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An Implementation of ID3 Decision Tree Learning Algorithm for Tax Fraud Control and Prevention System

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Abstract

Every month business ventures pay certain amount of money as tax to the government agency in-charge of collecting tax as internally generated revenue. This tax amount ought to be a certain percentage of their earnings or profit, but the agency in-charge has no structured means of apportioning or predicting the amount of money to levy the tax payers thereby over-estimating or under-estimating the tax amount charged. This scenario has posed serious financial fraud issues of cash suppression and diversion in the current tax collection system. For the purpose of this research work, ID3 classification technique based on decision tree has been used to properly classify tax payers into tears in order to monitor, control and reduce fraudulent tax activities in the present tax collection system. The result of this research work will assist the state government to control tax fraud of different kinds, and to properly predict the expected tax income to improve on the developmental projects of the state.

Keywords: ID3 Algorithm, Decision Tree, Machine Learning, Fraud, Tax Collection System

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I. Introduction

Fraud has become one of the constants of life; fraud can never stop but can be detected and reduced to an extent [14]. Edo state Inland Revenue Services is overwhelmed with gigabyte of disk capacity containing data about tax payers' in the state. The data stored on the database is increasing in size at an alarming rate; but this has resulted in a data rich but information poor situation where there is a widening gap between the explosive growth of data and its types, and the ability to analyze and interpret the data effectively has becomes a major challenge; hence fraudulent activities like cash suppression and diversion in the tax collection system is rampant because there is no proper structure for apportioning taxes/levies to petty shops, supermarkets saloons etc in the current or existing tax collection system. Tax is supposed to be based on a certain percentage of earnings/income or profit, but the tax officers give estimated levies or taxes to business ventures or organizations at random thereby either under estimating or overestimating the tax amount given to taxpayers.

Moreso, some of the monies collected from these petty shops as taxes/levies are not being remitted to the appropriate office, there by leading to tax amount suppression or loss in the current system, and the government have no way of knowing the exact number of business ventures or organizations that are paying taxes/levies; let alone the revenue generated monthly from the various organizations.

The government only makes financial decisions based on what its mechanism for collecting tax (board of internal revenue) presents as internally generated revenue (IGR) for the month. The specific objective of this study is to develop an automated model that will classify tax payers into tiers or segments based on their earnings or profit for effective monitoring, controlling, and reduction of fraudulent activities in the state tax collection system using ID3 decision tree learning algorithm.

2. Literature Review

Iterative Dichotomizer 3 (ID3) according to [1, 5, and 6] is a decision tree learning algorithm developed by Ross Quinlan in 1983. The main idea behind ID3 algorithm is to create a decision tree of a given set using top-down greedy search to check each attribute at every node. ID3 operates recursively on 'n' partitioned subsets in order to get the best attribute until it classifies the training sets after which it stops [7].

According to [8] most decision tree algorithms are faced with the issues of choosing and splitting attributes, number of splits to be taken, stopping criteria, order of splitting attributes and balancing of tree structure and pruning. [2] Applied classification technique using DID3 algorithm to improve decision support system under uncertain situations. The proposed system supported top level management to make a good decision in any time under any uncertain environment using the classification technique by DID3 algorithm. [3] Is of the opinion that each branch of the tree is a classification question and the leaves of the tree are partitions of the dataset with their classification.

Also from literatures reviewed, some other interesting implementation or uses of ID3 algorithm are as follows;[4] Modified ID3 algorithm and implemented it to create a decision tree for bank loan seekers. The changes were done in order to remove the shortcomings of the algorithm, while the modified version is helpful to bankers in order to predict the credit risk of people seeking for loans from banks. [9] Adapted ID3 decision tree algorithm for job placement prediction based for the applicant's Cumulative Grade Point Average (CGPA) in the University.

