algorithm"

select a value for the parameter k

▪ **Input:**

- Give a sample of N cases and their related object. The objects of an sample x is C(x):
 Give a new sample y:
- Define the k nearest neighbors of y by computing the distances.
- Collect the classes of these y examples in one object O

▪ **Output:**

- The class of y is C(Y) = O
-

The K Nearest Neighbor (KNN) algorithm is commonly used in data identification [23]. The KNN identify the new test element by computing the distance between it and all the other training cases. The appropriate functioning of this algorithm depends on the selection of the K parameter which denotes the number of neighbors elected to allocate the test object to the new test element and the selection of the distance [24].

D. Fuzzy k-Nearest Neighbor (FKNN)

Fuzzy K-Nearest Neighbor identifier (FKNN) is feature based system. FKNN training set can readily be maintained overtime can be modified often and can operate with few cases for each class as the experimental result in this paper shown. FKNN identification system becomes a special area with in the field of Nearest Neighbor classification systems [25].

Fuzzy K-NN Classifier is the most popular choice for classification applications because it gives information about the certainty of the classification decision and it is simple. Fuzzy K-Nearest Neighbor Classifier (FKNN) is an improved algorithm of the standard K-Nearest Neighbor

(KNN) algorithm. Fuzzy K-NN Classifier can maintain very good classification accuracy with appropriate few training data as in breast cancer case, also the lack in breast cancer database the accuracy rate was highly than any other machine learning algorithms. FKNN based on learning and training scheme of breast cancer class memberships. The fuzzy K-nearest neighbor (FKNN) algorithm uses to classify the test objects based on their similarity to a given number K of neighbors with the training objects and these neighbors' membership degrees to the class labels [26].

Algorithm 2 " Fuzzy K- Nearest Neighbor Classifier (FKNN)"

- 1: Consider $w = \{w_1, w_2, \dots, w_n\}$ a set of t labelled data. Where w_i is denote by I characteristics
 $w_i = (w_{i1}, w_{i2}, \dots, w_{iI})$
- 2: Set input of y as unclassified elements.
- 3: $K \leftarrow$ is the number of closest neighbors of y .
- 4: $E \leftarrow$ the set of K nearest neighbors (NN).
- 5: $M_i(y) \leftarrow$ is the membership of y in class i .
- 6: $M_{ij} \leftarrow$ is the membership in i^{th} class of j^{th} vector of the label set (label w_i in class i).
- 7: Set $t \leftarrow$ the number of elements that identify the classes.
- 8: Set $c \leftarrow$ the number of classes.
- 9: Set $W \leftarrow$ is the set that contain t elements where each cluster is represent by a subset of elements from w .
- 10: Set K value.
- 11: Calculate NN.
- 12: for $i=1$ to t
- 13: Calculate the distance from y to x_i
- 14: If $i \leq K$
- 15: Then add x_i to E
- 16: else if x_i is closer to y than any previous NN
- 17: then delete the farthest neighbor and include x_i in the set E
- 18: end for
- 19: Calculate $M_i(y)$ using:
 for $i = 1$ to c where c is the number of classes

$$M_i(y) = \frac{\sum_{j=1}^K M_{ij} \left(\frac{1}{||y - x_j||^{2/(m-1)}} \right)}{\sum_{j=1}^K \left(\frac{1}{||y - x_j||^{2/(m-1)}} \right)}$$

