Towards An Efficient Real-time Approach To Loan Credit Approval Using Deep Learning

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***Abstract*—The last decade has seen an important rise of data gathering, especially in the financial sectors. Banks are indeed one of the biggest producers of big data, as a matter of fact no other company than the bank has so much data gathered on its customers. Gathering and analyzing this data is a key feature for decision making, particularly in banking sector. One of the most important and frequent decision banks has to make, is loan approval. The challenge is to know how to build a proactive, powerful, responsible and ethical exploitation of personal data, to make loan applicant proposals more relevant and personalized. Machine learning is a promising solution to deal with this problem. Therefor, in the last years, many algorithms based on machine learning have been proposed to solve loan approval issue. However, these algorithms have not taken into consideration Real-time paradigm during processing. In this paper, we propose a Real-Time Binary classification model to deal with loan approval. Our proposed model is based on a deep neural network, and it permits to classify loan applicant as good or bad risk. Experimental results prove that our proposed Real-Time model, based on deep neural network, outperforms typical binary classifiers, in terms of precision recall and accuracy.**

***Index Terms*—Machine learning; Deep Learning; Loan approval; Real-time data;**

I. Introduction

The benefit of Big Data lies generally in the capacity to analyze a set of data in order to extract useful information. The data gathered by different organizations and companies are characterized by Volume, Velocity and Variety. At times, the accuracy and precision depends not only on the rightness of the data, but as well on the time it is delivered. Example of such data can be found in the financial sphere, especially in banking sector. As Christine Lejoux, a finance journalist in Les Echos, points out: ”Salary, propensity to spend or on the contrary to save, favorite businesses,...Banks know everything about their customers, or almost. A gold mine that is better than ever to exploit. ”. This makes the financial sector one of the biggest potential for big data. With effective analyzing methods, this data can quickly be transformed into added value, and profitable decision making tools [1].

To the question on how to analyze this data, the answer is Machine Learning [2]. Using artificial intelligence offers functionalities that came with a lesser cost, in both time and resources [3]. In addition, it offers new insights, and unprecedented ways to classify data. Today, in banking and financial institutions, machine learning is actively used actively for different applications, notably in trading, portfolio management, fraud detection and loan approval. In the financial landscape, artificial intelligence is used to build the so called ”robo-advisor”, an intelligent portfolio system that can adapt to the risks and goals of the user. Algorithmic Trading or decision trading support systems, are used to make extremely fast decisions [4]. For fraud detection, machine learning brought promising new methods to analyze the behavior of users and detect fraudulent transactions [5] [6] [7]. Loan providers, especially large companies such as banks and insurance firms, use large amount of consumers data, and financial lending results, to train machine learning algorithms. Which can be used to make valuable decision, regarding lending and insurance [10] [24] [11]. In this work, we are aiming our attention at the latter : loan approval decision making.

In a data analysis view, loan approval is a binary classification problem, a set of loan applicants data is analyzed and classified in ”good” or ”bad” risk. Binary classification is a simple case of classification, where based on some features a set of data is classified into two classes. For the most part, this type of classification is used when we want to predict a specific outcome, that can only take two distinct values. Some typical examples include spam detection, medical diagnosis, credit card fraud detection, or in our case : loan approval. Although rather simple, binary classification is a very basic problem. There are various paradigms used for learning binary classifiers, such as: Support Vector Machines, Decision Trees, K-nearest neighborhood, Bayesian Classification, Logistic regression, Neural Networks, and more recently, deep learning. [12]

Deep Learning is a new effective way to deal with machine learning, in the recent years, it has exhibited unrivaled performance for an extensive range of applications. Notably in computer vision and natural language processing. With the advances of Big Data and the continuous increase of computing power, deep learning rebooted artificial neural networks, and opened new ways towards efficient artificial intelligence. Artificial neural network (ANN) is a computing system consisting of networks of computing units, assembled in layers, and connected to each other like neurons. Deep learning is a new artificial neural network technology. It is a biologically

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inspired model of human neurons; composed of multilevel hidden layers of nonlinear processing units, where each neuron is sending information to a connected neuron within hidden layers [21]. Deep neural networks attracted much attention in the field of machine learning. It is currently providing the best results in many problems, providing promising new solutions in many field, notably in binary classification.

