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A proposed model for loan approval prediction using XAI

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Abstract

With the rapid growth in the banking sector due to the current inflation in Egypt, many people go to the bank for a loan. This paper proposes a model which predicts loan approval of bank applicants using explainable artificial intelligence, this study is based on the "Give Me Some Credit" dataset with more than 120k rows so the paper could train the model on earlier records of bank applicants that applied before for a bank loan.

Keywords—: Loan, XAI, prediction, machine learning, banking sector

Introduction

In the era of rapid communication technology developments which ease for any person to communicate with anybody all over the world, also has a great impact on different domains, for example in the financial sector, the use of technologies facilitates payments, depositing, and withdrawing cash and it improved with the development from 1G to 5G and the future is 6G [1], the banks seek to invest their assets in safe hands and grant loans to those who can repay them, so loan prediction is a problem that needs to be solved. Also, the number of clients is increasing yearly, so how to provide services and products that enhance customers' profits. Another dimension is that people are relying on personal loans to cover unplanned expenses with growth improving to 19.5% in August 2022 from 12.8% a year ago [2] [3]. The number of consumer credits in Egypt increased from approx. EGP 270,000 million in 2018 to approx. EGP 700,000 million in 2022 [2], this paper is going to talk about the bank's loan, which is one of the important factors that affect Egypt's economy.

Background and Literature Review

Machine Learning Algorithms used to analyze bank's credit data:

- Random Forest (RF): A combination of tree predictors, each tree depends on the values of a random vector sampled independently, and all the trees in the forest have the same distribution, used for both classification and regression problems [4].

- Decision Trees: Used for both classification and regression problems but it is more used for classification where it consists of a tree structure, the dataset is at the root node and other attributes are placed at the leaf node, where each node is a decision took place giving the results at the leaf node [5].

- Support Vector Machine (SVM): A supervised machine learning algorithm that can be used for both classification and regression problems, widely used in classification problems, in which every data item is represented as a point in n-dimensional space where n is the number of features split by a line to differentiate between differently classified groups [6].

• Logistic Regression (LR): A supervised machine learning algorithm that is used for classification problems, the Logistic Regression is used to predict the likelihood of a categorical dependent variable and the dependent variable is a binary variable coded as 1(true, yes, normal, etc.) or 0(false, no, abnormal, etc.) the Logistic Regression model is similar to a Linear Regression model, except that the Logistic Regression utilizes a more sophisticated cost function, which is known as the “Sigmoid function” or “logistic function” instead of a linear function also Linear Regression model is used for regression problems [7].

• Neural Network (N-Net): A nonlinear statistical modeling tool used to model complex relationships between input and output and find patterns in data, supporting classification and regression algorithms [8].

• Adaboost (ADB): short for Adaptive boosting, is an Ensemble method where it uses weak classifiers and combines them into a stronger one, each weak learn is represented as a decision tree with a single split which is called decision strumps, unlike the SVM Adaboost can learn a non-linear boundary so it can perform better than SVM if the data is not linearly separated also used for both classification and regression problems [9].

• Explainable Artificial Intelligence (XAI): A field of artificial intelligence (AI) that includes a set of processes, tools, techniques, and algorithms that allow humans to better understand and see the explanations of AI decisions which change the decision maker from a machine learning algorithm to be the human mind [10].

Proposed Model

In this paper, an XAI model has been applied to see its results in the bank loan approval classification problem, the components of the proposed model are presented in the following figure.