4. THE PROPOSED CLASSIFICATION SYSTEMS

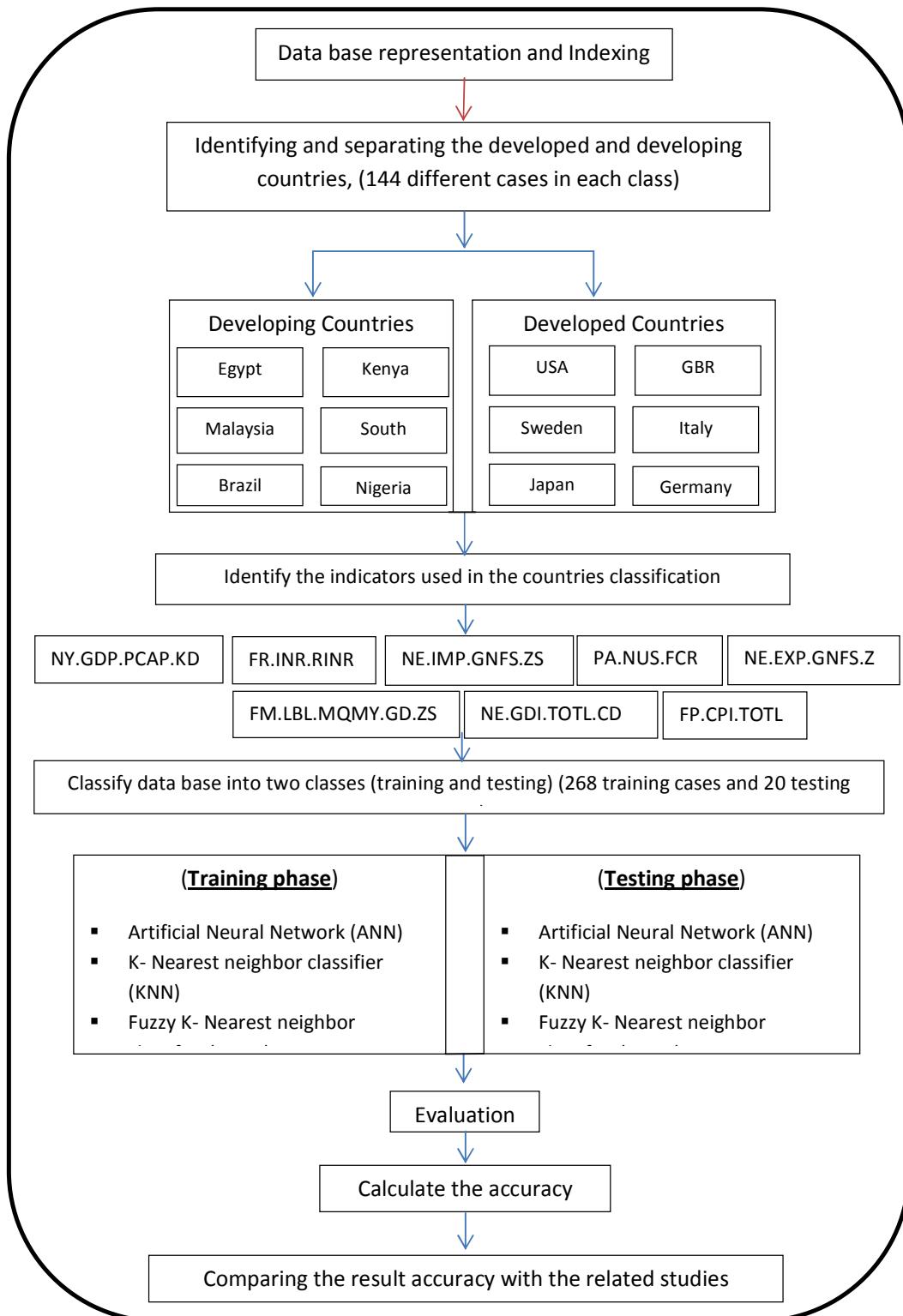


Figure 1. The proposed Classification systems scenario

The first step in our systems is to collect large data base to use it in the presented study. This data base collected from 1990 to 2013 for twelve different countries; six countries are developed and six are developing countries. Then the artificial techniques are used to determine the type of the test cases if it (developed or developing) country. This paper consists of using three different artificial techniques; namely Artificial Neural Network (ANN), K- Nearest neighbor classifier (KNN) and Fuzzy K- Nearest neighbor classifier (FKNN). After calculating the classification accuracy for each system a comparative study used to denote the most accurate system and the end user can rely on it.

5. EXPERIMENTAL RESULT

To evaluate the proposed system, we have used Matlab R2009b program to implement and test our system. A number of experiments have been conducted using laptop with the following specifications: 6 GB of RAM, Intel® Core™ i5-4210U CPU running at 2.40 GHz and under Windows® 64-bit operating system.

The studied subjects were divided into two groups as follows: Group I: (n=144) different cases for six developed countries during time period from 1990 to 2013 as a developed group. Group II: (n=144) different cases for six developing countries during the same time period as a developing group. The developed countries in this study are United States (USA), United Kingdom (GBR), Sweden (SWE), Italy (ITA), Japan (JPN) and Germany (DEU). The developing countries are Egypt, Arab Rep. (EGY), Kenya (KEN), Malaysia (MYS), South Africa (ZAF), Brazil (BRA) and Nigeria (NGA).The structure of the data is as follows: GDP per capita (constant 2005 US\$), Real interest rate (%), Official exchange rate (LCU per US\$, period average), Money and quasi money (M2) as % of GDP, Exports of goods and services (% of GDP), Imports of goods and services (% of GDP), Consumer price index (2010 = 100) and Gross capital formation (current US\$). This data base consists of 288 different cases, these data divided to training data and test data. The training phase uses 268 cases for each developing and developed counties and 20 different cases for the test phase. Table 1 shows sample of the data used within the case study.

Table 1. Sample of cases used for the developed and developing data base

Type	Developed	Developed	Developed	Developing	Developing
Country Name	United States	Japan	Italy	Egypt, Arab Rep.	Malaysia
Year	1990	2013	1998	2013	1991
GDP per capita	32965.64739	37573.36975	29509.60696	1566.540802	3355.571355
Real interest rate	6.070686754	1.86239124	5.962582599	3.027227209	5.563263512
Official exchange rate	1	97.59565828	1736.207383	6.870325	2.750066667
Money and quasi money	71.0275102	247.7865486	48.36471636	79.14723211	66.30928857
Exports of goods and services	9.229714362	16.15140129	24.1135245	17.6239092	77.82612879
Imports of goods and services	10.53080474	18.99106072	21.0792733	24.65065876	81.48649749
Consumer price index	59.91976049	100.0416667	77.43638084	129.0627973	59.24722643
Gross capital formation	1.2984E+12	1.03938E+12	2.46792E+11	38562963423	18568052764

As shown in table 1, there are three different developed countries and two different developing countries as a sample of the whole data in the data base. The first indicator which is GDP per capita (constant 2005 US\$) and its code is (NY.GDP.PCAP.KD) used as the first parameter in the classification process and it is a highly effective parameter in the separation process because the value of this parameter is highly separated between the developed and the developing countries.

As shown in table 1 the value of this parameter in the developed countries starts from values above that 25000 but the value to this parameter in the developing countries less than 5000. The following three figures (2, 3 and 4) represent the statistical representation for the developed, developing and both kinds of countries merged in one statistical representation.

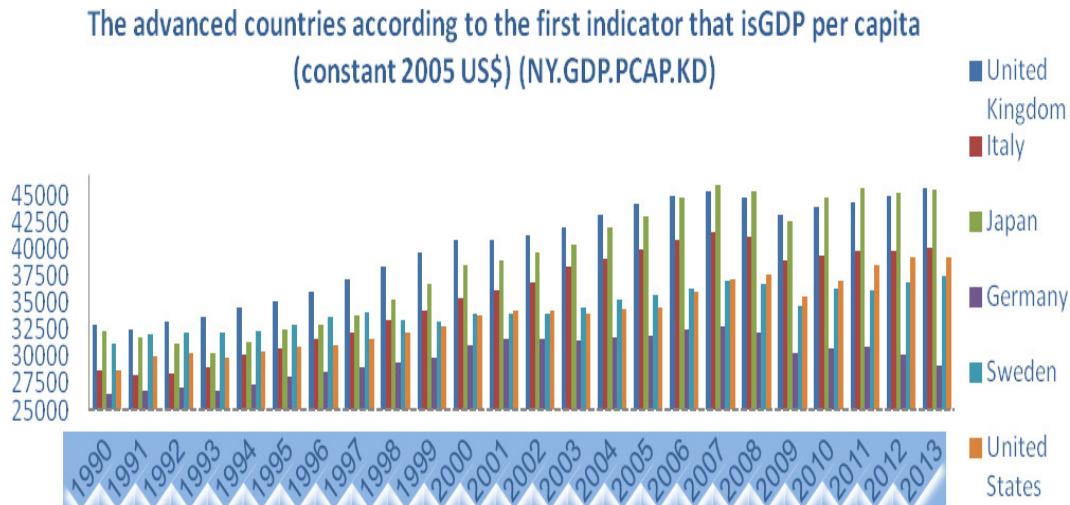


Figure 2. Statistical representation that represent the developed countries according to the NY.GDP.PCAP.KD indicator