From another stand point, Real-time data processing has become a significant field of research. The major approaches are either statistical or based on artificial intelligence [22]. Real time implies the ability to process data on-the-fly, rather than retrieving and storing it. As James Martin cited in his book Design of Real-time Computer Systems in 1967 "A real-time computer system may be defined as one which controls an environment by receiving data, processing them, and taking action or returning results sufficiently quickly to affect the functioning of the environment at that time." This is the first characteristic factor of a real time data processing system: The data is in the present, making its correctness time dependent [14].

This paper presents two contributions. First, we propose a real-time deep learning approach for loan data. The aim is to classify, in real time, feeds of loan applicants, and to give a real-time decision : whether, or not, they should be approved for a loan. In the second contribution, we compare our proposed model with four binary classification methods: Linear SVM Regression, Logistic Regression, Non Linear Auto regression Neural network, and a basic neural network approach.

The rest of the paper is organized as follows: In Section 2 we give a short state of the art review related to our problem. Section 3 describes the architecture of our prediction model and gives a short review of the Deep Learning model used. In section 4, we give a description of our testing environment, the features of the data-set used, the paradigms used for evaluation and a description of the metrics used, in the same section we show and analyze the test results. Finally, in section 5 we draw some conclusions and we indicate the future works.

II. Related Work

In the financial area, loan approval may be a difficult task when the number of loan applicants is important. In the literature review, several algorithms based on machine learning have recently been proposed to cope with this problem. Some notable examples are: logistic regression, support vector machine, Artificial neural networks.

Statistical models are increasingly applied to financial data mining tasks, including logistic regression, regression analysis, multiple discriminant analysis, and Probit method, ext. [20]Regression is when we want to predict a continuous attribute, the predicted attribute can take infinite values; The most well-known and used regression type in the banking sector is linear regression [16]. On the other hand, when the attribute to predict is discrete, it is called classification. Despite the name, logistic regression is a method of classification, except it regresses on discrete attributes. The advantage is in addition to returning the predicted attribute, the algorithm returns a confidence indicator related to the prediction. In cases where we want to predict the presence, or absence, of a characteristic, or outcome, based on the values of a set of predictor variable, logistic regression might be useful [15]. In [24] the authors have compared various traditional model for a binary classification credit scoring system, logistic regression is found to be the most accurate of traditional methods.

SVMs approaches, in the other hand, are based on structural risk minimization. Using a nonlinear mapping, the input data is transformed into a multidimensional feature space. Support vector machines (SVM) were introduced in 1988 by Vapnik [18], and presented as a state-of-the art technique for solving binary classification problems. Over the last few years, there have been many researchers about the use of SVMs in financial binary classification related problems [17]. Using SVM, Sheng-Tun Li, demonstrated an evaluation of consumer loans, overcoming the over-fitting and local optimum in Artificial NN based models [13].

Some of the first and notable works on loan data using ANN is presented by Herbert L. Jensen, who used back-propagation neural network running on a DOS personal computer with 125 credit applicants whose loan outcomes are known. Applicant characteristics are described as input neurons, receiving values of the individuals demographic and credit info. This method was promising, with a 76%-80% of correctness of the sample used [10].

Various works followed using neural network for loan approval and credit scoring. Notably [24], a paper where the authors have presented an extensive review of five neural network models (learning vector quantization, multilayer perceptron, fuzzy adaptive resonance, mixture-of-experts, and radial basis function), it has been demonstrated that the multilayer perceptron was not the most accurate neural network model, and that basis function neural network models could be considered for this kind of problems.

Since Deep learning is a new approach in machine learning, there is not much work on loan approval. In a recent paper a peer-to-peer crowd-lending system bases on a deep learning architecture is presented. Deep Credit [8] acquires credit risk knowledge automatically form the sequences of activities that users conduct on the site. The model was proven to give high accuracy in predicting both good and bad loan risks. An other recent work [9], where the authors have used a multilayer perceptron with 2 hidden layers, for a loan default prediction. The proposed method was tested on a Lending club bank data, and proven to outperform other traditional classifiers.