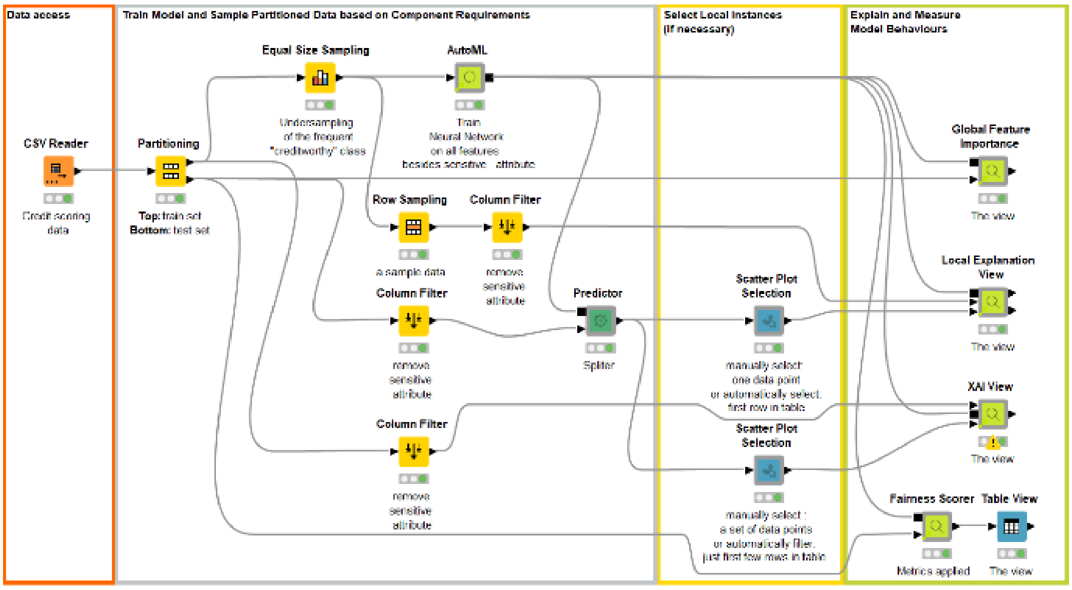


Figure 1, proposed model

A. Data Collection Phase

The data used in this work comprised 120270 records from the Kaggle repository [11], The data attributes include Creditworthiness, Debt-to-Limit Ratio, Age, Times in debt for 1-2 Months, Debt Ration, Monthly Income, Other Active Loans, Time in debt for 3 Months or More, Other Real Estate Loans, Time in Debt for 2-3 Months, Family Size, Gender.

B. *Data Preprocessing, Data filtering phase, and Classification phase*

Preprocessing is a crucial step for any machine learning model, firstly data partitioning was applied as follows: splitting the input table into two partitions top train set and the bottom test set. then the two partitions are available at the two output ports. Secondly, an equal-size sampling was utilized to ensure equal distribution of values in a categorical column by removing rows from the input data set of the same size. This feature helped in downsizing the data set so that the class attributes occur equally often in the data set. In this step, under-sampling the frequency of the creditworthy column in the table was applied two things in parallel were applied, column filter: This functionality enables the filtering of columns from the input table, ensuring that only the remaining columns are transmitted to the output table. Additionally, it includes an Auto Machine Learning component. By applying our black-box neural network algorithm, which is our main machine learning algorithm, this paper presents the implementation of a RProp Multi-layer Perceptron (MLP) neural network that has been trained using optimized values for the "Number of hidden layers" and "Number of hidden neurons per layer". to train our data on all features besides sensitive data was used then the output is going to the predictor node which takes the output from the Auto machine learning component and from the column filter to be an input in the Scatter plot to make our final step before showing the final result, in this phase two scatter plot selection was applied, the first one is manually selecting one data point or automatically select the first row in the table this step will lead to a final output the local explanation, the second scatter plot selection is manually selecting a set of data points or automatically filter just a few rows in the table in this step it will lead to the final step which is the XAI output the paper is going to talk about it in the next phase.

C. *Explaining and measuring model behavior Phase*

In this final phase, the paper will present the results gathered from each node and use them to demonstrate various measurement and explanation techniques. The first node discussed will be the global feature importance explanation, which will cover Global Surrogates, Permutation Feature Importance, and Partial Dependence Plot. The second node will focus on local explanations, including counterfactual explanations, Local Surrogates, ICE, and SHAP. The third node will explore explainability techniques (XAI) using four graphs: Partial Dependence Plot (PDP), Explanations Bubble Chart, Surrogate Decision Tree, and Explanations Feature Violins. The last node is the fairness score, which includes the demographic parity metric, equal opportunity metric, and equalized odds metric.

❖ Dataset:

This paper used a public Credit dataset for testing and training our XAI model which can be found in Kaggle under the name “Give Me Some Credit” [11], figure two shows each column in the dataset and each type and in Figure three a sample snapshot of the dataset including about 42 rows

		Column	New name	Type
⠿	☑	Creditworthiness		S String
⠿	☑	Debt-to-Limit Ratio		D Number (double)
⠿	☑	Age		I Number (integer)
⠿	☑	Times in Debt for 1-2 Months		I Number (integer)
⠿	☑	Debt Ratio		D Number (double)
⠿	☑	Monthly Income		I Number (integer)
⠿	☑	Other Active Loans		I Number (integer)
⠿	☑	Times in Debt for 3 Months or More		I Number (integer)
⠿	☑	Other Real Estate Loans		I Number (integer)
⠿	☑	Times in Debt for 2-3 Months		I Number (integer)
⠿	☑	Family Size		I Number (integer)
⠿	☑	Gender		S String