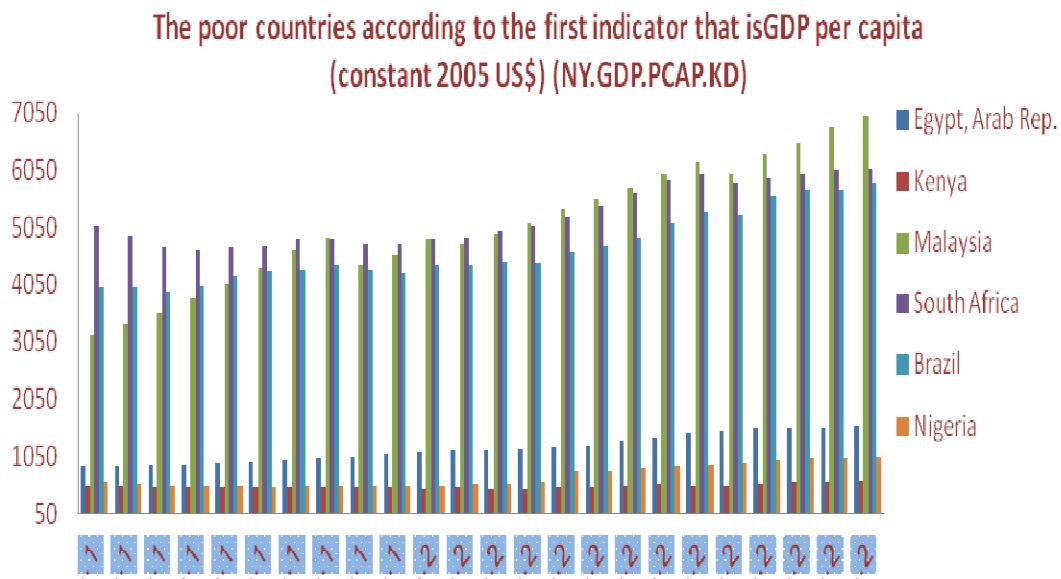


Figure 3. Statistical representation that represent the developing countries according to the NY.GDP.PCAP.KD indicator

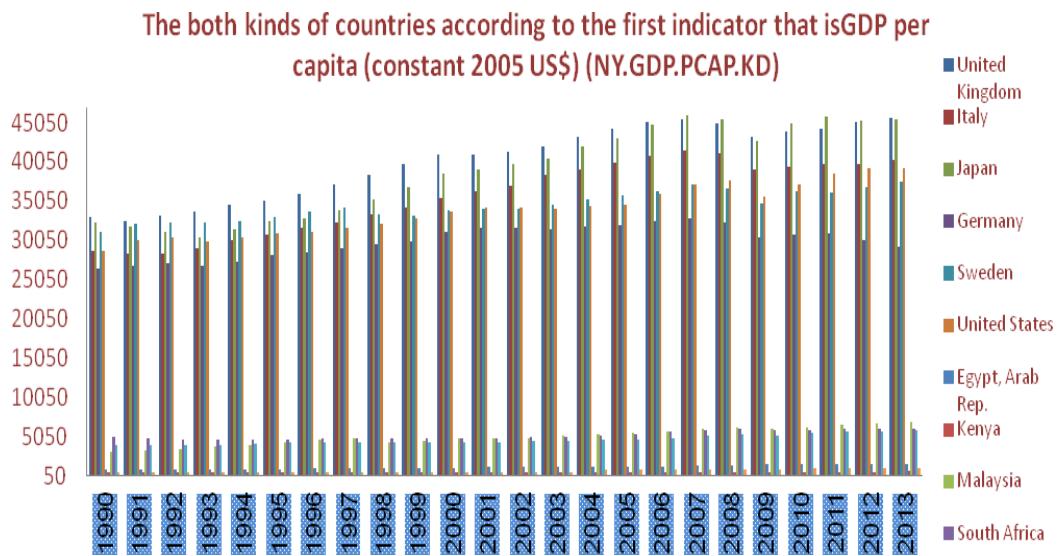


Figure 4. Statistical representation that represent both the developing countries and developing countries according to the NY.GDP.PCAP.KD indicator

Real interest rate (%) and its code is (FR.INR.RINR) is the second indicators which is the highly effective parameter in the classification because the values for the developed countries are highly separated than the value for the developing countries. The following figures (5, 6 and 7) are showing the statistical representation for the developed countries and the developing countries and the combination between both kinds in one statistical graph. If this parameter and the first one are the only parameter used in the classification problem the accuracy rate still 100% this means that those two parameters are highly effective parameter in this study.

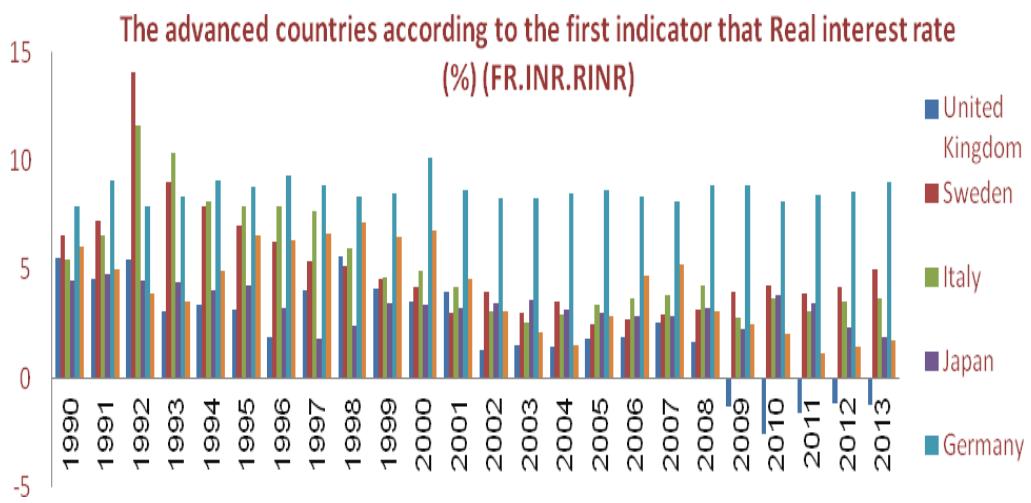


Figure 5. Statistical representation that that represent the developed countries according to the FR.INR.RINR indicator