As mentioned above, to the best of our knowledge, there is no much references that deals with this data problem in a real-time approach by using deep learning. To cope with this problem, in this work we propose two contributions. In the first one, we develop a new real-time deep learning approach based on auto-encoder [27].

In our second contribution, we propose a thorough analysis and comparison with some typical binary classification algorithms. Tab. IV shows our motivation behind the chosen algorithms for benchmark.

III. Our Real-time Classification approach

A. Prediction model

Our approach is based on a two stages classification method: first, our ML model is built by a periodical offline training of the historical data : By a feature engineering process, the loan data is transformed into labels and features for our ML classification. Next, The data is split into two sets, for test and training. The models are then built with the training labels and features. Afterward, our models are tested with the test features to obtain our first predictions. The test prediction is then compared with our test labels. This process is repeated multiple times until we get a satisfying accuracy. The second stage consists of a live classification process : the built models are then used for predictions on a live stream of new data. Fig. 1 shows the methodology followed to produce the results. The following technologies were used to build our model:

- Tensorflow : to build and set up our machine learning model
- Kafka : to build and set up our Real-Time streaming data pipeline.
- Memsql : As data pipelines.

The different level of implementation of the technologies in our live classification model is shown in Fig.2.

For implementation, experiment and analysis the following environment were used: GPU GTX 660, Memory 8 GB, Python 3.5, Keras over Tensorflow Back-end.

TensorFlow is an open-source software library for machine learning over a range of tasks. It is a symbolic math library, and also used as a system for building and training neural networks to detect and decipher patterns and correlations. [28]

Keras is an open source neural network library written in Python. It is capable of running on top of MXNet, Deeplearning4j, Tensorflow, CNTK or Theano [29].

Kafka is an Apache distributed streaming platform. It's an useful tool for building real-time streaming data pipes lines, that reliably get data between systems. Moreover, it is used to build real-time streaming application that react to streams of data and transforms it.

Memsql is a distributed SQL data base. Memsql being widely used with Apache Kafka, documentation about its implementation is extensively available.

B. Deep auto-encoder

For constructing our deep neural network we used an Auto-Encoder. Auto-Encoders are neural networks with an equal input and output. see Fig. 3. An Auto-encoder consists of two part, the encoder and the decoder :

- Encoder : compressing of the input into a fewer number of bits. This part of the network is called the bottleneck , due to the fewer number of neurons. It is also called the "maximum point of compression" since the compression at this point is at its maximum. We call These compressed bits an "encoding" of the input.

TABLE I
Data-set features

Data set Characteristics	Multivariate
Attribute characteristics	Categorical, Integer
Associated Task	Classification
Number of instances	1000
Number of Attributes	20
Missing Values	N/A

- Decoder : reconstructing the input using the encoding of the input. We consider an encoding successful when the decoder is able to reconstruct the input exactly as it has entered the encoder.

In this work, for the encoding and decoding of the input to the output we are using an hyperbolic function "tanh". The equations are presented below: Encoder

$$h(x) = tanh(W_x) \tag{1}$$

Decoder

$$\hat{x} = tanh(W * h(x)) \tag{2}$$

Back-propagation is used to reconstruct the error; the error signal is calculated and propagated backwards in the network. In our experiment the errors from the desired and actual output is used as a condition. Parameter gradients is applied for the back-propagation realization.

C. Deep Neural network

For building our Auto encoder Deep Neural Network we used three encoders and three decoders, totaling six hidden layers.Fig. 4 shows The composition of the neural network. Due its high AUC, "Tanh" has been used in every hidden layer for the Auto-encoder neural network as an activation function.

IV. Experimental Results

A. Data-set

The data-set Used is the German Credit, which is a publicly available data set from the UCI machine learning Repository [30]. The data specifications are shown in Tab. I and its attributes descriptions in Tab. II

All values were changed to Integer numbers for confidentiality. The data attributes are classified into numbers, see column "Type" in Tab. II. Some of the values were dropped due to their uselessness in the study.

