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The Development and Implementation of a Loan Classification Database System

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***Abstract*—**This work documents the development and implementation of a commercial bank's loan classification database system. It employed multiple discriminant analysis models to assess the relationship between relevant loan variables and existing bad loan problem. It also made use of mathematical model to replicate the Examiner's classification process to classify loans in a more objective and sober way. Classification of loan is grouping of loans in accordance to their likelihood of ultimate recovery from borrowers. Banking business is one of the most highly levered businesses especially on loan accounts. It is likely to collapse in case of a slight deterioration in quality of loans. Six important factors (propriety of use of funds borrowed; operation of Borrower's overdraft account; cooperation with the Bank, collateral and number of days the loan is past due) were identified and grouped as variables in determining the quality of loan portfolio. The developed classification model shows that there exists a linear relation between loan classification and the six variables considered. Four classification functions were developed and implemented in Microsoft Access database to assist in effective classification. The implementation of a database system makes it easy to store relevant classification information and revert to them whenever needed for comparative analysis on quarterly, half-yearly and annual basis.

Index Terms—Bank, Loan, Collateral, Classification, Provision, Loss, Database.

I. Introduction

Loans account for ten to fifteen times the equity of a Bank. Thus banking business is one of the most highly levered business and likely to collapse in case of a slight deterioration in quality of loans. Bad loans caused almost the collapse of the whole Norwegian banking industry and led to nationalization of three biggest Commercial Banks in the early 1990s [1]. The Japanese Government had to face a state of emergency as non-performing loans in Japanese Banks totalled 40 trillion Yens in the second half of 1995 [2]. Due to the crisis, big financial institutions in Japan collapsed. In Nigeria the Central Bank in the year 2009 declared five banks unfit in their financial management due to bad loan problems [3] and [4].

There are generally five loan classification groups i.e. current, especially mentioned, substandard, doubtful and loss on which all loans are grouped [5], [6] and [7]. Both Commercial Bank's credit officers and Central Bank Examiners review loans during their routine credit monitoring. Bank Examiners review loans periodically as part of their supervisory responsibility to ensure that Bank's business is sound and financially healthy. Simply stated, classification of loans is grouping of loans in accordance to their likelihood of ultimate recovery from Borrowers [8]. Many factors both quantitative and qualitative variables relating to Borrowers are considered before arriving at a particular classification [9].

Objective variables are like sales and profitability figures, financial ratios for liquidity, activity and profitability from financial statements. Others are Borrower's Bank account records, loan covenants, correspondence between Borrower and the Bank and collateral. Borrower's loan account is, for example, reviewed to see if borrowing and repayments are in accordance to loan covenants. Review on collateral looks at the value of pledged claims with respect to loaned funds, perfection and completeness of the deeds assigning the claims to the Bank [10]. Correspondence in Borrower's file may give insights as to information that cannot be obtained in financial statements and collateral documents. For example, correspondences can highlight reasons for delayed submission of statements or perfection of security documents [11].

Moreover correspondences can indicate the Borrower's integrity, cooperation, trustworthy, and his/her general organization. How calls are responded to, how advice is sought and how Borrower updates the Bank on pertinent matters that are of interest to the Bank are part of important information that can be obtained from Borrower's correspondences with the Bank [12].

Loan classification is basically a single person decision-making process. It is a tedious, time consuming, and thus expensive exercise. Yet it is the most important aspect of lending business after loan sanctioning decisions. The developed database system is an attempt to simplify this process. Previous similar works in linear classification of statistical model are Tiberius [13] and NeuroXL [14] using methods based on network training of variables.

Also, a number of data mining algorithmic solutions are documented in [15] which can be used in analysing borrowers' data in banks' database.

The primary objective was to replicate Examiner's judgment through a linear classification statistical model and build an early warning database system [16]. The model is also envisioned to be able to continuously predict the quality of loan portfolio through observing changes in scores that individual loans achieve as their attributes change. Further, efforts were made to determine which of the factors considered by Bank Examiners are significant given the bad loan problem globally [16, 17, and 18].