The result of the analysis assisted academic planners to design a strategy to improve the performance of students that will help them in getting placed at the earliest possible time. [10] Used decision tree algorithm to select the best path to follow in the standard division. They introduced ID3 algorithm and Havrda and Charvat Entropy instead of Shannon Entropy. The decision tree helps in making the better decision to the analysis of data. [11] Implemented decision tree classification alongside with fuzzy logic. The fuzzy ID3 results were based on information gain of the fuzzy dataset and fuzzy entropy.

The final result was an improved classification. Decision tree classification can be taught under the field of data mining as other courses such as operations research, project management, etc. [12] used Microsoft excel to teach decision tree classification algorithm by outlining a set of procedures to implement it. [13] Also adapted ID3 decision tree learning algorithm to the training set for two weeks. The ID3 was implemented using java programming language. The result shows a classified decision tree and decision rules.

3. Methodology

The methods used in the analysis, design and development of the proposed system are as follows: data gathering, profitability model/analysis, data mining analysis tool and classification model using ID3 decision tree learning algorithm. While jQuery, PHP, JavaScript, HTML and MySQL web programming languages were used to build the software prototype.

3.1 Data Gathering

This research work gathers data using structured questionnaire technique and personal observation of the existing system in order to understand the correct workflow process.

3.2 Profitability Model

Profitability model or analysis is the linear, deterministic algebraic model used implicitly to determine the profit earned in a business, starting with profit equals sales minus costs; it provides a structure for modeling cost elements such as materials, losses, multi-products, learning, depreciation etc. It also provides a mutable conceptual base for spreadsheet modelers. The basic profit model is sales minus costs. Sales are made up of quantity sold multiplied by their price. Costs are usually divided between fixed costs and variable costs.

From our variable definition above:

tp = ts – (tcs + toe)

Where:
tp = total profit
ts = total sales
tcs = total cost of sale
toe = total operating expense

Table 1: Tabular Representation of Sample data collected from proposed taxpayers

S/N	Business Name	Service	acc	cs	aoe	sa	Tax amount/month	Location
1	Kenny Barbers shop	Barbing	15	120	50	400	5,000	GRA Area
2	Mekus Barber International	Barbing	22	100	45	350	5,000	Ekewan Area
3	Sir Moris Saloon	Barbing	17	140	45	300	4,500	Ugbowo Area
4	Excite Barbers	Barbing	15	110	40	300	4,000	Ugbowo Area
5	Yuppies Beauty Salon	Barbing	10	100	50	300	3,000	Uselu Area
6	Double twins Plaza	Barbing	20	70	40	300	3,500	Ugbowo Area
7	Willmaz barber shop	Barbing	25	160	80	350	5,000	Ugbowo Area
8	Manners Wilmas Stores	Barbing	25	70	50	300	2,500	Uselu Area
9	Kome and Kome Barbers	Barbing	15	80	50	350	2,500	Uselu Area
10	Fantastic Barbers	Barbing	30	150	120	500	5,000	GRA Area
11	Daniels cute	Barbing	15	200	120	500	5,000	GRA Area
12	OsasAmas Mighty	Barbing	20	120	100	450	5,000	Ekewan Area

Applying the profitability model to the data in Table 1 considering the first three business outfits (Kenny, Mekus and Sir Moris barbing salon); the profit of each shop will be determined as shown below.

Kenny Barbers shop

ts = sa xacc
ts = 400 x 15
ts = **N6,000.00** daily
tcs = cs xacc
tcs = 120 x 15
tcs = **N1,800.00** daily
toe = aoe xacc
toe = 50 x 15
toe = **N750.00** daily
tp = ts – (tcs + toe)
where
ts = 6,000
tcs = 1,800
toe = 750

thus,

tp = 6000– (1800 + 750)
tp = 6,000 – 2,550
tp = **N3,450.00** daily

Mekus Barbers International

ts = sa xacc
ts = 350 x 22
ts = **N7,700.00** daily
tcs = cs xacc
tcs = 100 x 22
tcs = **N2,200.00** daily
toe = aoe xacc
toe = 45 x 22
toe = **N990.00** daily
tp = ts – (tcs + toe)

