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Credit Score Classification Using Machine Learning

Mosa M. M. Megdad, Samy S. Abu-Naser

Department of Information Technology,
Faculty of Engineering and Information Technology,
Al-Azhar University, Gaza, Palestine

Abstract: *Ensuring the proactive detection of transaction risks is paramount for financial institutions, particularly in the context of managing credit scores. In this study, we compare different machine learning algorithms to effectively and efficiently. The algorithms used in this study were: MLogisticRegressionCV, ExtraTreeClassifier,LGBMClassifier,AdaBoostClassifier, GradientBoostingClassifier,Perceptron,RandomForestClassifier,KNeighborsClassifier,BaggingClassifier, DecisionTreeClassifier, CalibratedClassifierCV, LabelPropagation, Deep Learning. The dataset was collected from Kaggle depository. It consists of 164 rows and 8 columns. The best classifier with unbalanced dataset was the LogisticRegressionCV. The Accuracy 100.0%, precession 100.0%,Recall100.0% and the F1-score 100.0%. However, the best classifier with balanced dataset was the LogisticRegressionCV. The Accuracy 100.0%, precession 100.0%, Recall 100.0% and the F1-score 100.0%.*

Keywords: Financial Transactions, Deep learning, Machine Learning

1. Introduction

Credit scoring, an essential practice in the financial industry, involves assessing individuals' creditworthiness based on various factors such as payment history, credit utilization, and length of credit history. Traditionally, financial institutions have employed manual methods and statistical analysis to evaluate credit scores and determine individuals' likelihood of repaying loans or managing credit responsibly. However, with the emergence of advanced data analytics and machine learning techniques, there has been a transformative shift in how credit scoring is conducted. By leveraging large datasets and sophisticated algorithms, financial institutions can now automate and refine the credit scoring process, enabling faster and more accurate assessments. This evolution has not only streamlined lending decisions but also enhanced risk management practices, resulting in improved customer experiences and reduced financial losses for lenders [2].

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves [1-10].

The process of learning begins with observations or data, such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that we provide [11-20]. The primary aim is to allow the computers learn automatically without human intervention or assistance an adjust actions accordingly [21-30].

Deep learning is a subset of machine learning in artificial intelligence that has networks capable of learning unsupervised from data that is unstructured or unlabeled [31-40]. Deep learning is a technique used to generate face detection and recognize it for real or fake by using profile images and determine the differences between them [41-50].

Machine learning has revealed to be very rewarding at detecting and classification of Credit Score[51-60]. In spite of the fact that supervised learning has been tremendously successful in detecting Credit Score, the progression of Credit Score analysis technologies will never end [2]. A Small enhancement in the classifier will save For companies interested in on credit a noteworthy amount of money.

2. Literature Survey

Numerous studies have discussed the fraudulent transactions. The study in [77] stated that the fast evolution of technology all around the world was more often used cards as compared to cash in their day to day life. The MasterCard became the highly useable equipment for Internet shopping. This up surged in use causes a considerable damage and fraud cases also. It was very much necessary to stop the fraud transactions because it impacted on financial conditions over time the anomaly detection was having some important application to detect the fraud detection. This paper is mainly focused on checking if the transaction was legal or fraud. They presented models like Bidirectional Long short-term memory and Bidirectional Gated recurrent unit. They also apply deep learning and Machine Learning algorithms. But their model shows much better results than the machine learning classifiers which was 91.37% score.

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The authors in [78] mainly focused on the solution that tackles the imbalance problem of classification they explore the solution for fraud detection using machine learning algorithms. They also find the summarized results and weakness that they get using credit card fraud labeled dataset. They give us the conclusion that the imbalanced classification is ineffective when the data are highly imbalanced. In this paper, the authors found that the existing methods were costlier and show many false alarms.

In the study [79] DT, LR, and RF algorithms were operated to measure the operation for credit card fraud identification. On behalf of a rather unbalanced dataset oversampling was required. After oversampling, 60% legal and 40% unlawful transactions are found. R language was used for the implementation of these algorithms. Accuracy of LR is 90.0%, RF 95.5%, and DT 94.3%. Sensitivity, error rates, and specificity are also measured. RF algorithm performs nicely amongst them.

In the study [80] an automatic classification and guide classification were used in fraud identification as properly as one of a kind ML algorithm is compared to pick out the frauds. RF, SVM, and LR were used. They find out about targets to advance a threat scoring model. All the algorithms were tested and RF was performed properly and accomplished with the best possible accuracy. And this algorithm was effortless to practice and works precisely on a massive dataset. The result confirmed that sort of algorithm performs very properly in the real-world.