Figure 2, Dataset elements

Row ID	Creditworthiness	Debt-to-Limit Ratio	Age	Times in Debt for 1-2 Months	Debt Ratio	Monthly Income	Other Active Loans	Times in Debt for 3 Months or More	Other Real Estate Loans	Times in Debt for 2-3 Months	Family Size	Gender
Row0	credit-worthy	0.014	46	0	0.436	9828	13	0	3	0	1	Male
Row1	credit-worthy	0.401	50	0	0.224	6083	7	0	1	0	2	Male
Row2	credit-worthy	0.1	39	0	0.442	4500	10	0	2	0	0	Female
Row3	credit-worthy	0.118	72	0	0.551	1795	9	0	2	0	1	Female
Row4	credit-worthy	0.049	44	0	3,238	0	7	0	2	0	2	Male
Row5	credit-worthy	0.733	32	0	0.348	7916	10	0	0	0	0	Male
Row6	credit-worthy	1	23	0	0	1	1	0	0	0	0	Male
Row7	credit-worthy	0.319	32	1	0.281	6083	3	0	1	0	0	Male
Row8	credit-worthy	0.042	63	0	0.466	3500	12	0	2	0	0	Female
Row9	credit-worthy	0.067	45	0	0.275	7833	6	0	2	0	4	Male
Row10	credit-worthy	0.429	42	1	0.025	1000	2	0	0	0	0	Female
Row11	credit-worthy	0.346	49	0	0.141	4300	2	0	0	0	1	Male
Row12	risky	0.553	33	0	0.682	5416	7	0	2	0	0	Male
Row13	risky	0.018	62	0	0.192	8500	19	0	2	0	1	Female
Row14	credit-worthy	0.11	63	0	0.042	4468	9	0	0	0	0	Male
Row15	credit-worthy	0.002	61	0	0.333	14050	12	0	2	0	0	Male
Row16	credit-worthy	0.007	27	1	0.681	764	3	0	0	0	0	Male
Row17	credit-worthy	0.028	76	0	0.085	900	7	0	0	0	0	Female
Row18	credit-worthy	0.211	37	0	1.405	2000	7	0	2	0	1	Male
Row19	credit-worthy	0.014	51	0	0.416	3060	7	0	1	1	0	Female
Row20	credit-worthy	0.035	69	0	0.308	3400	9	0	1	0	0	Male
Row21	credit-worthy	0.212	30	0	0.007	5583	2	0	0	0	0	Female
Row22	credit-worthy	0.013	67	0	0.273	6146	16	0	1	0	0	Male
Row23	credit-worthy	0.024	79	0	0.073	5500	9	0	1	0	0	Male
Row24	credit-worthy	0.056	55	0	0.238	15000	3	0	2	0	2	Female
Row25	credit-worthy	0.05	31	0	0.03	77274	6	0	1	0	0	Male
Row26	credit-worthy	9,684	45	1	0.423	9583	6	0	2	0	1	Male
Row27	credit-worthy	0.021	73	0	0.019	1666	11	0	0	0	0	Male
Row28	credit-worthy	0	55	0	0.148	12500	15	0	1	0	1	Male
Row29	credit-worthy	0	45	0	0.336	9974	5	0	3	0	0	Male
Row30	credit-worthy	0.615	57	0	0.53	5800	10	0	2	0	0	Male
Row31	credit-worthy	0.013	68	0	0.139	6661	14	0	1	0	1	Male
Row32	risky	0.049	62	1	0.414	11666	15	0	2	0	1	Male
Row33	credit-worthy	1	39	0	0.363	3000	1	0	1	1	2	Female
Row34	credit-worthy	0.198	61	0	0.348	5750	19	0	2	0	0	Male
Row35	credit-worthy	0.001	59	1	0.012	12161	20	0	1	0	0	Male
Row36	credit-worthy	0.042	44	0	0.206	29361	11	0	3	0	2	Male
Row37	credit-worthy	0.094	57	0	0.018	1250	6	0	0	0	0	Male
Row38	credit-worthy	0.031	65	0	0.268	8083	9	0	1	0	0	Male
Row39	credit-worthy	0.443	57	2	0.556	4150	12	0	2	0	1	Female
Row40	credit-worthy	0.147	73	0	645	0	9	0	0	0	1	Female
Row41	credit-worthy	0.234	48	0	0.293	5450	10	0	1	0	1	Male
Row42	credit-worthy	0.019	81	0	0.014	1800	5	0	0	0	0	Male

Figure 3, Dataset sample snapshot

Experimental study

To examine the proposed model, the paper used fairness, in this section, the paper conducted an experimental study to test the proposed model using fairness metrics. These metrics include demographic party, equal opportunity, and equalized odds. The paper utilized two confusion matrices [12] based on two partitions split into sensitive attribute classes: protected and unprotected partitions. The three metrics were computed using values and statistics from the two confusion matrices. For Demographic Parity and Equality of Opportunity fairness types, the model favors the protected partition if the metric is greater than 1 + ε, and it favors the unprotected partition if the metric is less than 1 - ε.

The Demographic Parity Metric computes the ratio of advantage class predictions overall predictions for each partition. The final metric is the division between the two ratios, which ignores ground truth data. The Equality of Opportunity Metric checks whether the classifier predicts the advantage class with the same performance for both protected and unprotected classes when considering false negatives. The True Positive Rate (TPR) from the confusion matrices is divided by the protected one by the unprotected one to compute the metric. The protected class is an advantage if this metric is greater than 1.

The Equalized Odds Metric checks whether the classifier predicts the advantage class with the same performance for both protected and unprotected classes regardless of the type of misclassification. It considers both false positives and false negatives. The metric is computed by taking both the TPR and True Negative Rate (TNR) from the confusion matrices, computing the differences between TPRs and TNRs, and normalizing between 0 and 1. TPR and TNR values do not vary between protected and unprotected partitions if the metric is close to one.. [13] This work simulates the proposed model to predict the loan's approval. All experiments were executed on a Processor: 2.5GHz Intel core i7 11th generation, 24.0MB cache, RAM: 32 GB 3200 MHz DDR4, Operating system: Windows 10, Hard Disk: Samsung SSD PM991a 512GB. The experiments used the KNIME Analytics Platform.