Secondly, another importance of this work is the establishment of a procedure for predicting changes in the classification status of a loan. By subjecting loan data to the model frequently, observation of the model scores for a loan over time will provide prediction of the loan's quality immediately. This will facilitate more timely corrective actions than is the current situation where loans are reviewed periodically.

Thirdly, the model developed is implemented as database system that can assist and simplify the work of Bank Examiners and credit review officers [19]. The model can be used as an assistant expert model in all classification problems that are based on objective data.

The remainder of this paper is organized as follows: Section II gives the overview of the design methods used in the development process. Section III describes the experiments and analysis carried out in the work. Section IV presents the results of experiments and systems administration issues. Conclusion and future work are given in the final section.

II. Design Methods

The system design and implementation is based on the detailed analysis of the loan risk management system conceptually proposed in previous work [20]. The design methods here highlight the simple steps on how the loan classification database system gathers data, operate and is accessed, helping to determine the right architecture.

2.1 Data Capturing and Analysis

(i) Data were captured from a core banking system to generate the 34 sub variables. The data come from loan summary data, borrowers' records, bank statements, collateral records, and previous loan classification records etc. using form depicted in Fig. 1.

(ii) For the purpose of implementation, records are captured using user interfaces in Fig. 3 through Fig. 6. Information in (i) was summarized by the system into 34 sub variables. This is a step where preliminary detailed analysis was conducted by the system. For example, while the input for the "Account Operations" can be the statement of the account and the "Approved loan amount", the system will determine if the operations of the account is such that the account is active or not, operates within the limits set or not etc. This way, the system is able to determine the right value for the "Account Operations". The variables "Years in business" is determined as the difference between the current date and the date of the company or borrower's incorporation.

DATA COLLECTION FORM

X_i	*a - f*		DATA COLM	WEIGHT		SCORES
		Subject No				
		Classification Previous	1 to 5			
X_{iv}	*b*	***Year in same bussines***	yyyy			
X_{xxxiv}	*f*	***Use of funds***	0 or 1			
		Days Past Due				
X_i	*a*	Sanction date of the loan	dd/mm/yy			
X_{ii}		expiry date	dd/mm/yy			
X_{iii}		Cut of date	dd/mm/yy			
		Borrower's cooperation and management strengths				
X_v	*c*	Date of last audited statements	N	0.7	0	**0**
X_{vi}		Date of last quarterly stock/debtors return	N	0.7	0	**0**
X_{vii}		Response to calls/demand notes	Y	0.7	1	**0.7**
X_{viii}		Previous default with NBC	N	0.7	1	**0.7**
X_{ix}		Previous default with other banks	N	0.7	1	**0.7**
X_x		Rolled over O/Ds	Y	0.7	0	**0**
X_{xi}		Renegotiated O/D to short term loans	Y	0.8	0	**0**
		Account operations:				
X_{xxiv}	*e*	Swings to credit	N	4.9	0	**0**
X_{xxv}		Swings to 50% of sanctioned limit	N	3.6	0	**0**
X_{xxvi}		Swings to 90% of sanctioned limit	N	3	0	**0**
X_{xxvii}		Expired with balance below 90% of sanctioned limit	N	2.3	0	**0**
X_{xxviii}		Outstanding balance equal sanctioned limit	N	1.7	0	**0**
X_{xxix}		Exceed limit sanctioned	Y	1	1	**1**
		Other factors:				
X_{xxx}		Persistent exceed limit sanctioned	N	0.3	0	**0**
X_{xxxi}		Sometimes swings to above limit sanctioned	N	0.2	0	**0**
X_{xxxii}		Inactive account	N	0.3	0	**0**
X_{xxxiii}		Active somewhat but deposits cannot cover interest ch	Y	0.2	-1	**-0.2**
		Collateral				
X_{xii}	*d*	Adequate FDR,TBs or bank deposit	N	4.8	0	**0**
X_{xiii}		Adequate fixed properties	Y	3.2	1	**3.2**
X_{xiv}		Adequate stocks and debtors	N	2.8	0	**0**
X_{xv}		Adequate other movable properties	N	0	0	**0**
X_{xvi}		Adequate if fixed assets and cash deposits are combin	N	4.2	0	**0**
X_{xvii}		Adequate if all assets are combined	N	3.4	0	**0**
X_{xviii}		Inadequate	N	2	0	**0**
X_{xix}		Unsecured	N	1	0	**0**
		Other factors:				
X_{xx}		Relevant and adequate insurrance policy	N	0.2	-1	**-0.2**
X_{xxi}		Recent valuation report	Y	0.2	0	**0**
X_{xxii}		Collateral documents authenticated and or complete	N	0.3	0	**0**
X_{xxiii}		Collateral documents located	Y	0.3	0	**0**

