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RESEARCH ARTICLE

MICROFINANCE MANAGEMENT MODEL: CASE OF CÔTE D'IVOIRE.

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Abstract

This article deals with the issue of client solvency in microfinance. Microfinance includes all financial products and services designed for a public excluded from traditional banking circuits. The development of these microfinances is a very important issue and makes it possible to reduce the unemployment rate. However, the lack of customer solvency makes the management of these microfinances complex. In this article, we propose a microfinance management technique based on the use of K-nearest neighbor (KNN) and smart contract algorithms. The proposed approach makes it possible to model the behavior of a customer to arrive at their solvency.

Introduction:-

Financing the informal sector is an important issue in the fight against poverty since the informal sector occupies 76.5% of the population and concentrates 70% of economic activity. Moreover, the rapid changes in the behavior and habits of our modern African societies make this change necessary in order to improve the standard of living of the populations [1]. In OECD countries, SMEs represent nearly 99% of the total number of enterprises and contribute nearly 70% of jobs and 50-60% of value added3. In Côte d'Ivoire, SMEs only contribute 20% of GDP4. This "Repère" indicates the creation of businesses and the difficulties of financing investment in Côte d'Ivoire, with a particular focus on SMEs [2]. Microfinance Institutions are set up to provide financial products to people excluded from classical or formal financial system. They generally relate to poor inhabitants of the developing countries. Indeed, microfinances allow low-income households or households belonging to the informal sectors to have permanent access to a range of quality financial services adapted to their needs. The main activities of these microfinances relate to access to credit, the development of savings, the provision of insurance services and the transfer of funds **[**3, 4 and 5]. However, these microfinances are facing economic difficulties because of the growth in the rate of insolvency of borrowers. According to the report evolution table of outstanding related to UNACOOPEC-CI farmers (in millions of CFA francs), the rate of non-solvency increased from 1.1% in 2012 to 3.3% in 2013 and continues to grow according to the data of the statistics institutions in Côte d'Ivoire [6 and 7].This rate of non-solvency causes the closing of some microfinance agencies. Also, there is no model adapted to our African and more specifically Ivorian reality in terms of lending. Our realities are explained by the fact that people with ideas often lack the initial contribution when applying for a loan. This situation prevents them from taking an interest in or approaching specialized structures in the management of micro-finance. Therefore, we wonder by which model can we guarantee solvency and sustainability of microfinance operation in Côte d'Ivoire?

To address this concern, we set ourselves the goal of using K-nearest neighbors-algorithm and the smart contract. The KNN will permit to know the behavior of customers. Indeed, the k-nearest neighbors-algorithm is a

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nonparametric supervised learning algorithm, which uses proximity to perform classifications or predictions on the clustering of a data point. The smart contract will apply in the implementation of the new SME according to the creditworthiness level of the customer.

We will first present related work on microfinance. Then describe the proposed approach with the main new algorithm and present the advantages of the new contribution.Then, we will devote ourselves to the experiments and analysis of the results. And finally conclude the article.

Theory and Method: -

The issue of credits has generated much enthusiasm in the literature. In fact, Khandani and al. used machine learning techniques including regression using K-Nearest Neighbors to create nonlinear, nonparametric forecasting approaches to measure consumer credit risk [8]. To identify credit cardholder defaults, the authors used a dataset of credit bureaus and commercial bank customer transactions to come up with a forecast estimate. As for Addo and al., they examined credit risk scoring using various artificial intelligence techniques [9]. So, they used binary classifiers based on KNNs and random forest to model and estimate the probability of default. These incorporated ten key features allowing them to test the stability of the classifiers by evaluating performance on distinct data. On the other hand, Deer and al. introduced machine learning models to compose credit score and default prediction estimation [10]. They used financial instruments, such as historical balance sheets, bankruptcy statuses and macroeconomic variables from a Moody's data set. This technique allowed them to observe excellent out-of-sample performance results to reduce the likelihood of bankruptcy or improve credit rating. Likewise, Zahoui and al. sought to assess, using the k-nearest algorithm, the factors explaining the repayment of loans by farmer borrowers [11]. A regression analysis on data collected on a sample of 576 loan files granted to farmers shows that factors related to borrowers (age, type of crop, household size), but also to the institution (form of loan, credit rank, interest rate, purpose of credit and land security) determine the repayment rate at farmer level. Jena and al. and Kumar and al. developed a predictive classification model based on KNNs for his country Germany [12 and 13]. The said model uses bank data to minimize losses when approving loans. The results of this model tested on 1000 individuals has generated a fairly reasonable rate of income. CARLSON and al. also used the logistic regression model to assess the lending level of the Greek economy [14]. This approach allowed them to accurately prove the performance and accuracy of the Greek financial system.