Table 1 Fairness Matrix of the three metrics applied

Metric Name	Metric Value	Status
Demographic Parity	0.9063425935074552	Passed
Equality of Opportunity	1.0222660471703746	Passed
Equalized Odds	0.9714091885091273	Passed

Performance and Evaluation Measure

First, the result of the global feature, is a Global Surrogate Generalized Linear Model (GLM) which is a trained model used to estimate the forecasts of the primary model. The GLM has been created through the utilization of KNIME H2O Machine Learning Integration. The input data has undergone standard pre-processing with optimized parameters "lambda" and "alpha" prior to being used for training purposes. The model type employed in this instance is binomial. The surrogate model was trained successfully with an ***F-measure*** equal to ***0.976*** to the original model predicted class of interest ***"Creditworthiness: credit-worthy"***.

GLM coefficient size shows feature importance. A positive (negative) coefficient means that a higher feature value leads to a higher (lower) probability of the event (***Creditworthiness*** is ***credit-worthy***). An increase of a normalized feature value by one-unit accounts for a change in the odds (probability of event divided by the probability of no event) ratio of exp(coefficient).

A Global Surrogate Decision Tree is a Decision Tree model trained to approximate the predictions of the original model. The decision tree has been trained using input data that has been pre-processed according to standard procedures, and the parameter "Min number records per node" has been optimized.

The surrogate model was trained successfully with an ***F-measure*** equal to ***0.984*** to the original model predicted class of interest ***"Creditworthiness: credit-worthy"***.

The diagram is showing the splits in the decision tree. By interacting with it you can visualize the decision process of the surrogate model. The features used at the top of the diagram have higher feature importance than the ones at the bottom.

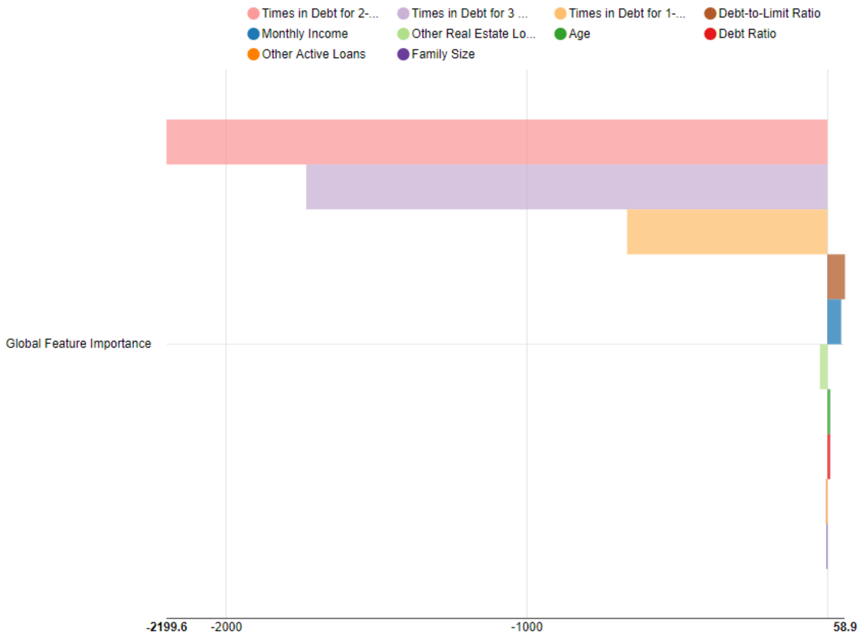


Figure 5, Surrogate Decision Tree

A Global Surrogate Random Forest is a type of Random Forest model that is trained to approximate the predictions of the original model. The model is trained using standard pre-processed input data with optimized parameters such as "Tree Depth," "Number of models," and "Minimum child node size. The surrogate model has been successfully trained with an F-measure of 0. 84 for the predicted class of interest, "Creditworthiness: credit-worthy. The significance of a feature is established by tallying the number of times it has been chosen for a split, and its position in the order of available features within the random forest's trees. A higher count indicates a higher level of importance for that feature.

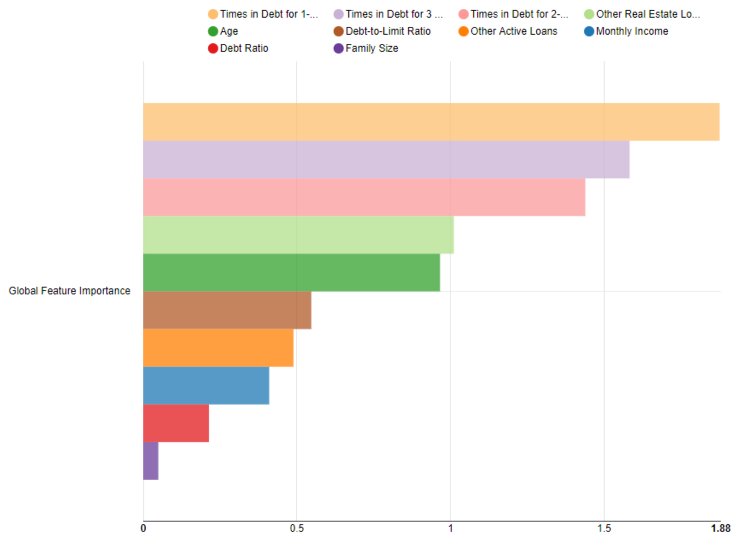


Figure 6, Surrogate Random Forest

Figure 6 shows the Surrogate Random Forest. Permutation feature importance is calculated by calculating the disparity between the model performance score, which is computed based on predictions using all the original features, and the model performance score calculated using all the original features except one. In the latter case, the feature that is excluded is randomly permuted. If a particular feature is permuted multiple times, the average difference is determined. The permutation feature importance was computed successfully by using the ***F-measure*** and the class of interest ***"Creditworthiness: credit-worthy"***.