Fig.1. Data Capturing Form

(iii) The system then summarizes the 34 sub variables into 6 key variables for running the model. The six variables are:

a. Days Past Due
b. Year in same business
c. Borrower's cooperation
d. Collateral
e. Accounts operation, and
f. Use of funds

Variables c, d and e consist of sub variables so separate user interfaces are designed for capturing the sub variables. Fig. 2 shows the screen for capturing the Borrower's cooperation sub variables.

Fig.2. Cooperation Details

Fig. 3 shows the screen for capturing the Borrower's collateral sub variables.

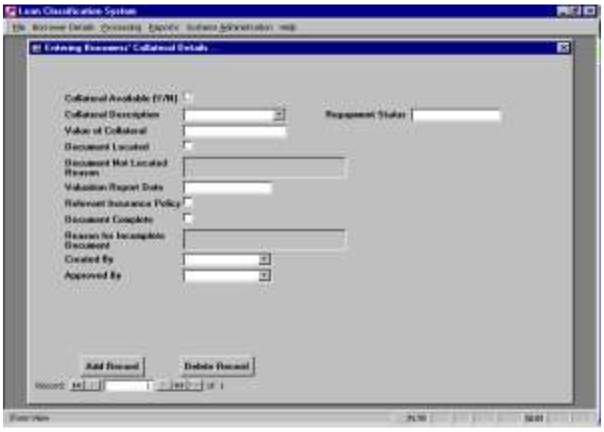

Fig.3. Borrower's Collateral Details Sub variables

Fig. 4 shows the screen for capturing the Borrower's account details sub variables.

Fig.4. Borrower's Account Details Sub variables

Other details relating to loan activities of the Borrower are captured through the screen shown in Fig. 5.

Fig.5. Borrower's Other Loan Details

The quarterly changes to borrowers' record can be updated using the screen in Fig. 6.

Fig.6. Updating Entered Sub Variables

(iv) The six variables are then subjected into the model where the following processes happen:

a. The model generates the scores for functions 1, 2, 3, and 4 in table 2.
b. The model determines the nearest centroid where the score belongs to
c. The model counterchecks with the territorial map on the most appropriate cluster the loan falls into
d. The model gives the classification, which is the classification of the cluster the loan was assigned into.

(v) Classification report. Individual loan classification report generated contains both the classification group the loan analysed belongs to, together with the narrative summary. The narrative summary is the complex text part that picks a variable from the 34 variables that had a more pronounced contribution in the final score that lead to the classification given to a specific loan. It is important that the report explain the impact of the variable picked e.g. that although the account operations were weak due to the borrower persistently operating close to the sanctioned limit, the loan was nevertheless classified satisfactory due to strength in collateral. The borrower offered Treasury bond as collateral that were risk free, more over the value of collateral was well above the amount borrowed with collateral documents authenticated and duly filed. Further, the borrower reported very profitable results and has been submitting his accounts in time.