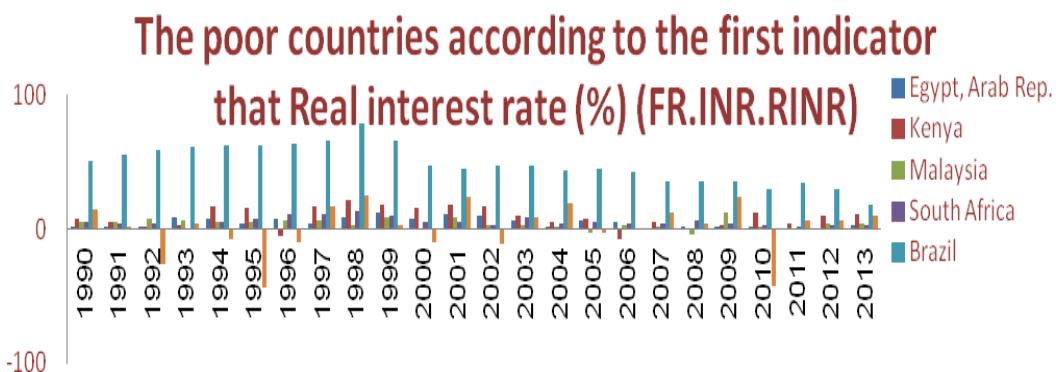


Figure 6. Statistical representation that represent the developing countries according to the FR.INR.RINR indicator

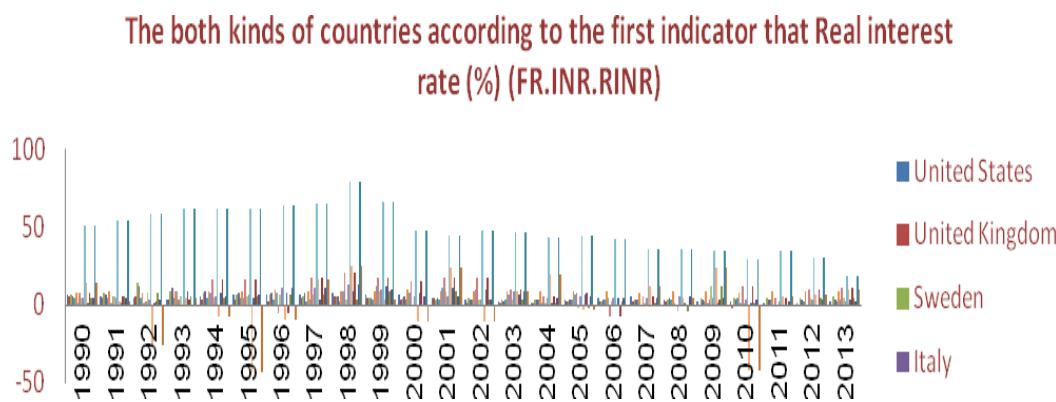


Figure 7. Statistical representation that represent both the developing countries and developing countries according to the FR.INR.RINR indicator

Official exchange rate (LCU per US\$, period average) and its code is (PA.NUS.FCRF) is the third parameter used to classify countries and this parameter is not effective even if we never used it because there are found intersection between the value for the developed and developing countries as shown in the following figures (8, 9 and 10).

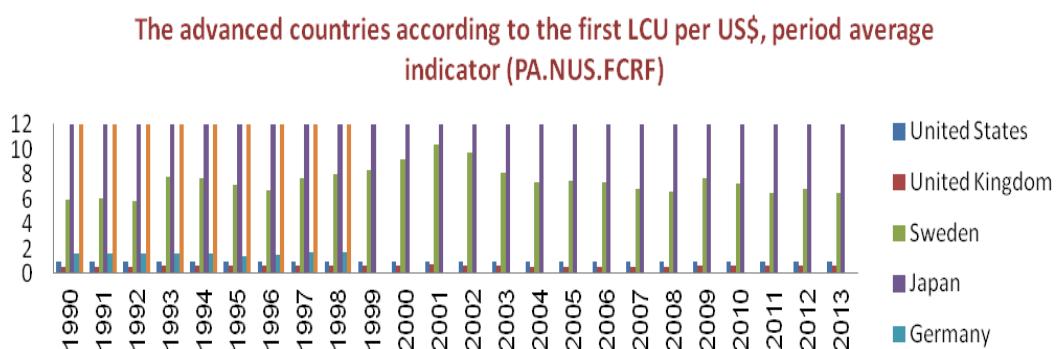


Figure 8. Statistical representation that represent the developed countries according to the PA.NUS.FCRF indicator

In figure 8 the maximum scale is 12 to show all the different values as shown (JAPAN) starts from 97.97 to the maximum value 144.79 and (ITALY) scale starts from 1198.102 to the maximum value that is 1736.207.

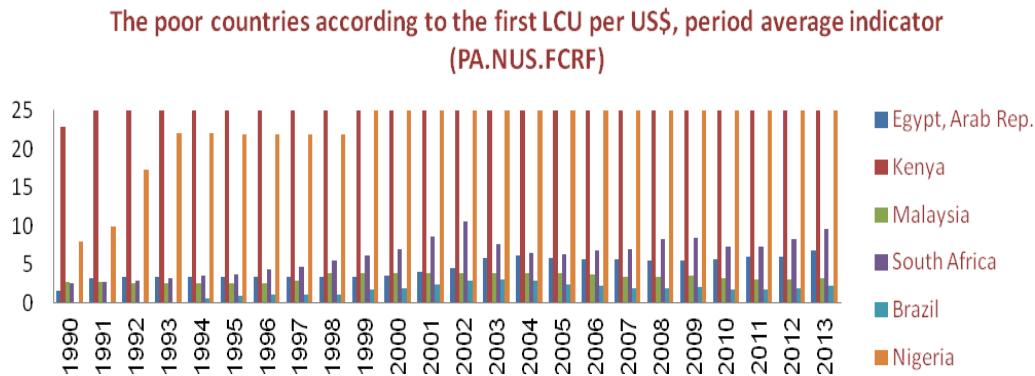


Figure 9. Statistical representation that represent the developing countries according to the PA.NUS.FCRF indicator

Figure 9 shows the representation of the poor countries and (KENYA, NIGERIA) exceed the scale because the minimum and maximum values for both countries are (22.91 to 88.81) and (8.03 to 157.49) respectively.