A large score difference shows that the feature was important for prediction since breaking the relationship between this feature and the target decreased the model performance. The difference around zero means that permuting the feature does not decrease the performance of the model. The negative difference shows that, for some reason, permuting the feature increases the model performance.

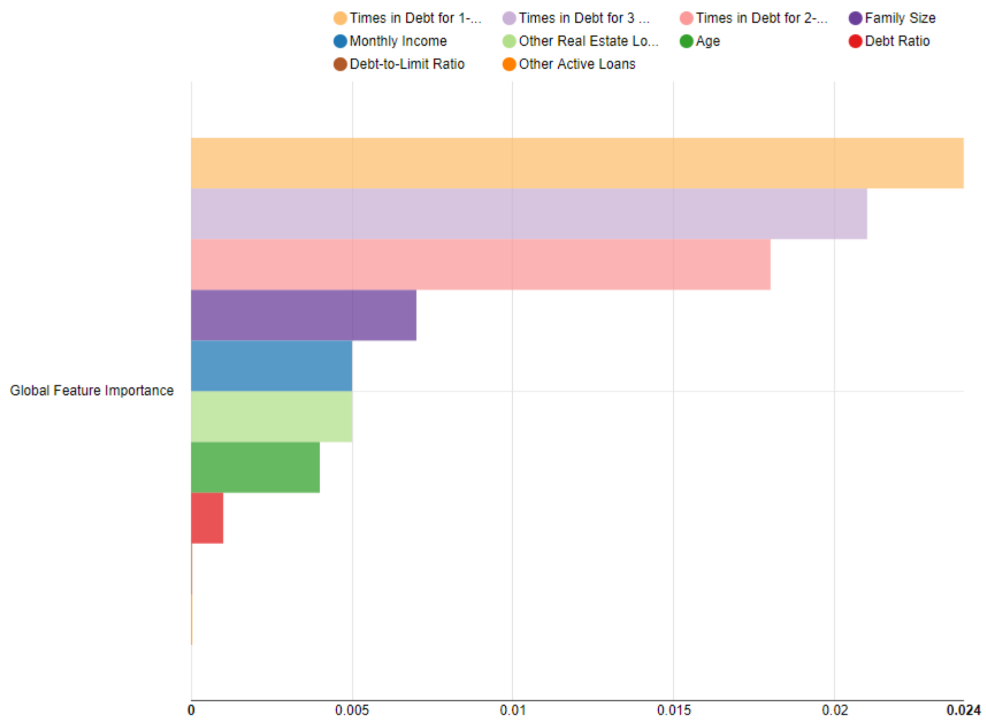


Figure 7, Permutation Feature Importance

Secondly, the results of the local explanation, in the following figure a Bar Chart displaying the impact of each input feature on the model prediction, these values are available as the first table output. Additionally, a list of Counterfactuals Instances is provided in a Tile View for comparison to the original instance.

Debt-to-Limit Ratio	Age	Times in Debt for 1-2 Months	Debt Ratio	Monthly Income	Other Active Loans	Times in Debt for 3 Months or More	Other Real Estate Loans	Times in Debt for 2-3 Months	Family Size	MODEL PREDICTION
0.937151835	49	0	0.266933267	3999.9999999999995	1	3.0000000000000004	0	0	7.000000000000001	risky

Figure 8, Original data point (The original prediction around which input model behavior is explained)

In the following figure, a bar chart displays the feature importance for the original data sample and similar data points. The displayed values are the normalized coefficients from a surrogate GLM, which was trained on a neighborhood of similar data points to mimic the original model's local behavior.