2.2 Users Access Security

The loan classification database system is implemented with a user's access security facility. After initial setup and running, the Admin user is the default and only user available with all administrative right. The Admin username cannot be deleted or modified within the system, but the password can be changed. Other users can be created in the system and can currently be assigned to two user groups: Supervisors and Managers.

Depending on the group, users are able to perform function available to their groups with Supervisors as the highest level. Every user has facility for changing their password.

New Users are created from the Systems Administration Menu by selecting the User Administration sub menu, Add Users menu item and completing the screen as appropriate.

User Properties can be edited from the Systems Administration Menu by selecting the User Administration sub menu, Edit Users menu item and completing the screen as appropriate.

After an initial system startup, the User logon screen is presented for user to enter the username and password as shown in Fig. 7.

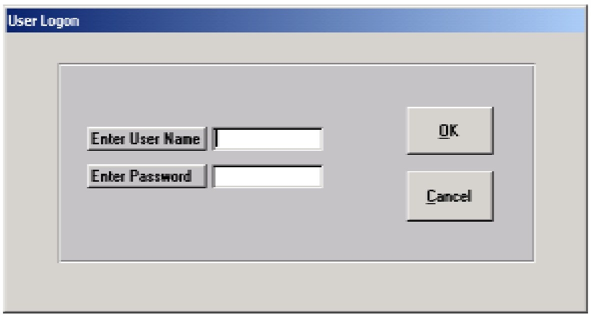

Fig.7. User Access Security Screen

III. Experiments and Analysis

A lot of data is used or mined in classifying loans information. Ninety nine percent of the information used can be summarized by the 34 variables shown Fig. 1. The major task of a credit reviewer is analysing the information from the 34 variables to decide the likelihood that the loan will be repaid. The different levels of the likelihood for the repayment are the five different classifications.

3.1. The Mathematical Models

The mathematical model was developed is as follows:

- A sample of a good number of loans classified by bank Examiners in loan classification is used to extract the data for the variables / properties x1 – x_{34}. Based on the actual loan classification data, the system generates the model using Statistical Package for Social Sciences (SPSS) [21, 22]. SPSS is applied here to simulate the parallel processing nature of loan classification into linear equations.
- The developed model is analysed for the six loan variables identified in 2.1. (iii) so the 34 sub variables are summarised into 6 key variables to get the classification from this model.

There are two approaches for designing the loan classification model, either going through SPSS in loan classification process or bypassing SPSS.

Going through SPSS implies that each time a loan is to be classified its properties (x_1 – x_{34}) are inputted into SPSS data input file containing data of the loans classified by the bank Examiners and then run the SPSS to get the classification. This is the most accurate approach as shown in the Territorial Map in Fig. 9 that classification process by SPSS is clustering different loans into five clusters and the clusters borders are not fine circles or squares. The problems with this approach are:

- It might be a bit slower as the statistical package must be run each time,
- It shall be involving in system design since designers need to understand and replicate what SPSS does.

While it is noted that this is the best approach, it was bypassed by the robustness of the alternative approach explained below.