Where

ts = 7,700
tcs = 2,200
toe = 990

thus,

tp = 7700 – (2200 + 990)
tp = 7700 – 1210
tp = **N6,490.00** daily

Sir Morris Salon

ts = sa xacc
ts = 300 x 17
ts = **N5,100.00** daily
tcs = cs xacc

tcs = 140 x 17
tcs = **N2,300.00** daily
toe = aoe xacc
toe = 45 x 17
toe = **N765.00** daily
tp = ts – (tcs + toe)

where

ts = 5,100
tcs = 2,300
toe = 765

thus,

tp = 5,100 – (2,300+ 765)
tp = 5,100 – 1,535
tp = **N3,565.00** daily

Again, considering the first three tax payers' from table 1 in different areas; the table 2a was deduced.

Table 2a: Tax payers table with estimated profit per day

S/N	Business Name	Customer Count	Estimated Profit/day(NGN)	No of days' work/Month	Estimated Profit/Month(NGN)
1	Kenny Barbers shop	15	3,450	24	82,800
2	Mekus Barber International	22	6,490	24	155,760
3	Sir Moris Saloon	17	3,565	24	85,560

Table 2b: Government Approved Tax Rate Guild

Tiers	Tax Rate (%)	Profit Earned (NGN)	Tax Amount (NGN)
T1	5	0 -30,000	0 – 1,500
T2	10	30,001 – 50,000	3,001 – 5,000
T3	15	50,001 – 110,000	7,500.15 – 16,500
T4	20	110,001 – 160,000	22,000.22 – 32,000
T5	25	Above 160,000	40,000.25 -

Table 2c shows the state government approved tax rate guild which is segmented into 5 tiers based on tax rate percentage, profit earned range and tax amount. Applying this approved tax rate guild in table 2b to table 2a, the table 2c was deduced.

Table 2c: Taxpayer table with Initial tax amount and Actual Tax Amount

S/N	Business Name	Estimated Profit/Month(NGN)	Tier	Initial Tax amount (NGN)	Proposed Tax amount (NGN)
1	Kenny Barbers shop	82,800	T3	5,000	12,420
2	Mekus Barber International	155,760	T4	5,000	31,152
3	Sir Moris Saloon	85,560	T3	4,500	12,834

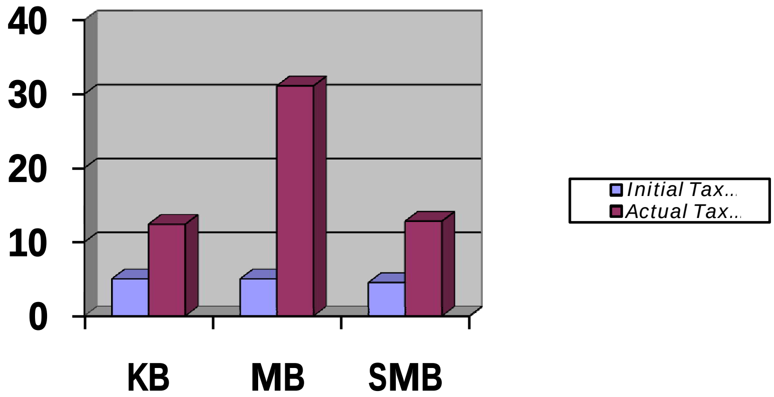


Figure 1: Graphical Representation of Table 2c

Figure 1 shows a graphical representation of table 2c. The parameters of the graph on vertical axis are the initial tax amount, which is plotted against the proposed tax amount on the horizontal axis as indicated in the graph using blue and purple color code.

KB *denotes* ***Kenny barbers***

MB *denotes* ***Mekus Barbers***

SMB *denotes* ***Sir Morris Barbers***

The amount is in thousands of Naira. ('000)

Figure1 also shows the difference in tax amount between the initial tax amount and the proposed or actual tax amount. This reveals that some tax payers are under paying tax because of the existing unstructured way of collecting these taxes thereby defrauding the government unknowingly.