This Data-set classifies people described by a set of attributes as good or bad credit risks. Fig.3 shows The distribution of the data. As shown the Data-set is well balanced.

The Data set is split into training and test sets. For a performance check of the pretrained model, we divide the data into two separate sets for training and one independent test set for the final model comparison. See Tab. III.

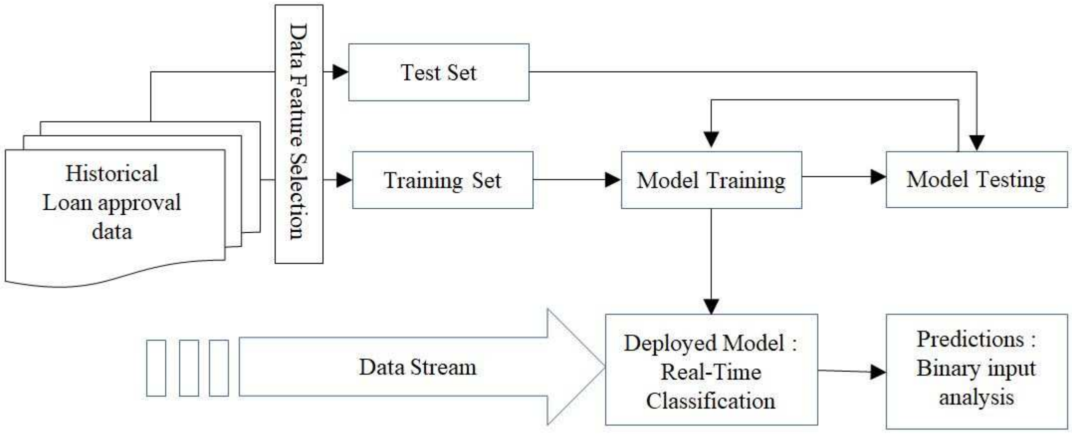

Fig. 1. Our architecture of the Real-Time classification model

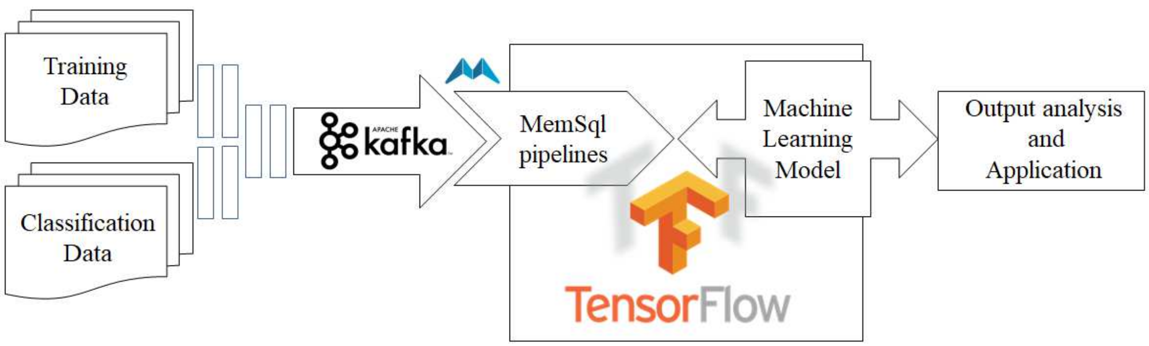

Fig. 2. Implementation model of the live data classification technologies used.