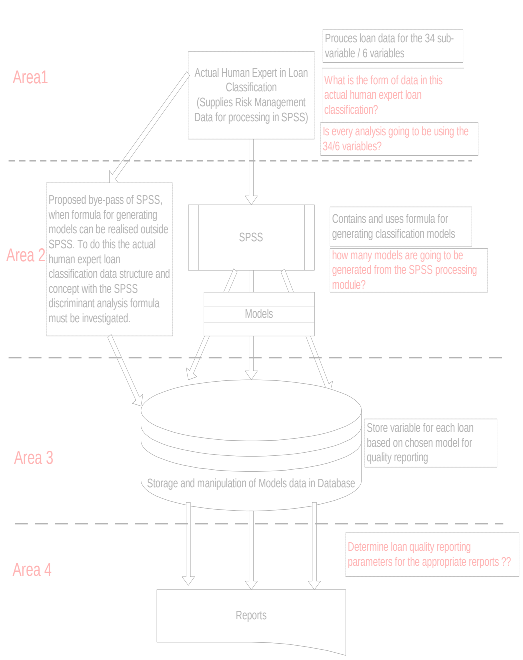

Fig.8. Functional Design of the Loan Classification Model

The alternative approach is using the linear equations developed by the SPSS model to replicate its classification process. In this case, the formulas are kept resident in the database and each time we have loan data fulfilling inputs for the six variables we run the system to get the classification. This is the easiest approach. However its accuracy is only limited to the difficulty in allocating classification group to loans whose equation results will be closer to the cluster boundaries. As explained below, SPSS will give the formula to get a score, the centroid of each cluster and the territorial map. The nearer the score to a particular centroid the easier is the classification decision. If the score is between two centroids, it is only through the territorial map that we can tell apart the appropriate clusters the respective loan belongs to. Accordingly, simulating the territorial map in the database shall heighten the robustness of this approach.

3.2. *Functional Expert Classification Model*

The revision of the SPSS based classification formulas was done through use of discriminant analysis on area 2 of the functional diagram in Fig. 8 and SPSS generates four functional models (F1, F2, F3 and F4) in Table 1. Here a clustering of the actual classifications is carried out to estimate the linear equations replicating the classification. Since this is in clusters, no single formula can explain the whole variance in the data. In practice however, most (up to 98%) of the variance will be explained by the first two formulas. In our case for example, the clustering is mapped using the first two functions and the resulting cluster patterns are shown in Fig. 9.

The star in the "middle" of each cluster is called a centroid. The four linear functions developed by discriminant analysis are as shown in Table 1.

Table 1. Classification Functions Coefficients

Canonical Discriminant Function Coefficients

	Function			
	1	2	3	4
Days Past Due	.000	.001	.001	.000
Age in Years	-.008	.059	-.022	.044
Borrower's Management	.761	-.235	-.621	.895
Collateral	.585	.920	-.486	-.814
Account Operation	.574	.523	.539	.159
Use of Borrowed Funds	3.688	-2.322	.621	-1.149
(Constant)	-7.992	-2.417	1.923	-1.279

Unstandardized coefficients

```
                                  Territorial Map
                (Assuming all functions but the first two are zero)
Canonical Discriminant
Function 2
       -6.0      -4.0      -2.0        .0       2.0       4.0       6.0
          ôòòòòòòòòòôòòòòòòòòòôòòòòòòòòòôòòòòòòòòòôòòòòòòòòòôòòòòòòòòòô
     6.0 ô            12              25                               ô
         ó            12              25                               ó
         ó            12              25                               ó
         ó            12              25                               ó
         ó            12              25                               ó
         ó            12               25                              ó
     4.0 ô          ô 12      ô        25         ô         ô          ô
         ó            12               25                              ó
         ó             12              25                              ó
         ó             12              25                              ó
         ó             12              25                              ó
         ó             12              2355                            ó
     2.0 ô          ô  12     ô       23ô335      ô         ô          ô
         ó             12             23   35                          ó
         ó             12            23     35                         ó
         ó             12            23      35                        ó
         ó             12           23        355      *               ó
         ó              12  *        23         34555                  ó
      .0 ô        * ô   12    ô    23   ô       34444555     ô          ô
         ó              12         23          34   44455              ó
         ó              12        23        *  34 *    44555           ó
         ó              12        23           34        444555        ó
         ó              12       23            34           44455      ó
         ó              12       23            34              44555   ó
    -2.0 ô          ô   12    ô 23      ô      34 ô         ô    444555ô
         ó              12      23             34                   444ó
         ó              12      23             34                      ó
         ó               12    23              34                      ó
         ó               12    23              34                      ó
         ó               12   23               34                      ó
    -4.0 ô          ô    12   23        ô      34 ô         ô          ô
         ó               12  23                 34                     ó
         ó               12  23                 34                     ó
         ó               12 23                  34                     ó
         ó               12 23                  34                     ó
         ó               1223                   34                     ó
    -6.0 ô                123                   34                     ô
          ôòòòòòòòòòôòòòòòòòòòôòòòòòòòòòôòòòòòòòòòôòòòòòòòòòôòòòòòòòòòô
       -6.0      -4.0      -2.0        .0       2.0       4.0       6.0
                         Canonical Discriminant Function 1
```