3.3 Data Mining

Data mining could also be seen as data cleansing or data scrubbing. This concept involves the searching and removal of noise, incomplete, missing and irrelevant data from a dataset and then formatting the refined data according to the required format using a Miner extractor.

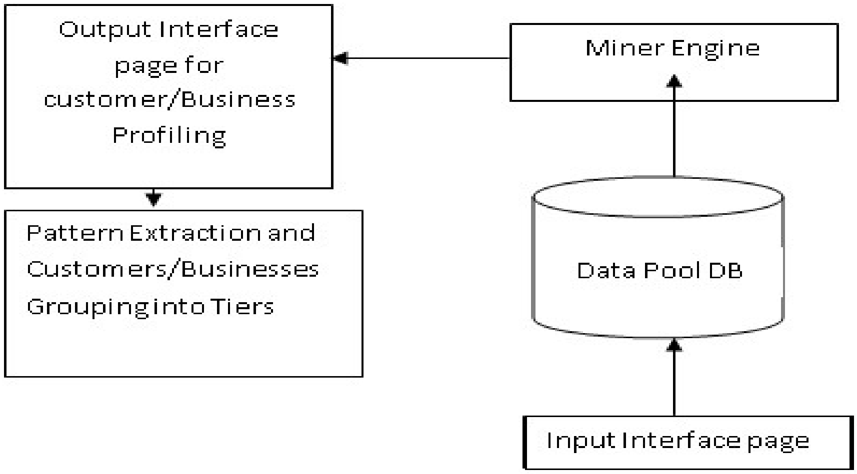


Figure 2: Proposed Data Miner Extractor Architecture

3.4 Classification Model

This is a systematic approach of building classification algorithm from an input data set. Grouping taxpayers businesses into tiers; the active variables required are profit earned and customer count. The technique of classification model used in this research work is the Decision Tree Model. The ID3 decision tree learning algorithm is adapted to classify taxpayer's business into various tiers. The model is expressed mathematically as:

Entropy (B) = -p(C) log2 p(C)

Where: p(C) is the proportion of B belonging to class C is over tp.

Gain (B, A) is information gain of sample set B on attribute A is defined as

*Gain (B, A) = Entropy (B) - ((|B_v| / |B|) * Entropy (B_v))*

Recall: the active variables required are the profit earned and customer count. The profit earned in any of the business is analyzed and determined by the profitability model. If the profit earned is zero (0) or negative then such business cannot be classified into any tier because it is seen as not viable.

Table 3: Classes of Tiers

Classes	TP (NGN)
Tier1	0 -30,000
Tier2	30,001 – 50,000
Tier3	50,001 – 110,000
Tier4	110,001 – 160,000
Tier5	Above 160,000

3.4.1 ModifiedID3 Decision Tree Algorithm for Tax Payers' Classification

/* ID3 Decision tree algorithm for tax payers classification*/

/ Parameters use to represent variable in the algorithms are*

B -> Set of Business sample

T -> Set of Tiers. In this research work T is definite. (t1, t2, … t5) - i.e. T == 5)

TP -> Set of Total Profit sample from B

tp -> actual total profit for a given business b.

Recall that the defined attributes for classifying into classes (Tiers) are:

**/*

PROCEDURE MAIN BEGIN

; Upload sample dataset B from taxpayer table in emma_phd database for classification using ID3 algorithm;

STEP 1: *If (all instances in TP are positive)*

// using Entropy (information gain) expressed as

{

Entropy (B) = -p(C) log2 p(C) // the businesses are partially random.

Where: p(C) is the proportion of B belonging to class C is over tp.}

Gain (B, A) is information gain of sample set B on attribute A is defined as

*Gain (B, A) = Entropy (B) - ((|B_v| / |B|) * Entropy(B_v))*

Then

{

Classification exists;

Classify into tier

}

END

If (all instances in TP are negative or zero)

then

// using Entropy expressed as

{

Entropy (B) = -p(C) log2 p(C) // all the businesses B are perfectly classified.