TABLE II
DATA-SET ATTRIBUTES

Variable name	Description	Type
Creditability	Yes, No	0 or 1
Account Balance	No account, None, Some Balance	1, 2, 3
Duration	In month	Integer
Payment Status of Previous Credit	Some Problems, Paid Up, No Problems	1, 2, 3
Purpose	New car, Used car, Home Related, Other	1, 2, 3,..10
Credit Amount	Amount	Integer
Value Savings/Stocks	None, Below 100 DM, [100,1000] DM, Above 1000 DM	0, 1, 2, 4
Length of current employment	In years	Integer
Instalment per cent	percentage	0 - 100
Sex & Marital Status	Male Divorced/Single, Male Married/Widowed, Female	1, 2, 3, 4, 5
Guarantors	None, Yes	0 or 1
Duration in Current address	In years	Integer
Most valuable available asset	Amount	Integer
Age	Years	Integer
Concurrent Credits	Other Banks or Dept Stores, None	Integer
Type of apartment	dropped	None
No of Credits at this Bank	1, More than 1	Integer
Occupation	Type of occupation	Integer
No of dependents	dropped	None
Telephone	dropped	None
Foreign Worker	Yes, No	0 or 1

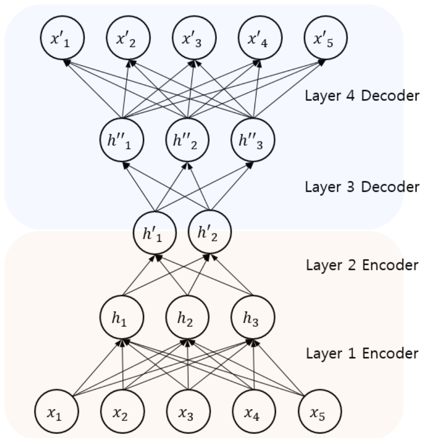

Fig. 3. Auto-encoder

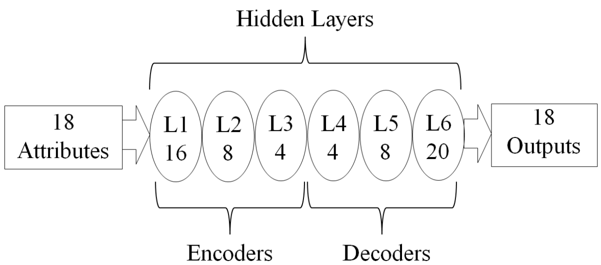

Fig. 4. Neural network design: Each hidden layer is denoted by L1, L2... followed by the number of neurons in each layers

B. Paradigms

To test the effectiveness of our model, three different binary classification methods are used for benchmark, totaling 4 typical algorithm models. The methods used for benchmark were chosen by their redundancy and good results in various binary classification research papers. Although the loan approval criteria differs from one institution to another, the use of linear models is well known in the banking and loan sectors [15] [16]. Accordingly in this work, we have selected linear SVM regression as one of the comparison paradigms, as well as logistic regression. In recent studies, SVMs have drawn a lot of attention, showing major performances as classifiers. Nevertheless, non linear regression ANN has shown good results in comparison with other linear models [24]. therefore, we have also selected a non linear artificial neural network algorithms as a benchmark. See Tab. IV.

TABLE III
INSTANCES DISTRIBUTION

Number of Instances	1000
Number of Instance for Pre-training	400
Number of Instance for Training	400
Number of Instance for Test	200

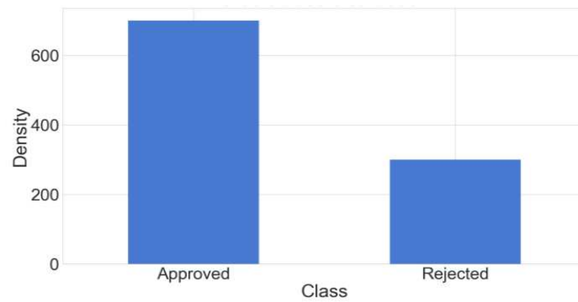

Fig. 5. Data set distribution

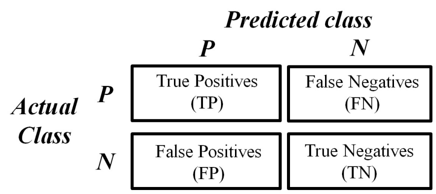

Fig. 6. Confusion Matrix illustration

C. Performance metrics

As benchmark metrics we used confusion matrices presented in a column chart, precision, recall and F1 score for each algorithm. The confusion matrix of a classical binary classifier is a two by two table showing the number of instances classified correctly and incorrectly for each class. An illustration of the confusion matrix for a binary classifier is shown in Fig. 6.