However, no model in the literature is adapted to Ivorian reality. Hence, the interest of a typical Ivorian model proposal capable of evaluating the solvency of different categories of Ivorian customers since they are divided according to their sectors of activity.

Method:-

A field survey of small and medium-sized enterprises (SMEs) in the municipality of Adjamé (Côte d'Ivoire) enabled us to obtain a database of 300 observations. The first five (5) rows are shown in Table 1 below. The variables in that table are mainly numeric and made up of:

1. LOY_MAG: rent of a shop ;
2. COU_CHAR: cost of the store charges ;
3. COU_CHAR: cost of domestic charges ;
4. MON_EPA: The amount saved ;
5. TRI_MON: Triple of the amount saved;
6. DUR_CPT_EPA: The duration of the activity;
7. BENEF: The monthly profit;
8. MON_DMAD: The requested amount;
9. T_INTERT: The interest rate;
10. DUR_ACTIV: The monthly duration of the activity;
11. SOLV: Customer's ability to obtain credit or not: YES or NO test

Table 1:- SME data.

	A	B	C	D	E	F	G	H	I	J	K
1	LOY_MAG	COU_CHAR_I	COU_CHAR_	MON_EPA	TRI_MON	DUR_CPT_EP	BENEF	MON_DMAD	T_INTERT	DUR_ACTIV	SOLV
2	20000	10000	80000	100000	300000	9	360000	500000	50000	24	NON
3	120000	90000	295000	1500000	4500000	7	330000	4000000	400000	26	OUI
4	90000	40000	129200	1900000	5700000	12	300000	6850000	685000	34	NON
5	50000	13650	46990	48200	144600	2	120000	150000	15000	37	OUI

The analysis of the microfinance data reconciled in the table above exemplifies the Fig.1 operation of the model proposed below.