{

Classification does not exist;

}

END.

Function miner Engine(){

If(TP > 0)

{

Classification == 1; (Classification will take place)

If (tp<=30,000){

b == t1;

}

else{

if(tp>30,000 & & <= 50,000){

b == t2;

```
}
else
{
if (tp>50,000 & & <= 110,000){
b == t3;
}
else{
if (tp>110,000 & & <= 160,000){
b == t4;
}
else{
b == t5;
}
}
}
}
LOAD NEXT B;
end;
}
Else{
if (TP < 0){
Classification == 0; (Classification will not take place)
end;
}
Else{
if (TP == 0){
Classifications == 1;
b1, b2, …bn == t1 || t2 || t3 || t4 || t5;
//(that is, all tp are equal in value and b1, b2 … bn are classified into one of t1, t2…t5)
```

```
end;
}
}
}
```

STEP 2: *Partition or divide the training instances into subsets tp_1, tp_2, ….tp_n according to value of t.*

```
Select * from datapool LIMIT 5;
```

STEP 3: *Repeat the steps recursively*

```
while (!B->EOF) {
if (B== eof){
end;
}
Else{
MoveNext();
}
}
```

3.4.2 Decision Tree Classification

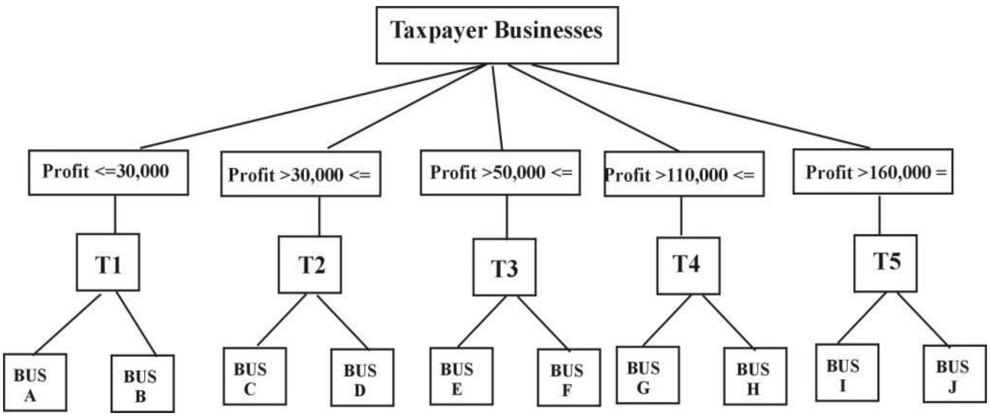


Figure 3: Decision tree classification diagram for taxpayers businesses

Figure 3 depicts the decision tree classification diagram for tax payers businesses under review in Benin City, Edo State, Nigeria.

4. Results and Discussion

The following are the results from the research work: (1) data can be cleansed properly using the miner extractor (2) profits can be computed automatically and correctly using the profitability module (3) tax payers can be classified automatically without issues, and these are depicted in figures 4, 5, 6a, 6b, 7 and 8 respectively in order to control fraudulent tax activities.