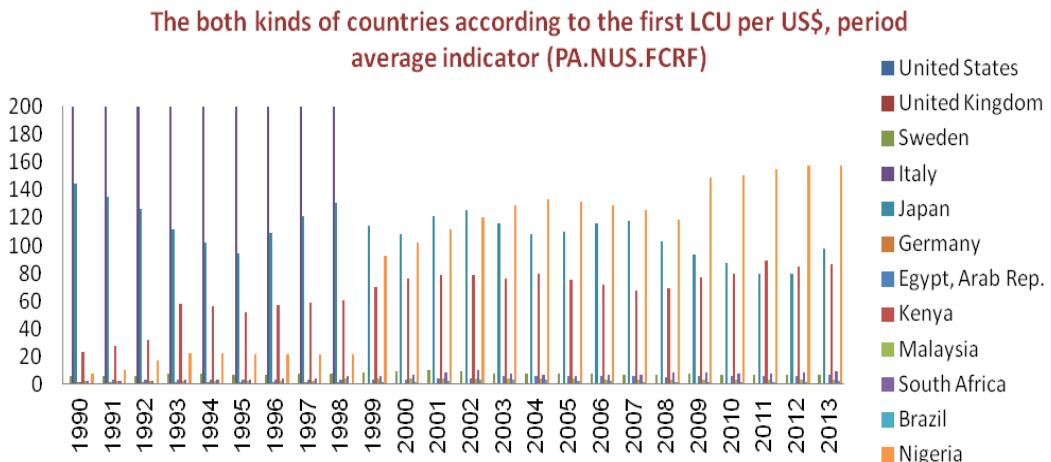


Figure 10. Statistical representation that represent both the developing countries and developed countries according to the PA.NUS.FCRF indicator

As figure 10 indicates that the developed countries and the developing countries values is not separated for example in 2004 and 2005 the value for Nigeria which is developing country is approximately equal to the value Japan which is the developed country. So in this parameter there is not clearly value to separate data values above or under it. So this parameter is not highly effective in result accuracy.

Money and quasi money (M2) as % of GDP and its code is (FM.LBL.MQMY.GD.ZS) is the fourth indicator used in this study but it is not effective like the third parameter because there is not clearly point to separate data from it so if we use it with the third and fifth parameter only the accuracy rate reduce to 30% but if we use this parameter with the fifth parameter only the

accuracy rate reduce to 45%. The following figures (11, 12 and 13) represent the statistical representation for developed, developing and both countries respectively.

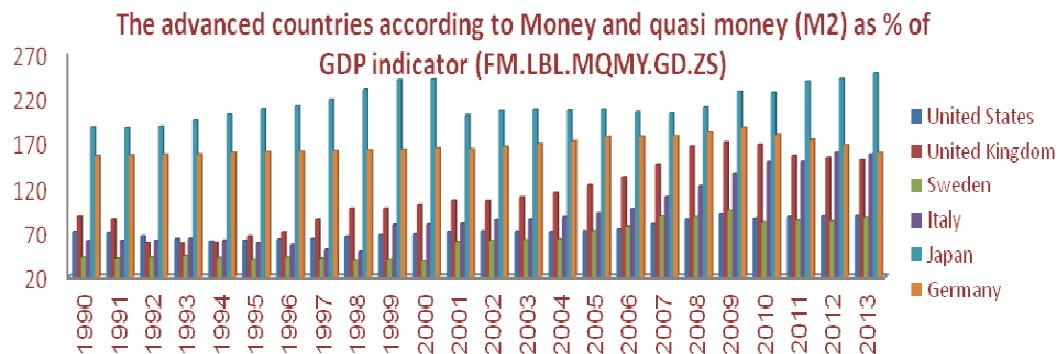


Figure 11. Statistical representation that that represent the developed countries according to the FM.LBL.MQMY.GD.ZS indicator

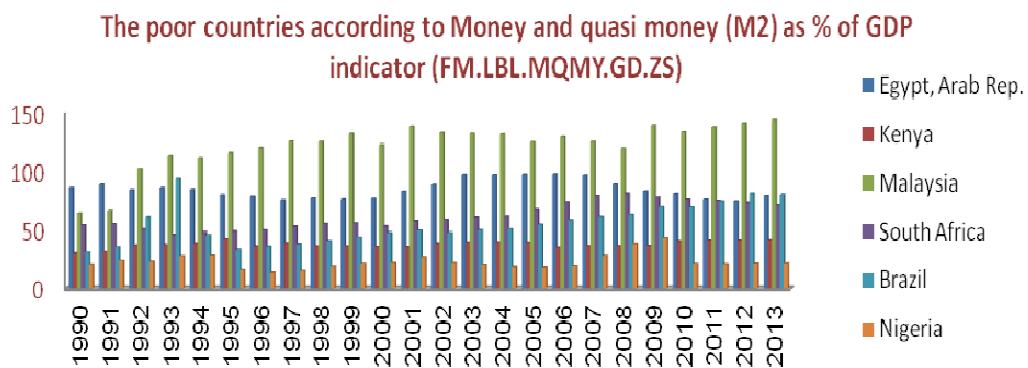


Figure 12. Statistical representation that that represent the developing countries according to the FM.LBL.MQMY.GD.ZS indicator