Fig.9. Cluster Territorial map Output from SPSS

3.3. *Classification Functions*

Using the values of variables corresponding to functions 1 and 2 in Table 1, two formulas for F1 and F2 are derived to analyse the six variables. If a computed function's value falls within the range of one of the five clusters is received, then the classification of that particular loan will belong to that cluster.

$$F1 = \sum_{1}^{6} \text{var}_i * coeff_i \qquad (1)$$

and

$$F2 = \sum_{1}^{6} \text{var}_i * coeff_i \qquad (2)$$

The result of classified loan, whether it is a Loss, Doubtful, etc., is determined from the sum of ith variable for Function1 and/or Function2. There are two ways to determine that the function's results ended up in a certain cluster:

1. Comparing the result with the centroid and allocating it to a classification group belonging to the closest centroid,
2. Mapping the territorial map in Fig. 9 in the database and classifying into groups exactly in accordance with the result of the function.

The second approach, which is adopted in this work, is more accurate. Here, the six variables are subjected to the above formulas loaded into the database and not the SPSS. The values of functions at the centroids in this case are listed in Table 2 for Functions 1 to 4 but only Functions 1 and 2 are used in this work. The results of the first (F1) and second (F2) formula are crucial and are the only ones used in this classification.

Table 2. Classification Grouping using Functions' Values

Functions at Group Centroids

CLASSIFICATION	Function 1	2	3	4
Loss	-4.466	.104	.333	-.019
Doubtful	-2.694	.216	-1.084	.127
Substandard	.841	-.797	-.432	-.242
Especially Mentioned	2.090	-.752	.200	.106
Satisfactory	2.973	.677	.059	-.021

Unstandardized canonical discriminant functions evaluated at group means

The two functions F1 and F2 were coded in Access Visual Basic [23, 24] producing visual basic functions checkGroupF1, checkGroupF2 and MinOfList to determine the classification groups. The developed codes are depicted in Tables 3, 4 and 5 respectively.

The output of the model will be any of the five classification groups for each loan and a classification report where all 34 sub variables will be considered and the ones contributing to the final result of the function will be singled out. Loss provision or grouping is the determination of a percentage the bank feels that may never be collected given the quality of the underlying loan [25, 26]. If the loan is classed Loss for example, it is fully provided for loss i.e. 100%. A full list of loss provision is as follows:

1. Loss – 100%
2. Doubtful – 50%
3. Substandard – 10%

Table 3. Visual Basic Code for Determining Classification Group

```
Function checkGroupF1(axx As Single)
Dim y1 As Single, y2 As Single, y3 As Single, y4 As Single, y5 As
Single, minY2 As Single, y12 As Single, minY1 As Single,
grp1centroid As Single, grp2centroid As Single, grp3centroid As
Single, grp4centroid As Single, grp5centroid As Single

grp1centroid = -4.466
grp2centroid = -2.694
grp3centroid = 0.842
grp4centroid = 2.09
grp5centroid = 2.973

'do analysis here for groups 1, 2,3,4 and 5
   y1 = Abs(grp1centroid - axx)
   y2 = Abs(grp2centroid - axx)
   y3 = Abs(grp3centroid - axx)
   y4 = Abs(grp4centroid - axx)
   y5 = Abs(grp5centroid - axx)
   minY2 = MinOfList(y1, y2, y3, y4, y5)

   Select Case minY2
   Case Is = y1
      checkGroupF1 = 1
   Case Is = y2
      checkGroupF1 = 2
   Case Is = y3
      'MsgBox "Group 3"
      checkGroupF1 = 3
   Case Is = y4
      'MsgBox "Group 4"
      checkGroupF1 = 4
   Case Is = y5
      'MsgBox "Group 5"
      checkGroupF1 = 5
   End Select
End Function
```