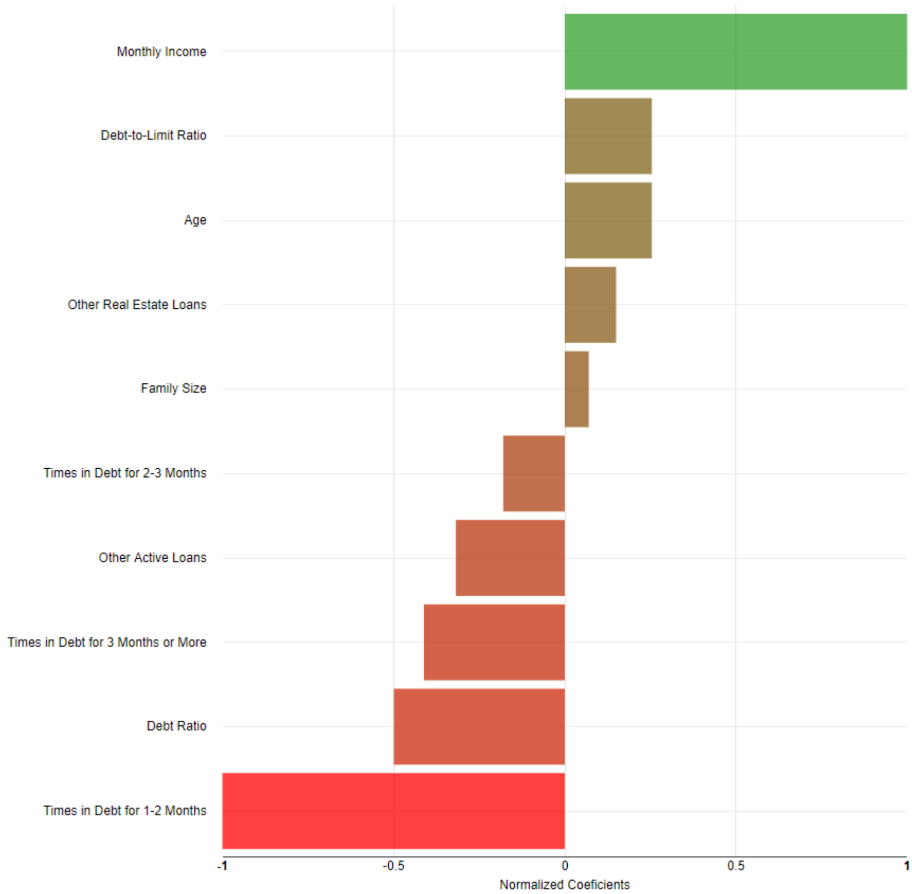
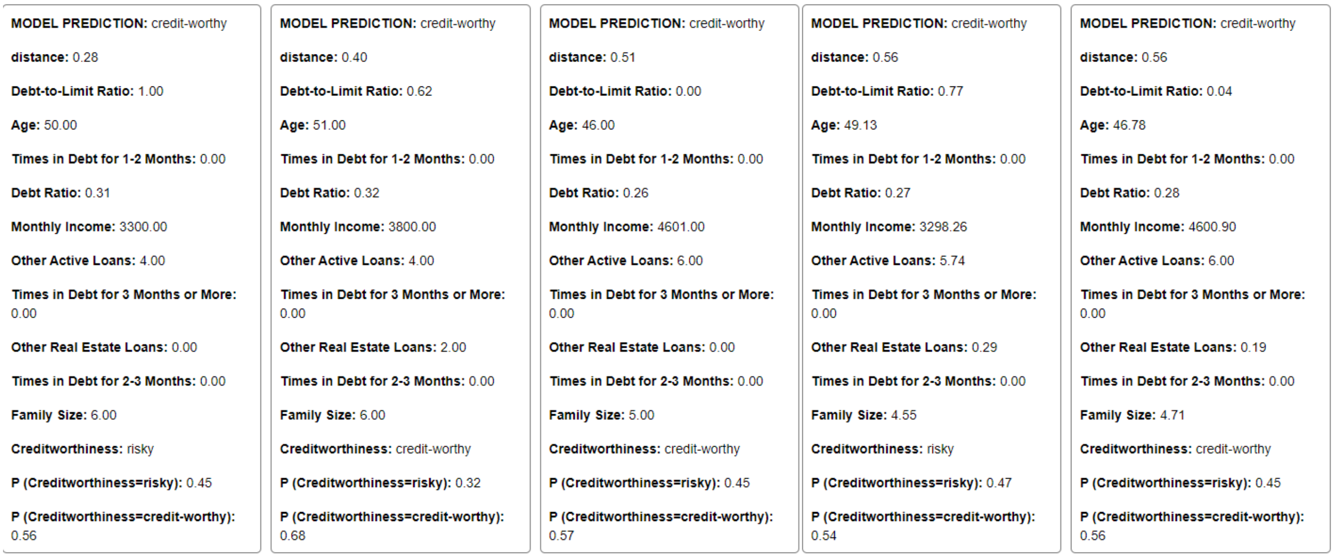


Figure 9, Local Feature Importance

The following figure shows the input data points resulting in the configuration dialog's desired model prediction set. They are sorted by distance to the original sample point, so the most similar counterfactuals are displayed first. the classification probability output can be shown by the input model for each counterfactual data point.