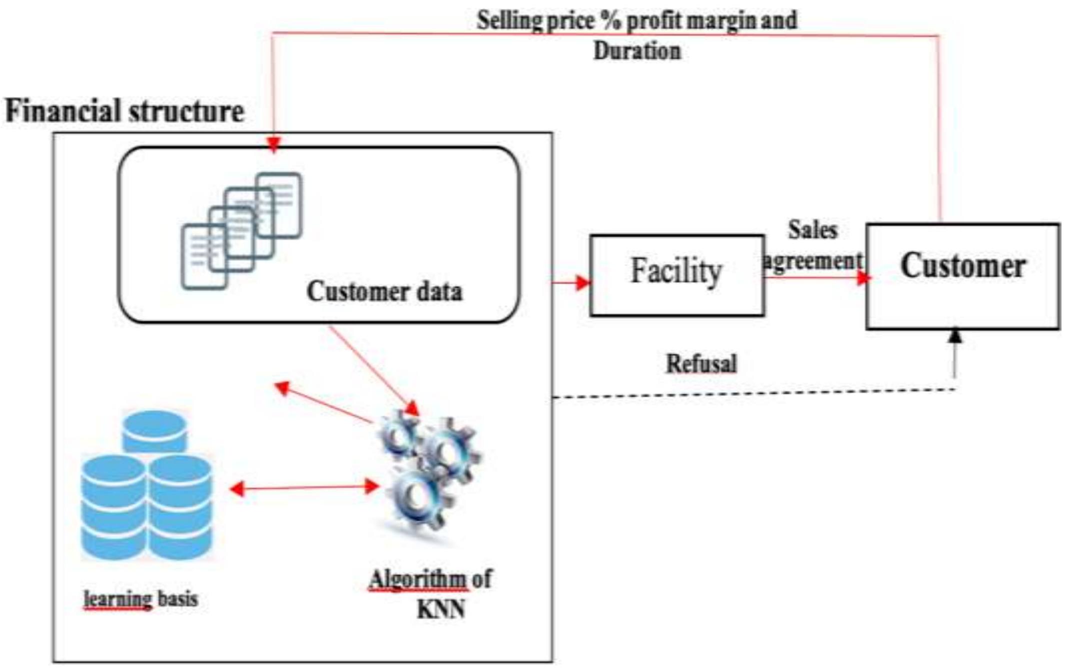

Fig. 1:- New operating model for SMEs in Côte d'Ivoire.

The diagram of the system in Fig.1 is as follows: when a client or an SME requests support from a financial structure, they are required to provide the financial structure with all the information relating to themselves, including the business plan of their projects. It falls to the structure to use the K-nearest neighbors-algorithm to assess the credibility of that client's documents. This Evaluation assumes that similar criteria of the new customer can be found next to one another. criteria of existing former customers in the company's database. They are criteria that have been used to assess former customers already registered and held according to their level of creditworthiness. When the new customer's information is close to the criteria of the old customers, the financial structure will declare them eligible for the loan and will take the responsibility of accompanying them in the establishment of their project. Moreover, the client or even the eligible SME does not automatically have the funds at their disposal. The financial structure will set up a team in which the customer or the SME will be considered a simple participant according to the contract clauses with a well-established periodicity. The established periodicity will allow the two entities (Financial structure VS client or SME) to work together until they meet the deadlines. The strategy will enable the financial structure to get its funds and eventually give back the final business to the customer.

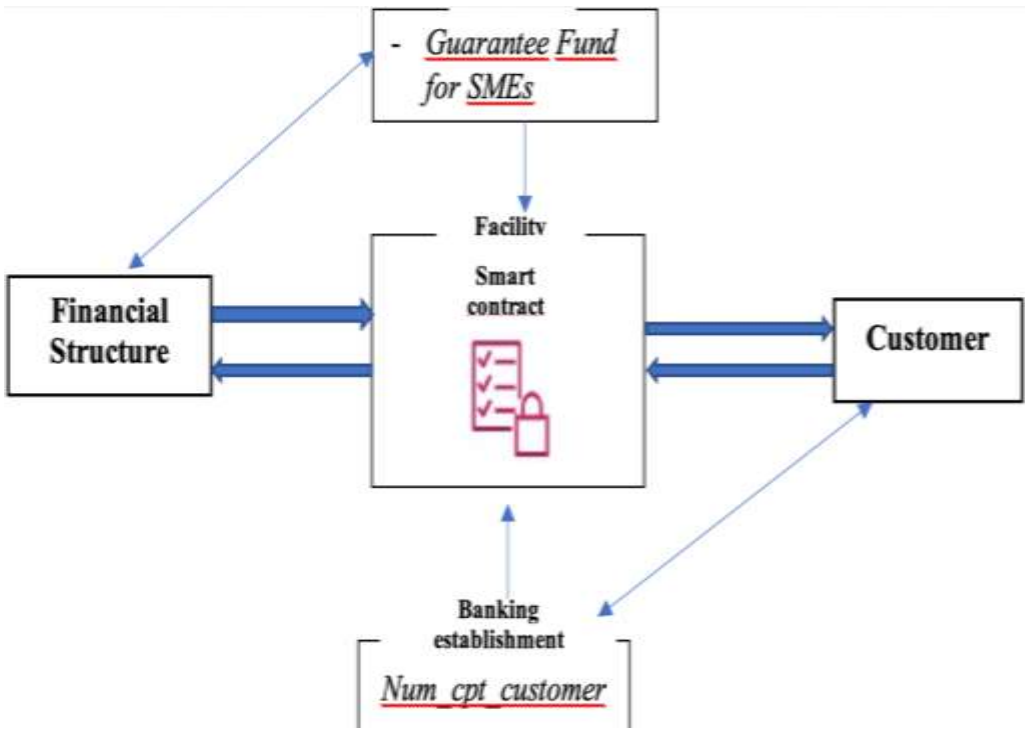

Fig. 2:- Smart contract approach proposed in the installation phase.