Table 4. Visual Basic Code for Determining Classification Group

```
Function checkGroupF2(bxx As Single)
Dim y1 As Single, y2 As Single, y3 As Single, y4 As Single, y5 As
Single, minY2 As Single, y12 As Single, minY1 As Single,
grp1centroid As Single, grp2centroid As Single, grp3centroid As
Single, grp4centroid As Single, grp5centroid As Single

grp1centroid = 0.104
grp2centroid = 0.216
grp3centroid = -0.797
grp4centroid = -0.752
grp5centroid = 0.677

'do analysis here for groups 1, 2,3,4 and 5
   y1 = Abs(grp1centroid - bxx)
   y2 = Abs(grp2centroid - bxx)
   y3 = Abs(grp3centroid - bxx)
   y4 = Abs(grp4centroid - bxx)
   y5 = Abs(grp5centroid - bxx)
            minY2 = MinOfList(y1, y2, y3, y4, y5)

 Select Case minY2
   Case Is = y1
      checkGroupF2 = 1
   Case Is = y2
         checkGroupF2 = 2
   Case Is = y3
      checkGroupF2 = 3
   Case Is = y4
      'MsgBox "Group 4"
      checkGroupF2 = 4
   Case Is = y5
      'MsgBox "Group 5"
      checkGroupF2 = 5
   End Select
End Function
```

4. Especial Mention – 5%
5. Satisfactory – 0%

The above determines the various groups to which each loan considered will be classified into.

Table 5. Visual Basic Code for Determining Classification Group

```
Function MinOfList(ParamArray varValues()) As Variant
    Dim i As Integer , varMin As Variant
    varMin = Null         'Initialize to null

    For i = LBound(varValues) To UBound(varValues)
        If IsNumeric(varValues(i)) Then
            If varMin <= varValues(i) Then
                'do nothing
            Else
                varMin = varValues(i)
            End If
        End If
    Next

    MinOfList = varMin
End Function
```

IV. Results and System Administration

The results of the classification process are presented in various reports that can be generated from the database system. Accessing the list of available report is shown in Fig. 10. A number of system administration issues such as updating borrower's details on quarterly basis and system backup / restore facility are included to ensure timely availability of information.

4.1. List of Loan Classification Reports

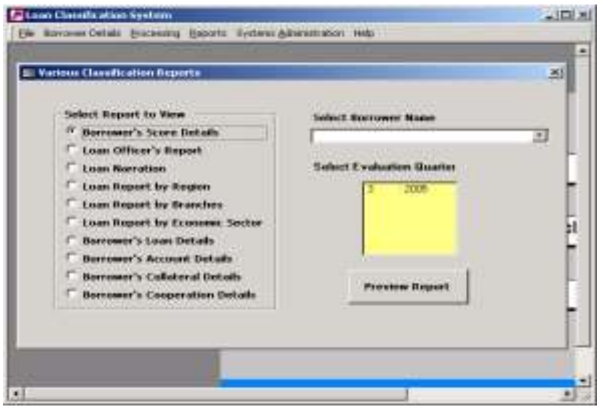

Fig.10. List of Possible Classification Reports

To view this report select Other Loan Classification from the Report Menu and from the screen select any of the following report to view. This includes amongst other reports Individual Borrower's Loan Details, Loan Officers Report and Loan Narration.