MODEL PREDICTION: credit-worthy	**MODEL PREDICTION:** credit-worthy	**MODEL PREDICTION:** credit-worthy	**MODEL PREDICTION:** credit-worthy	**MODEL PREDICTION:** credit-worthy
distance: 0.28	**distance:** 0.40	**distance:** 0.51	**distance:** 0.56	**distance:** 0.56
Debt-to-Limit Ratio: 1.00	**Debt-to-Limit Ratio:** 0.62	**Debt-to-Limit Ratio:** 0.00	**Debt-to-Limit Ratio:** 0.77	**Debt-to-Limit Ratio:** 0.04
Age: 50.00	**Age:** 51.00	**Age:** 46.00	**Age:** 49.13	**Age:** 46.78
Times in Debt for 1-2 Months: 0.00	**Times in Debt for 1-2 Months:** 0.00	**Times in Debt for 1-2 Months:** 0.00	**Times in Debt for 1-2 Months:** 0.00	**Times in Debt for 1-2 Months:** 0.00
Debt Ratio: 0.31	**Debt Ratio:** 0.32	**Debt Ratio:** 0.26	**Debt Ratio:** 0.27	**Debt Ratio:** 0.28
Monthly Income: 3300.00	**Monthly Income:** 3800.00	**Monthly Income:** 4601.00	**Monthly Income:** 3298.26	**Monthly Income:** 4600.90
Other Active Loans: 4.00	**Other Active Loans:** 4.00	**Other Active Loans:** 6.00	**Other Active Loans:** 5.74	**Other Active Loans:** 6.00
Times in Debt for 3 Months or More: 0.00	**Times in Debt for 3 Months or More:** 0.00	**Times in Debt for 3 Months or More:** 0.00	**Times in Debt for 3 Months or More:** 0.00	**Times in Debt for 3 Months or More:** 0.00
Other Real Estate Loans: 0.00	**Other Real Estate Loans:** 2.00	**Other Real Estate Loans:** 0.00	**Other Real Estate Loans:** 0.29	**Other Real Estate Loans:** 0.19
Times in Debt for 2-3 Months: 0.00	**Times in Debt for 2-3 Months:** 0.00	**Times in Debt for 2-3 Months:** 0.00	**Times in Debt for 2-3 Months:** 0.00	**Times in Debt for 2-3 Months:** 0.00
Family Size: 6.00	**Family Size:** 6.00	**Family Size:** 5.00	**Family Size:** 4.55	**Family Size:** 4.71
Creditworthiness: risky	**Creditworthiness:** credit-worthy	**Creditworthiness:** credit-worthy	**Creditworthiness:** risky	**Creditworthiness:** credit-worthy
P (Creditworthiness=risky): 0.45	**P (Creditworthiness=risky):** 0.32	**P (Creditworthiness=risky):** 0.45	**P (Creditworthiness=risky):** 0.47	**P (Creditworthiness=risky):** 0.45
P (Creditworthiness=credit-worthy): 0.56	**P (Creditworthiness=credit-worthy):** 0.68	**P (Creditworthiness=credit-worthy):** 0.57	**P (Creditworthiness=credit-worthy):** 0.54	**P (Creditworthiness=credit-worthy):** 0.56

Figure 10, The Counterfactuals

Finally, the XAI results, The Explainable Artificial Intelligence (XAI) view is a useful tool to comprehend the decision-making mechanism of a black-box model. This component is designed for the purpose of developing machine learning classifiers. with binary and multiclass targets and generates an interactive dashboard view that visualizes explanations for a set of instances provided, as well as other charts and Machine Learning Interpretability (MLI) techniques. The component has the capability to calculate SHAP explanations, Partial Dependence Plot (PDP), Individual Conditional Expectation (ICE) curves, and surrogate decision tree view. These features aid in explaining the prediction by determining the contribution of each feature to the said prediction.

The interactive dashboard enables users to choose explanation bubbles, which will display the corresponding predictions highlighted in the other views. But if the component is nested, more charts can be added to visualize its output in other ways. To use this component, users must supply a sample of the dataset used to train a model, the model itself, and a set of instances (rows) from the test set.

With regards to the data input requirements, it is imperative that both the top and bottom port input data tables contain identical columns, except for the target column. In the case of the bottom port, the target column can be omitted if necessary. It is important to note that the bottom input, which includes instances to be explained, should not contain more than one hundred rows. This is because additional rows would not only clutter the visualization but also increase the time required for computation. When it comes to requirements for black-box models, it is recommended to utilize the Auto Machine Learning component to assess the XAI View. However, any model that behaves as a black box and is captured with Integrated Deployment can be explained by the component. The model must have a single input and output of Data type, with all feature columns provided at the input. Additional columns that do not feature may also be provided at the input. The output should contain all input data (features and non-features) and present attached output predictions columns. The output predictions should consist of one String type and "n" Double type, where “n” is the number of classes in the target column. The String type prediction column should be named “Prediction([T])”, where [T] is the name of the target class. The Double type of prediction columns should be named “P ([T]=[C1])”, “P ([T]=[C2]) “and” P (T=[Cn])”, where [Cn] is the name of the class that the probability is predicting. In this paper, the black-box algorithm used for the model was the Neural Network, the target column in the dataset is Creditworthiness, its type is Binary, and the value of the class is credit-worthy.