Fig.2 above describes the operation mode of SME establishment phase at Fig.1 level after the selection of the best customer profiles. It involves using a new smart contract made up of the following elements:

1. The financial structure creates SME with key attributes such as Penal Code (jurisdiction), share amount, project location and ownership details.
2. The customer provides their bank account information if they are an employee.
3. The client and the financial structure accept the terms of the contract by digitally signing it. Thus, a digital key that represents the identity of both entities will be generated and it now becomes a legally required digital document published.
4. The Smart Contract withdraws from the customer's account every month and the money is immediately paid into the account of the financial structure. When the customer is unable to pay, the smart contract allocates a portion of the deposit from the other structures to fill the void.
5. At the end of the payment schedule, the guarantee of the financial structure is paid to the client according to what has been agreed between the two parties to cover any damages or other expenses.

As for the SME Guarantee Fund (FGPME), which is a public fund set up by the government with financial structures (banks, microfinance, etc.) to serve as a guarantor for SMEs in their request for financing. Once the ideal customer profile is known, the guarantor will automatically be activated for customer financing.

Mathematical Formalism Of The KNN

Let us consider the set of data belonging to a microfinance. It is made up of the training sample:Ω

$$\Omega = \{(y_i, x_i), i = 1, \dots, n_l\}$$

Where $y_i \in \{1, \dots, c\}$ with $c \in \mathbb{N}$denotes the class of the individual and the vector $y_i \in \{1, \dots, c\}$ avec $c \in \mathbb{N} i\big(x_i = (y_{i1}, x_{ip}\big)$represents the predictor variables of the customer. The nearest neighbor determination is based on an arbitrary distance function. The Euclidean distance or dissimilarity between two customers characterized by covariates is defined by:$id(.,.)p$

$$d\left(\left(x_1, x_2, \dots, x_p\right), \left(u_1, u_2, \dots u_p\right)\right) = \sqrt{(x_1 - u_1)^2 + (x_2 - u_2)^2 + \dots + (x_p - u_p)^2}$$

Thus, for a new nearest neighbor customer in the training sample, the nearest neighbor is determined by:$(y, x)(y(1), x(1))$

$$d(x, x_{(1)}) = \min_i (d(x, x_i))$$

and $\hat{y} = y_{(1)}$, the nearest neighbor class, is selected for the prediction of y . The notations and respectively represent the nearest neighbor of $\hat{y} = y_{(1)} y x_{(j)} y_{(j)} j^{\text{ème}}$ xand its class to which it belongs. Among the standard distance functions, the Minkowski distance is defined as follows:

$$d(x_i, x_j) = \left(\sum_{s=1}^{p} \left| x_{is} - x_{js} \right|^2 \right)^{\frac{1}{2}}$$

Algorithm KNN algorithm
KNN()
Inputs:
X_{rc}: tableaud′ensemblesdedonnéesd′entraînement;// r is the row of the table, this is the dimension of the table
Y: class labels of;// y can take two value: 1 or 0X_{rc}
k: number of nearest neighbors;
x: unknown sample sequence;
Outputs:
y: multiple clusters of size k from x;
Beginning
For i =1 to r do
Compute distance d (X_{ic}, X);
End for
Sort distance d(X_{ic}, X);
Select k reference point with smallest distance to x;
End for
Return multiple clusters of size k from x;
End

Result:-

Out[2]:

	LOY_MAG	COU_CHAR_MAG	COU_CHAR_DOMES	MON_EPA	TRI_MON	DUR_CPT_EPAR	BENEF	MON_DMAD	T_INTERT	DUR_ACTIV	SOLV
0	20000	10000	80000	100000	300000	9	360000	500000	50000	24	NON
1	120000	90000	295000	1500000	4500000	7	330000	4000000	400000	26	OUI
2	90000	40000	129200	1900000	5700000	12	300000	6850000	685000	34	NON
3	50000	13650	46990	48200	144600	2	120000	150000	15000	37	OUI
4	50000	50000	0	655670	1967010	24	50000	1500000	150000	57	OUI
...	...	...	...	...	...	...	...	...	...	...	...
295	210000	30000	200000	1500000	4500000	21	340000	4000000	400000	29	OUI
296	20000	2500	50000	350000	1050000	11	100000	1000000	100000	22	OUI
297	150000	45000	0	0	0	8	130000	1000000	100000	46	NON
298	380000	155000	680000	0	0	1	1400000	2500000	250000	32	NON
299	20000	5000	50000	400000	1200000	12	120000	1000000	100000	24	OUI

300 rows × 11 columns

Fig. 3:- Data from local SMEs.

As part of our model evaluation, we used Jupyter notebook from python. For the test we took a database containing 299 SMEs. They are microfinances located in the municipality of Adjamé as shown in Fig.3 below.

As part of the evaluation of the proposed k-nearest-neighbors model, we used the k-block cross-validation:

- We divide the original sample of data into two (2) parts (training / validation) then we divide the training sample into k samples, we select one of the k samples as the validation set while the k-1 other samples constitute the training set;
- After learning, we calculate a validation performance as shown in Fig. 4 and the error rate shown in Fig. 5below ;
- The operation was repeated nine times, selecting another validation sample from the predefined blocks. At the end of the procedure, we thus obtain k performance scores as presented in the table 2 below.

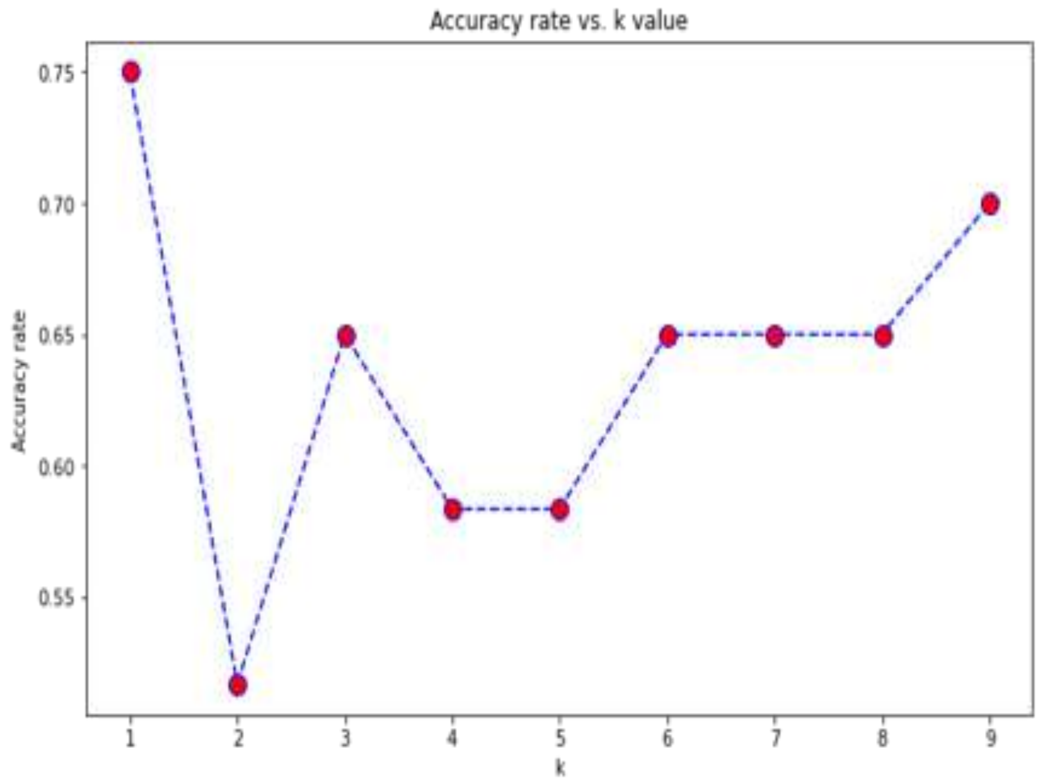

Fig 4:-Accuracy Rate.