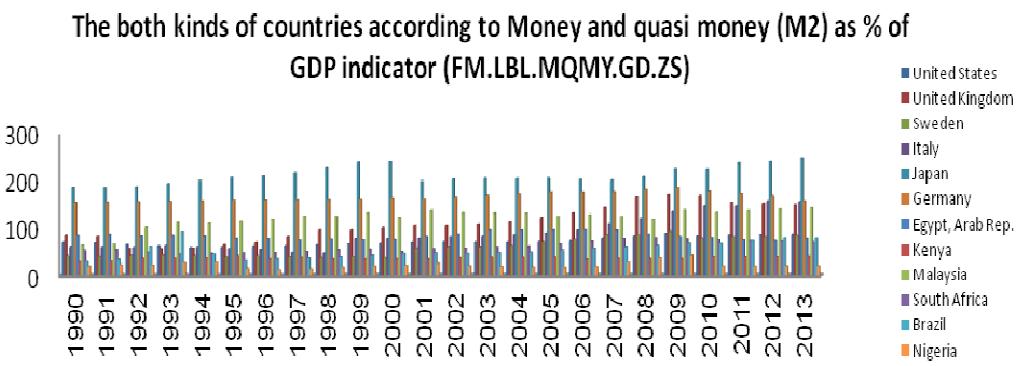


Figure 13. Statistical representation that represent both the developing countries and developing countries according to the FM.LBL.MQMY.GD.ZS indicator

An export of goods and services (% of GDP) and its code is (NE.EXP.GNFS.ZS) is the fifth indicator and it is equal to the third and fourth indicators because the values for both developed and developing countries is not purely separated. The following figures (14, 15 and 16) represent the statistical representation for this parameter.

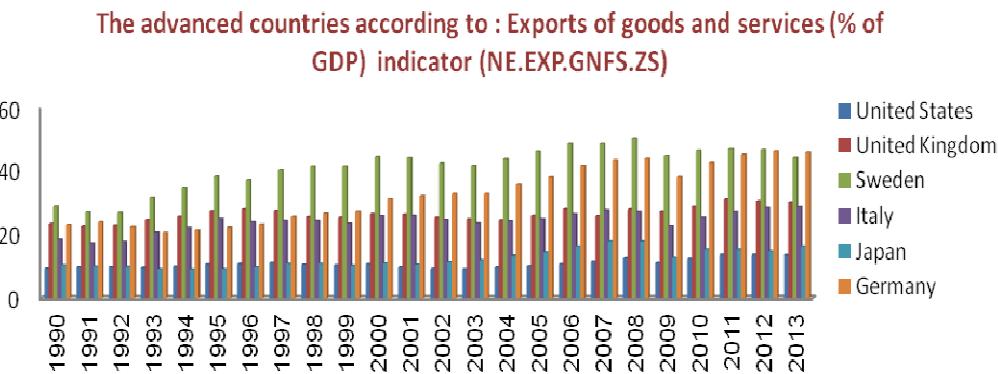


Figure 14. Statistical representation that represent the developed countries according to the NE.EXP.GNFS.ZS indicator

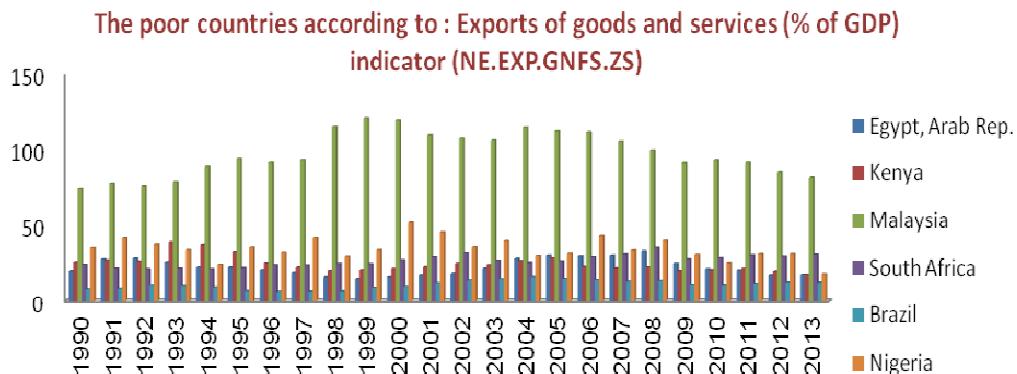


Figure 15. Statistical representation that represent the developing countries according to the NE.EXP.GNFS.ZS indicator

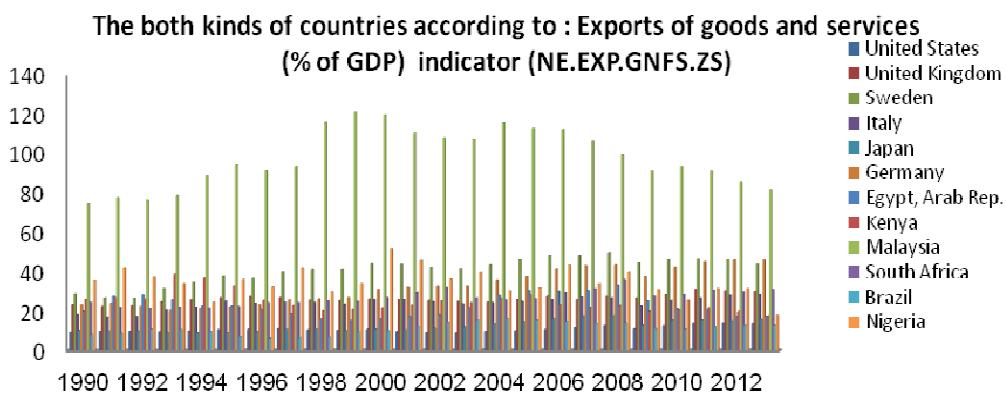


Figure 16. Statistical representation that represent both the developing countries and developing countries according to the NE.EXP.GNFS.ZS indicator

Imports of goods and services (% of GDP) and its code is (NE.IMP.GNFS.ZS) is the sixth parameter and the statistical representation for both countries developed and developing is shown in figure (17).