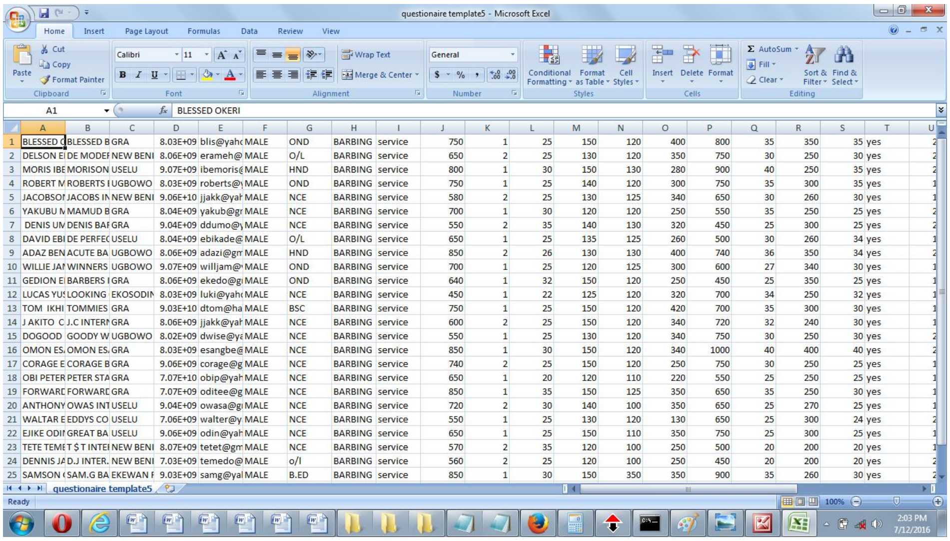


Figure 4: Sample tax payers' data in Microsoft Excel format

Figure 4 shows the tax payers' raw data from the questionnaire captured using Microsoft Excel. The data is saved as Comma, Separated Value (CSV) format before uploading it to the proposed system at once to prevent data entry error.

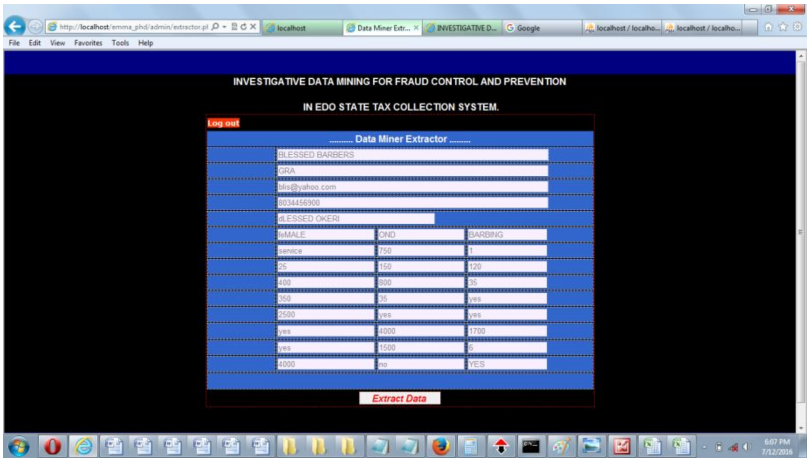


Figure 5: Screenshot of the developed Data Miner Extractor Interface

Figure 5 shows the Data Miner Extractor interface. This interface helps to retrieve the raw data of individual business venture record uploaded before the extraction is done.

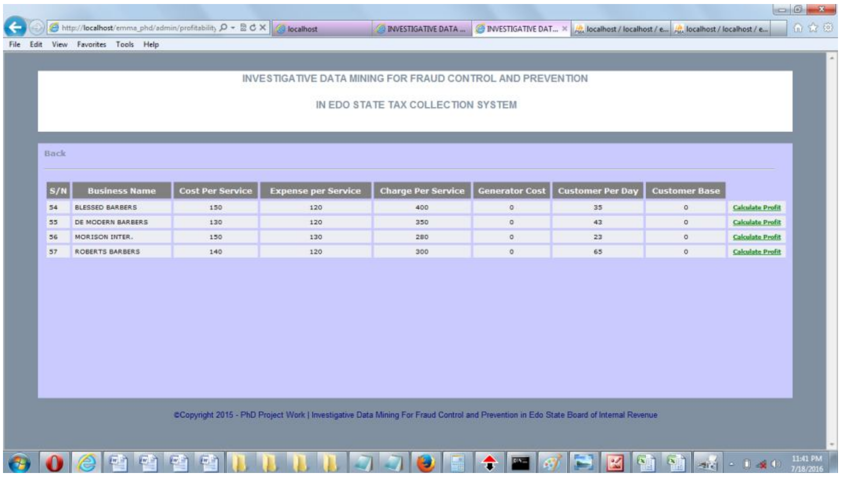


Figure 6a: Screenshot of the developed profitability module

Figure 6a shows the snapshot of the profitability module displaying some business ventures profile ready for profitability computation.