4.2. Updating of Borrowers' Record

In order that the database is current and able to give accurate quarterly classification report it is expedient that Borrower's records are regularly updated and where deficient a list of those that have not submitted data for the current quarter is automatically generated for loan Officers' attention. The Quarterly Outstanding list is can be generated from the graphical user interface shown in Fig. 11.

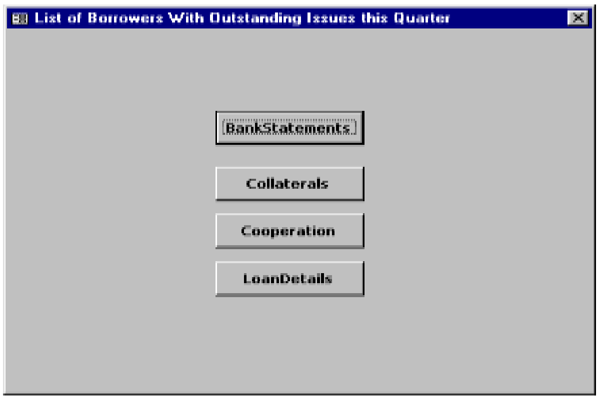

Fig.11. Generation of Quarterly Outstanding Issues

The list of borrowers whose data has not been captured for the current quarter in relation to data pertaining to the collateral variable can be generated using the screen in Fig. 12.

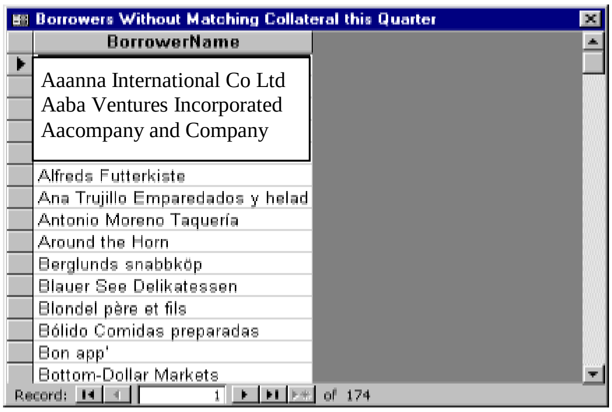

Fig.12. Borrowers without Quarterly Data on Collateral

4.3. System Backup Procedure

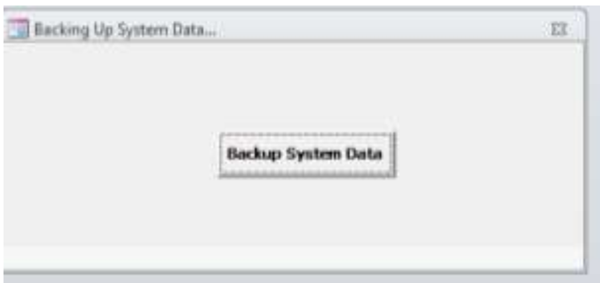

Fig.13. System Data Backup Facility

During installation a backup folder (LCSBackup) is created under the LoanClassification folder where tables are backed up wherever the backup script is run. The data backup process is automated by selecting the backup button as indicated in Fig. 13. To complete the backup process, the content of the LCSBackup residing in the Backup folder must be copied to tape or CD. This represents the current state of system data at the given time. In case of any system problem, the data in the LCSBackup database can be restored for business continuity.

V. Conclusion

The need for loan data classification cannot be overemphasized in the banking and financial industry such is also the design of appropriate classification systems. This work is an attempt to implement a database-based classification system. It models and uses multiple discriminant analysis, a proven, widely used technology to solve complex classification problems. It is loosely modeled after the Examiner's reasoning, and made use of such concepts as discriminant analysis to realize the loan classification processes.

Using the loan classification database system requires no prior knowledge of multiple discriminant analysis or neural networks, and its interface is extremely easy-to-use. The actual application is currently implemented on Microsoft Access eliminating the need to export data and import the results. Since Microsoft Access is limited in usage and capability, there are opportunities to upgrade the currently developed system to other highly robust database systems.

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