In our case, positive represents the good risks and negative represents the bad risk. True positive (TP) represents the good risk data classified as loan approved. True negative (TN) represents the bad risk data classified as loan rejected. False positive (FP) represents the misclassified good risk data as loan rejected. False negative (FN) represents the misclassified bad risk data as loan accepted.

The precision is the measure of the exactness of the model. It is defined as the number of positive predictions divided by the total number of positive class predicted by the model. See equation below:

$$Precision \quad = \quad TP/TP + FP. \tag{3}$$

The recall is the measure of the completeness of the model. It is defined as the number of positive predictions divided by the number of positive class values of the test data. See equation below:

$$Recall \quad = \quad TP/TP + FN. \tag{4}$$

To convey the balance between our precisions and recalls, F1 scores are calculated for each algorithm. This latter is defined as follow:

TABLE IV
COMPARISON ALGORITHMS

Support Vector Machine	Linear SVM Regression	SVM has shown better result than traditional neural network models in general performance, especially in binary classification and loan scoring application [25] [26]
Regression	Logistic Regression	As mentioned in section 2, in [23] the author used logistic regression in a credit scoring model, the latter is found to be the most accurate in comparison of the traditional methods
Classical ANN	Non Linear Auto regression NN	Using non linear regression ANN has been proven to surpass other linear models [24]
Deep Learning	Deep Neural network (DNN) based on Auto-encoders	In addition to being data-specific, Auto-encoders don't need specific labels to train on, the labels are auto generated withing the model. Due to the diversity of the loan applicant data, we believe that auto-encoders is the most fitted for this task.

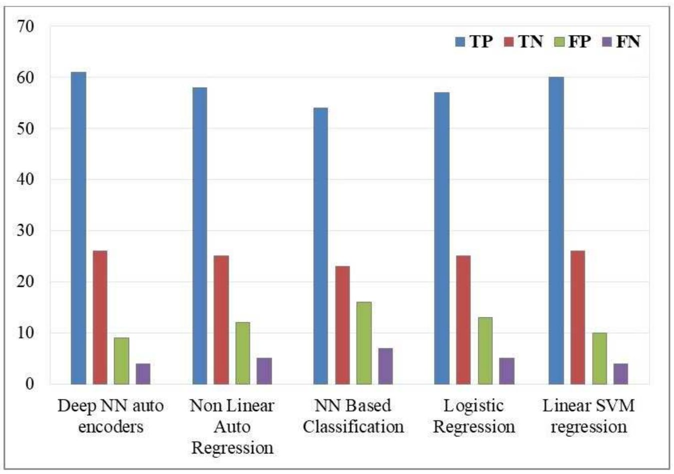

Fig. 7. Paradigms comparison

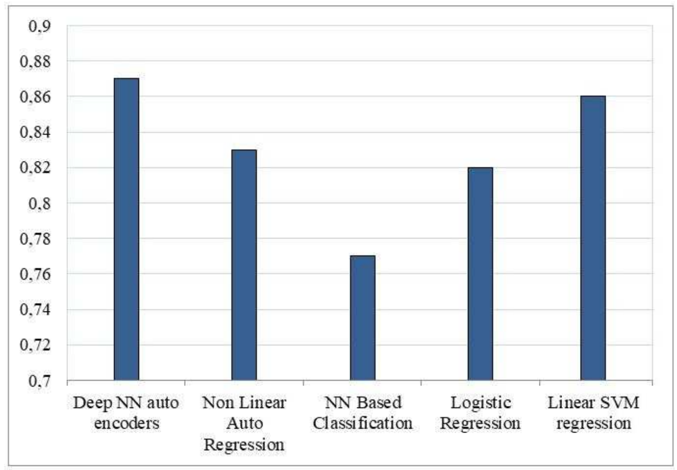

Fig. 8. Accuracy of each algorithm

$$F1Score = 2\dot{(}(precision * recall)/(precision + recall)). \quad (5)$$

D. Results

Fig. 5 shows the experimental result of our implemented algorithms. Each algorithm was tested four times and we presented the average result. For each algorithm we calculated the confusion matrix, and conveyed the TP FN FP TN values on a column graph. Deep learning has the lowest false flags overall, meaning the lowest rate of bad loan classified as good and good loan classified as bad, which in our case of study, is promising and beneficial for minimizing loan loss. Let's see the other metrics. Fig. 8 shows the accuracy of each algorithm; the accuracy is determined by dividing the correct predictions made by the total number of all predictions made.