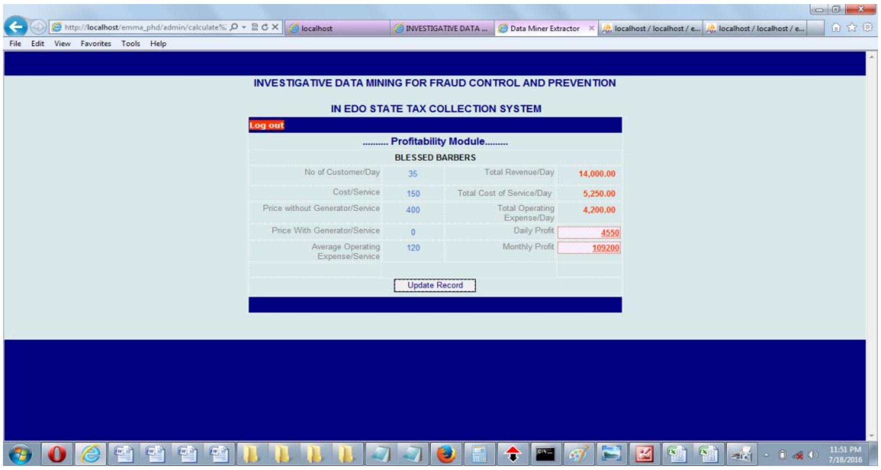


Figure 6b: Screenshot of the developed profitability analysis interface

Figure 6b shows the profitability analysis interface executed for a particular business venture. The interface reveals name of the business venture, and analyzes the following: cost of service, average operating cost, total revenue per day, total cost of service per day, and total operating expenses in order to determine the daily and monthly profit.

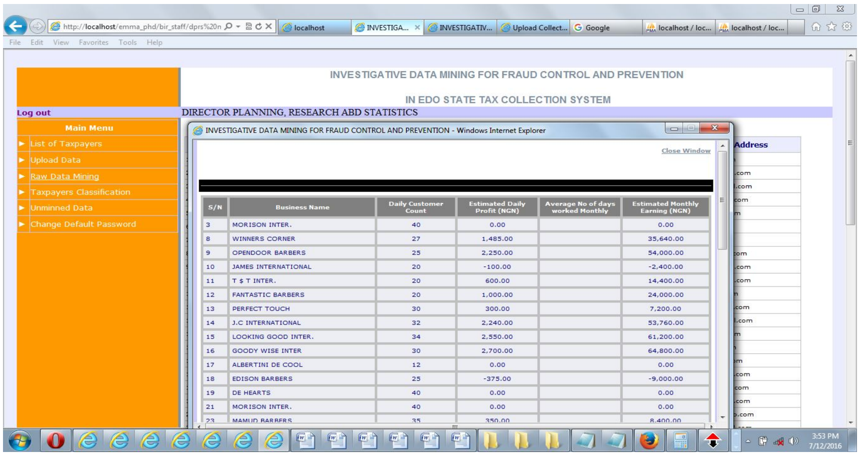
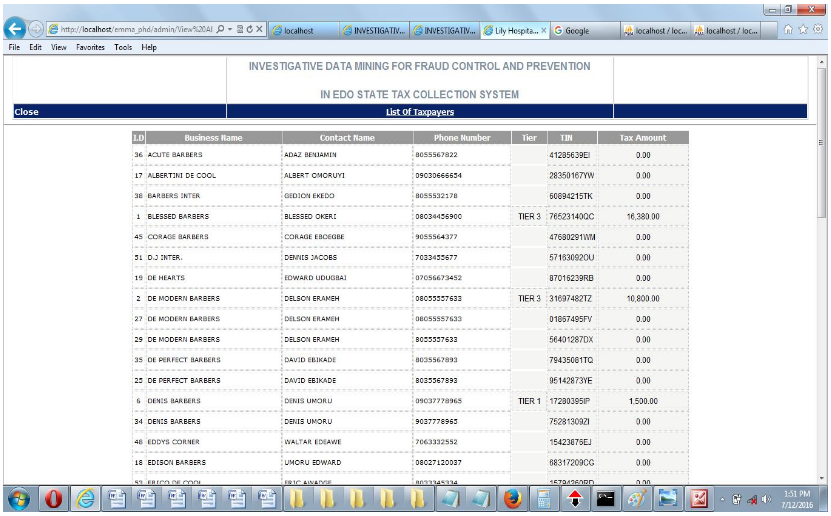