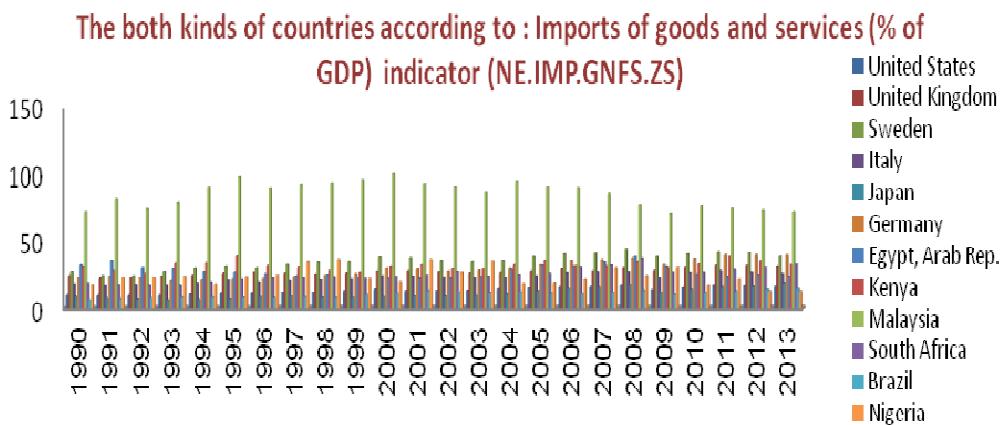


Figure 17. Statistical representation that represent both the developing countries and developing countries according to the NE.IMP.GNFS.ZS indicator

Consumer price index (2010 = 100) and its code is (FP.CPI.TOTL) is the seventh parameter and the statistical representation for both countries developed and developing is shown in figure (18).

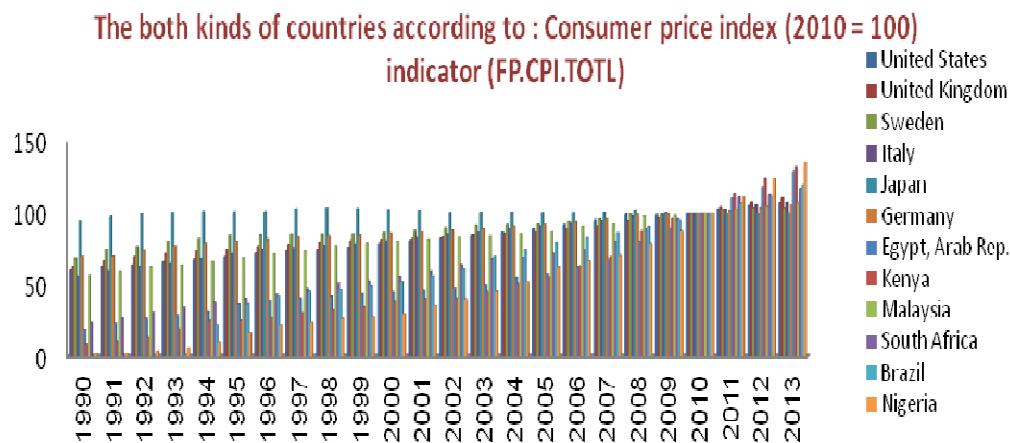
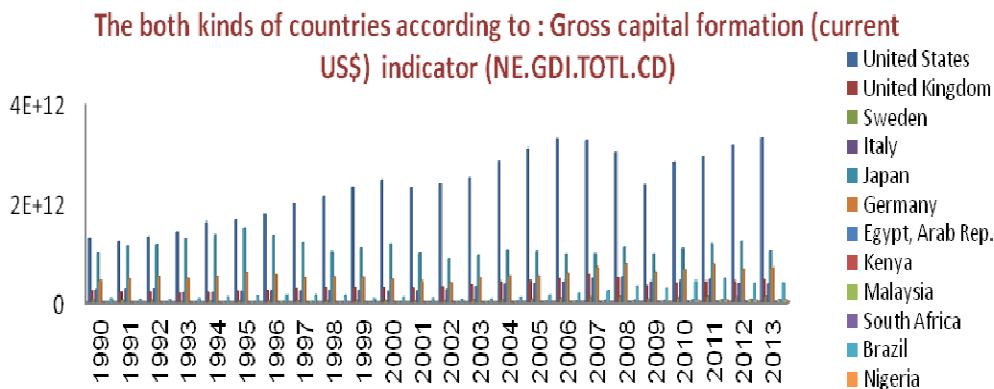


Figure 18. Statistical representation that represent both the developing countries and developing countries according to the FP.CPI.TOTL indicator

Gross capital formation (current US\$) and its code is (NE.GDI.TOTL.CD) is the last parameter and the statistical representation for both countries developed and developing is shown in figure (19).



The first classification technique that used in this study is Artificial Neural Network (ANN). The accuracy rate after implement ANN with the all eight feature is 100%. Also the ANN used in determining the most effective features (indicators) and the less ones. Table 2 shows the detail explanation and illustrated the relation between the parameter and the accuracy rate.

Table 2. detailed study that represent the high and less effective parameters depending on the result accuracy

	Indicator (1)	Indicator (2)	Indicator (3)	Indicator (4)	Indicator (5)	Indicator (6)	Indicator (7)	Indicator (8)	Accuracy rate
Is the indicator used	Yes	100%							
Is the indicator used	Yes	Yes	No	No	No	No	No	Yes	100%
Is the indicator used	Yes	Yes	No	No	No	No	Yes	No	100%
Is the indicator used	Yes	Yes	No	No	No	No	No	No	100%
Is the indicator used	No	No	Yes	Yes	Yes	Yes	Yes	No	75%
Is the indicator used	No	No	No	Yes	Yes	No	No	No	60%
Is the indicator used	No	No	Yes	Yes	Yes	Yes	No	No	55%
Is the indicator used	No	No	No	No	No	No	Yes	Yes	50%
Is the indicator used	No	NO	No	Yes	Yes	No	No	No	45%
Is the indicator used	No	No	Yes	Yes	No	No	Yes	No	45%
Is the indicator used	No	No	Yes	Yes	Yes	No	No	No	30%

Table 2 shows that the highly effective parameters are the first and the second parameter. The less effective parameters are the third, the fourth and fifth parameters. The most important alternatives to get on 100% accuracy rate are; using all parameter, use the first, second and last indicators, use the first, second and seventh indicators and use only the first and second indicators.

The second classifier that this study uses is K-nearest neighbor (KNN). The accuracy rate in case of using ($K=1$) is 100%, and when ($K=2$ or 3) the accuracy rate is 91.66% because the test cases is 24 and the accurate cases is 22 and the wrong is only 2 cases.