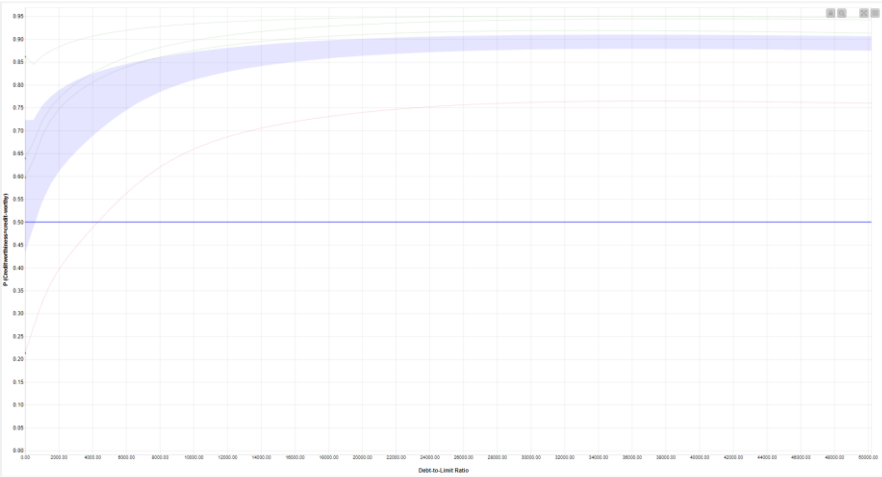


Figure 11, Partial Dependence Plot (PDP)

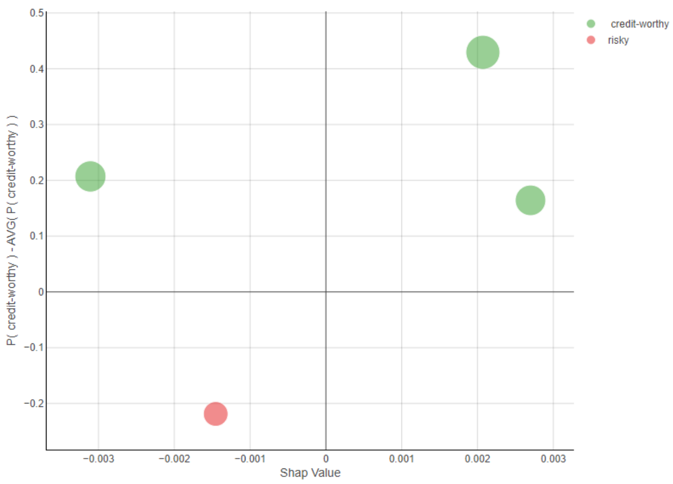


Figure 12, Explanations Bubble Chart

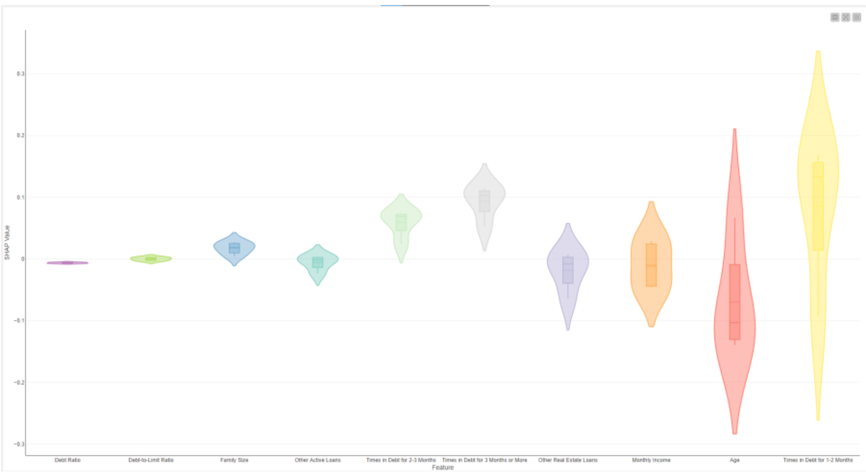


Figure 13, Explanations Feature Violins

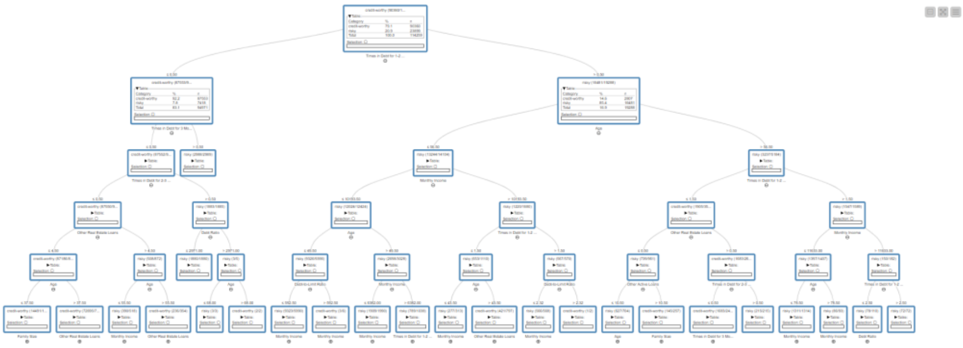


Figure 14, Surrogate Decision Tree

Conclusion and future direction

This paper shows the importance of applying the XAI model to the loan approval prediction problem. It showed the potential difference between different outputs like SHAP, ICE, PDP, local explanations, and global explanations, this approach helps decision-makers to understand their model results not just accepted or declined loans, so this will help not only bankers but also will help end-users to enhance their weakness if their loan was not accepted and was considered risky by the algorithm, In our future work, we plan to change the black-box algorithm and see the different results of a different algorithm rather than the used Neural Network algorithm.

Acknowledgment

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