Figure 7: Screenshot of the profitability analysis output report

Figure 7 shows the output report as a result of the profitability computation executed. The report reveals evidence of some business ventures estimated monthly earning having zero, positive, and negative values respectively. It should be noted that only the business ventures whose estimated monthly earning is having positive value meaning the business is making profit that can be taxed and therefore classified into a particular tier.


INVESTIGATIVE DATA MINING FOR FRAUD CONTROL AND PREVENTION

IN EDO STATE TAX COLLECTION SYSTEM

Close

List Of Taxpayers

I.D	Business Name	Contact Name	Phone Number	Tier	TIN	Tax Amount
36	ACUTE BARBERS	ADAZ BENJAMIN	8055567822		41285639EI	0.00
17	ALBERTINI DE COOL	ALBERT OMORUYI	09030666654		28350167YW	0.00
38	BARBERS INTER	GEDION EKEDO	8055532178		60894215TK	0.00
1	BLESSED BARBERS	BLESSED OKERI	08034456900	TIER 3	76523140QC	16,380.00
45	CORAGE BARBERS	CORAGE EBOEGBE	9055564377		47680291WM	0.00
51	D.J INTER.	DENNIS JACOBS	7033455677		57163092OU	0.00
19	DE HEARTS	EDWARD UDUGBAI	07056673452		87016239RB	0.00
2	DE MODERN BARBERS	DELSON ERAMEH	08055557633	TIER 3	31697482TZ	10,800.00
27	DE MODERN BARBERS	DELSON ERAMEH	08055557633		01867495FV	0.00
29	DE MODERN BARBERS	DELSON ERAMEH	8055557633		56401287DX	0.00
35	DE PERFECT BARBERS	DAVID EBIKADE	8035567893		79435081TQ	0.00
25	DE PERFECT BARBERS	DAVID EBIKADE	8035567893		95142873YE	0.00
6	DENIS BARBERS	DENIS UMORU	09037778965	TIER 1	17280395IP	1,500.00
34	DENIS BARBERS	DENIS UMORU	9037778965		75281309ZI	0.00
48	EDDYS CORNER	WALTAR EDEAWE	7063332552		15423876EJ	0.00
18	EDISON BARBERS	UMORU EDWARD	08027120037		68317209CG	0.00

Figure 8: Screenshot of list of tax payers report classified into tiers

Figure 8 displays a report of list of tax payers classified into various tiers which is based on their monthly earnings.

5. Conclusion

This research work provides a detailed study for the need to develop an automated system that could properly classify tax payers earning into tears in order to monitor, secure, control and prevent fraudulent activities like cash suppression and diversion in the current Edo state tax collection system.

The Iterative Dichotomizer 3 (ID3) Decision Tree Learning Algorithm was to classifier the tax payers into their proper tiers. The experiment conducted concludes that ID3 works very well on classification problems having datasets with nominal attribute values.

6. Recommendations

This research work on tax fraud activities monitoring and control is highly recommended to the Edo state Board of Inland Revenue for full deployment in order to checkmate most loopholes in the present tax collection system of the state; and also to other states tax collection system.

7. Acknowledgments

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