The third and last technique is Fuzzy K-nearest neighbor (FKNN) and the accuracy rate is 100% and the all indicators are used in the training phase.

6. CONCLUSION AND FUTURE WORK

The objective of this paper is to study the efficiency of using the artificial intelligent techniques for classify the developed and developing countries according to used different data to increase the quality assurance process. The proposed systems achieved 100% accuracy rate for ANN, KNN and FKNN. Several performance techniques are used to calculate the performance of these

different techniques and a comparative study is done between the accuracy rate after and before selecting the highest effective indicators and the less ones. The proposed systems in this paper achieved the highest accuracy score than the other comparative studies. In the future, different data mining techniques will be applied. Also increase the number of cases in the developed and developing countries database and decrease number of indicators and evaluate our system whether it will give the same good results.

REFERENCES

- [1] Peter R. Senn, (1999) "Monetary policy and the definition of money: Implications for the European Monetary Union", *Journal of Economic Studies*, Vol. 26 Iss: 4/5, pp.338 – 382
- [2] Subrata Ghatak, Willy Spanjers, (2007) "Monetary policy rules in transition economies: the impact of ambiguity", *International Journal of Development Issues*, Vol. 6 Iss: 1, pp.26 – 37
- [3] Magda Kandil, (2006) "The growth of government spending and the money supply: Evidence and implications within and across industrial countries", *Journal of Economic Studies*, Vol. 33 Iss: 6, pp.406 – 436
- [4] Abdul Rashid , Zainab Jehan , (2014) "The response of macroeconomic aggregates to monetary policy shocks in Pakistan", *Journal of Financial Economic Policy*, Vol. 6 Iss: 4, pp.314 – 330
- [5] Fazel Shokoofeh, (2006) "How effective is the monetary policy?", *Humanomics*, Vol. 22 Iss: 3, pp.139 – 144.
- [6] Forni, M. and Gambetti, L. (2010), "The dynamic effects of monetary policy: a structural factor model approach", *Journal of Monetary Economics*, Vol. 57 No. 2, pp. 203-216
- [7] Bernanke, B. and Mihov, I. (1998), "Measuring monetary policy", *Quarterly Journal of Economics*, Vol. 113 No. 3, pp. 869-902.
- [8] Bjørnland, H. (2008), "Monetary policy and exchange rate interactions in a small open economy", *Scandinavian Journal of Economics*, Vol. 110 No. 1, pp. 197-221
- [9] Jang, K. and Ogaki, M. (2004), "The effects of monetary policy shocks on exchange rates: a structural vector error correction model approach", *Journal of the Japanese and International Economies*, Vol. 18 No. 1, pp. 99-114
- [10] Fullerton, T., Hattori, M. and Calderón, C. (2001), "Error correction exchange rate modeling: evidence for Mexico", *Journal of Economics and Finance*, Vol. 25 No. 3, pp. 358-368
- [11] Wong, K. (2000), "Variability in the effects of monetary policy on economic activity", *Journal of Money, Credit and Banking*, Vol. 32 No. 2, pp. 179-198
- [12] Eichenbaum, M. and Evans, C. (1995), "Some empirical evidence on the effects of shocks to monetary policy on exchange rates", *Quarterly Journal of Economics*, Vol. 110 No. 4, pp. 975-1009
- [13] L. Thai, T. Hai and T. Thuy, "Image Classification using Support Vector Machine and Artificial Neural Network". *Information Technology and Computer Science*, DOI: 10.5815/ijitcs, 2012.05.05.
- [14] S. Haykin, "Neural Networks and Learning Machines", third Edition, Prentice Hall, New York, NY, 2009.
- [15] M. Moavenian, H. Khorrami, "A qualitative comparison of Artificial Neural Net- works and Support Vector Machines in ECG arrhythmias classification", *Expert Systems with Applications*, vol. 37, pp. 3088 - 3093, 2010.
- [16] Z.H. Che, "PSO-based back-propagation artificial neural network for product and mold cost estimation of plastic injection molding", *Computers and Industrial Engineering*, vol. 58, pp. 625-637, 2010.
- [17] H. Zhang, C. Berg, M. Maire and M. Svm-knn, "Discriminative nearest neighbor classification for visual category recognition", In: CVPR '06, pp. 2126–2136. IEEE Computer Society, Los Alamitos, CA, USA, 2006.

- [18] M. Latourrette, "Toward an explanatory similarity measure for nearest-neighbor classification", In: ECML '00: Proceedings of the 11th European Conference on Machine Learning, London, UK, pp. 238–245. Springer-Verlag, Heidelberg, 2000.
- [19] C. Domeniconi, J. Peng, and D. Gunopulos, "Locally adaptive metric nearest-neighbor classification", IEEE Trans. Pattern Anal. Mach. Intell. vol. 24, no. 9, pp. 1281–1285, 2002.
- [20] J. S. Snchez, R. A. Mollineda, and J. M. Sotoca, "An analysis of how training data complexity affects the nearest neighbor classifiers", Pattern Analysis and Applications, vol. 10, no. 3, 2007.
- [21] M. Raniszewski, "Sequential reduction algorithm for nearest neighbor rule", Computer Vision and Graphics, 6375, 2010.
- [22] D. Coomans and D. L. Massart, "Alternative k-nearest neighbor rules in supervised pattern recognition", Analytica Chimica Acta, 136, 1982.
- [23] P. Shi, S. Ray, Q. Zhu, and M. A. Kon, "Top scoring pairs for feature selection in machine learning and applications to cancer outcome prediction", BMC Bioinformatics, 12, 2011.
- [24] S. A. Medjahed and T. A. Saadi, " Breast Cancer Diagnosis by using k-Nearest Neighbor with Different Distances and Classification Rules", International Journal of Computer Applications (0975 - 8887), vol. 62, no. 1, 2013.
- [25] D. Joquin, G. Salvador, and H. Francisco, " fuzzy nearest neighbor algorithms: taxonomy, experimental analysis and prospects," Elsevier Inc, vol. 260, no. 9, pp. 98-119, 2014.
- [26] J. M. Keller, M. R. Gray and J. A. Givens, "A fuzzy K-nearest neighbor algorithm", IEEE Trans. Systems Man Cybernet., vol. 15, no. 4, pp. 580-585, 1985.