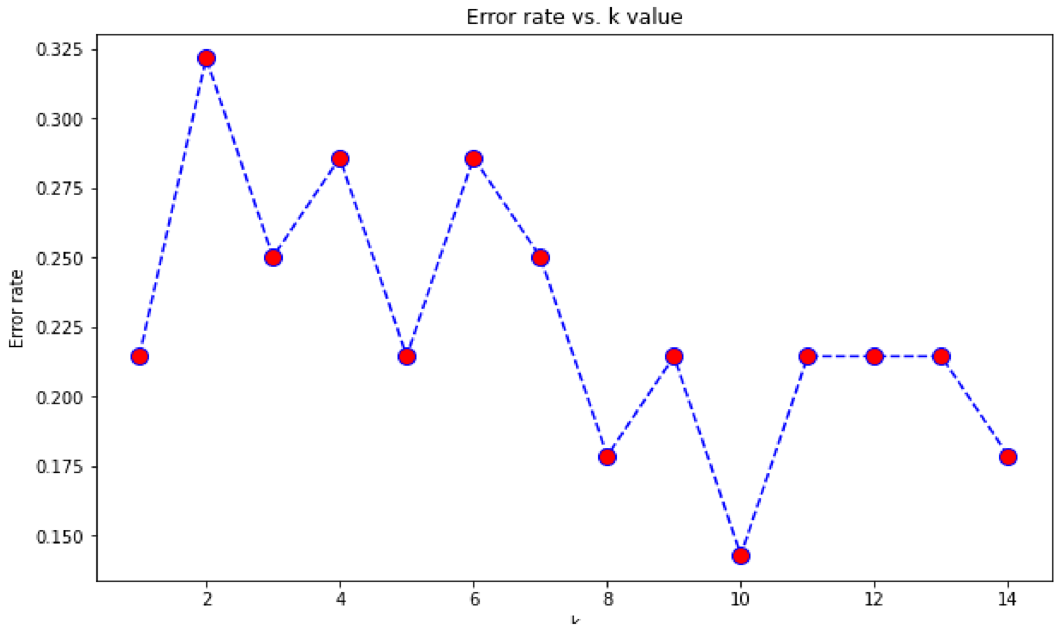

Fig 5:-Error rate.

Fig. 5 above shows us a rapid increase in error rates when we set k=1. At k=2 k=6 we observe a fluctuation of the error rate up to k=6 before relapsing. Then we observe a new peak up to k= 11 before maintaining its progressively decreasing error rate.

Here we can see that after about k>8 the error rate tends to oscillate around 0.23 and 0.25. It means that to have the perfect profile of a solvent client, the characteristics of the latter must be assessed with a minimum of 8 individuals. Thus, we embarked on checking the classification ratio while varying k as shown in Table 2 below.

Table 2:- Tests according to groups

Group_test	Error_rate	Accuracy rate
K=1	0.21-0.32	68%
K=3	0.25-0.26	75%
K=5	0.21-0.22	79%
K=8	0.17-0.18	82%

This model has been tested which has prevailed an accuracy rate of 82%

	precision	recall	f1-score	support
NON	0.80	0.73	0.76	11
OUI	0.83	0.88	0.86	17
accuracy			0.82	28
macro avg	0.82	0.80	0.81	28
weighted avg	0.82	0.82	0.82	28

Performance scores were averaged to estimate the bias and variance of validation performance. The best model obtained is evaluated with the validation set, which gave us a score of 89%.

```
knn_gscv.best_score_
Out[57]: 0.8933823529411764
```

Conclusion :-

The article presented an SME management model in Côte d'Ivoire. This study, which focuses on micro finance, used the KNN algorithm and the smart contract. The smart contract has been proposed and contains various components of the customer's contract with the financial structure. While the KNN allowed us to assess the level of solvency of any customer without an initial contribution. We carried out tests using data from some SMEs of local financial structures. Moreover, although the proposed model gives satisfactory results, many problems still remain to be solved with regard to taking into account the actors of the informal sector. For this purpose, a model based on the hidden Markov model and the smart contracts would allow to analyze the approach findings in order to anticipate field participants' decision is on the way

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