The data shows that the Deep Learning has the best accuracy. But since the accuracy can be miss leading due to its dependencies (accuracy paradox) [32], we shouldn't draw conclusions. Recall and precision are shown in Fig. 9.

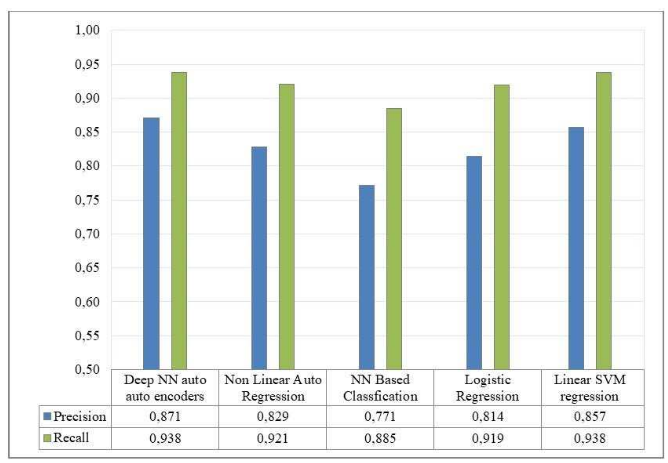

Fig. 9. Results metrics comparison

The results show that Deep learning with Auto-encoder, gives the best result in this case of study followed by linear Kernel SVM Regression with almost a similar result. The deep learning algorithm used in this study is fairly simple; we may get better results with some more tuning of the parameter (Hyper-parameter Tuning with Grid Search). Tab. V shows F1 scores results of the conducted experiment, which confirms that the Auto Encoder is the best classifier, followed by the other algorithms.

TABLE V
F1 SCORES RESULTS

Classifier	F1 score
Deep NN with auto encoders	0,904
Linear SVM regression	0,896
Non Linear Auto Regression	0,872
Logistic Regression	0,864
NN Based Classification	0,824

E. 8-fold cross validation

To validate the stability of our results, we are using a 8-fold cross validation on the Deep learning Auto-Encoder. See Tab. VI.

TABLE VI
DEEP LEARNING WITH AUTO-ENCODER 8-FOLD CROSS VALIDATION)

False	Number of instance	error
138	948	0.14556
160	951	0.16824
171	942	0.18152
131	936	0.13995
144	934	0.15478
141	949	0.14892
150	925	0.16243
137	934	0.14763
	Error Average	0.15612

Form results presented above in this paper, it is clear that Deep Learning with Auto-Encoder has the best performance within this case of study, since it provides the best accuracy and precision among the tested methods. Our experiments gives us good insight into the algorithm choice for building our prediction model, and we choose Deep Neural network with Auto-encoder as the final method.

V. CONCLUSION

In this paper we proposed : a Real-time classification method for a real-life data set of loan approval, using Deep learning. After a test and a comparison study on the performance, of some typical real-time binary classifiers versus Deep learning with auto-encoder, the benchmark experiment shows that Deep learning has very promising result. in his case of study, our model on auto-encoder demonstrated the best F1 score. The experiment confirmed that, although the well known performance of SVM for binary classification, Deep learning out performs it. The proposed Framework can be used by loan providers, to select the best candidates for a loan credit in Real-Time. Deep Learning have gained much prominence in the recent years due to its performance in different fields. Although we used a basic Deep Learning method in our benchmark we had a very good result. Hence we believe that with more tuning of the hyper-parameter, deep learning will show even better results. Therefore, our future studies will mainly focus on state of the art Deep Learning paradigms for this type of Real-time Data Classification problems.

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