In the study [81] some ML algorithms were proposed to test the performance of fairly unbalanced data. SVM, RF, DT, and LR are operated to take a look at the potential. These algorithms were examined on pre-processed and uncooked data. The accuracy of these algorithms was SVM 97.5%, RF 98.6%. DT 95.5% and LR 97.7% respectively. The RF performs very well on a large quantity of information however it suffers from speed. If records are more pre-processed then SVM can work properly amongst them.

In the study [82] SVM was used to identify transactions as valid or fraudulent. The SVM analyzed the past transaction habits of the cardholder. When a new transaction happens, by marking it as an unlawful transaction, it deviates from its previous behavior. On SVM, the highest fraud detection score was 91%.

The study in [83] suggested a deep network method for fraud detection. To manipulate the data skew troubles that occur in the dataset, the log transformation was used. For the training of difficult examples, the focal reduction is utilized to the network. The effects showed that the different classical models such as SVM and LR are outperformed by using the neural network model.

In the study [84] a hybrid strategy was proposed for identifying credit card frauds by operating the DT and Rough Set method that can be used in detection. The total work has utilized the usage of the software's WEKA and MATLAB. After the 10-time execution of the proposed and existing method, the proposed technique performed well with 84.25%.

In the study [85] an algorithm Lightgbm was proposed for detecting frauds. After that, a comparison was made with other methods like Logistic Regression, SVM, and Xgboost. The accuracy of Lightgbm was 98% as opposed to Logistic Regression 92.60%, SVM 95.20%, and Xgboost 97.10% but Lightgbm performed very properly when is compared to others.

In the study [86] REDBSCAN algorithm was used to decrease the number of samples and it helped to remain the form of data. The comparison made with the SVM technique and AUC of SVDD was 97.75% and SVM 94.60%. When SVDD was applied except REDBSCAN, it took 194 seconds and when utilized with REDBSCAN, it took 1.69 seconds which was much faster. REDCSCAN algorithm provided faster and preferred results.

3. Methodology

The researchers are attempting to develop credit technologies that uses machine learning and deep learning techniques to determine whether the credit score are High, average or low.

3.1 Dataset

We collected the dataset called “Credit Score” from Kaggle Depository for Credit Score detection. The dataset consists of 164 records with 8 features.

The features of the fraudulent transaction dataset are shown in Table 1.

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Table1: shows the features in the dataset

Features	Description
Credit Score	object credit score (High, Average, Low)
Age	Age of the person
Gender	object gender (Female, Male)
Income	Income level of the person
Education	object education ("Bachelor's Degree", "Master's Degree", 'Doctorate', 'High School Diploma', "Associate's Degree")
Marital Status	object marital education (Single, Married)
Number of Children	Number of Children
Home Ownership	object home ownership (Rented, Owned)

3.2 Dataset Analysis

Model efficiency is measured using product performance metrics such as accuracy, recall, precision and F1-Score.

The target feature is class which is a multilevel categorical variable feature with 0 (Low), 1 (Average) and 2 (High). There are 113 High (68.9%), 36 Average (22%) and 15 Low (9.1%) As expected, more than half of the data is High and the rest of the data is divided between Average and Low. The following visualization confirms this large discrepancy (see Figure 1).

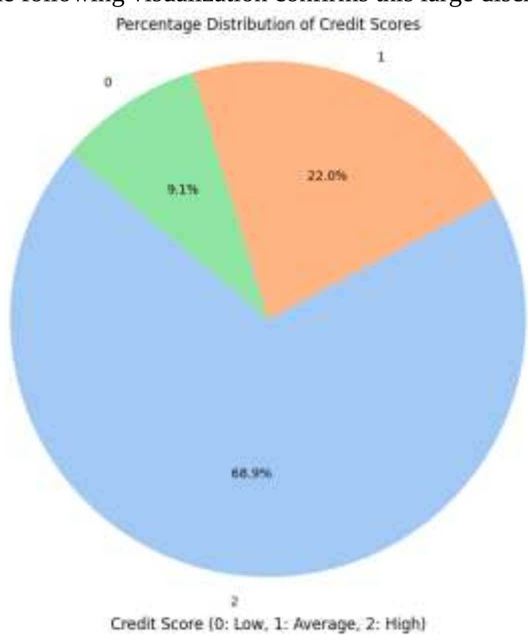

Figure 1: shows the distribution of credit scores.

Finally, it would be interesting to know if there are any significant correlations between our predictors, especially with regards to our class variable (class). One of the most visually appealing ways to determine that is by using a heatmap.

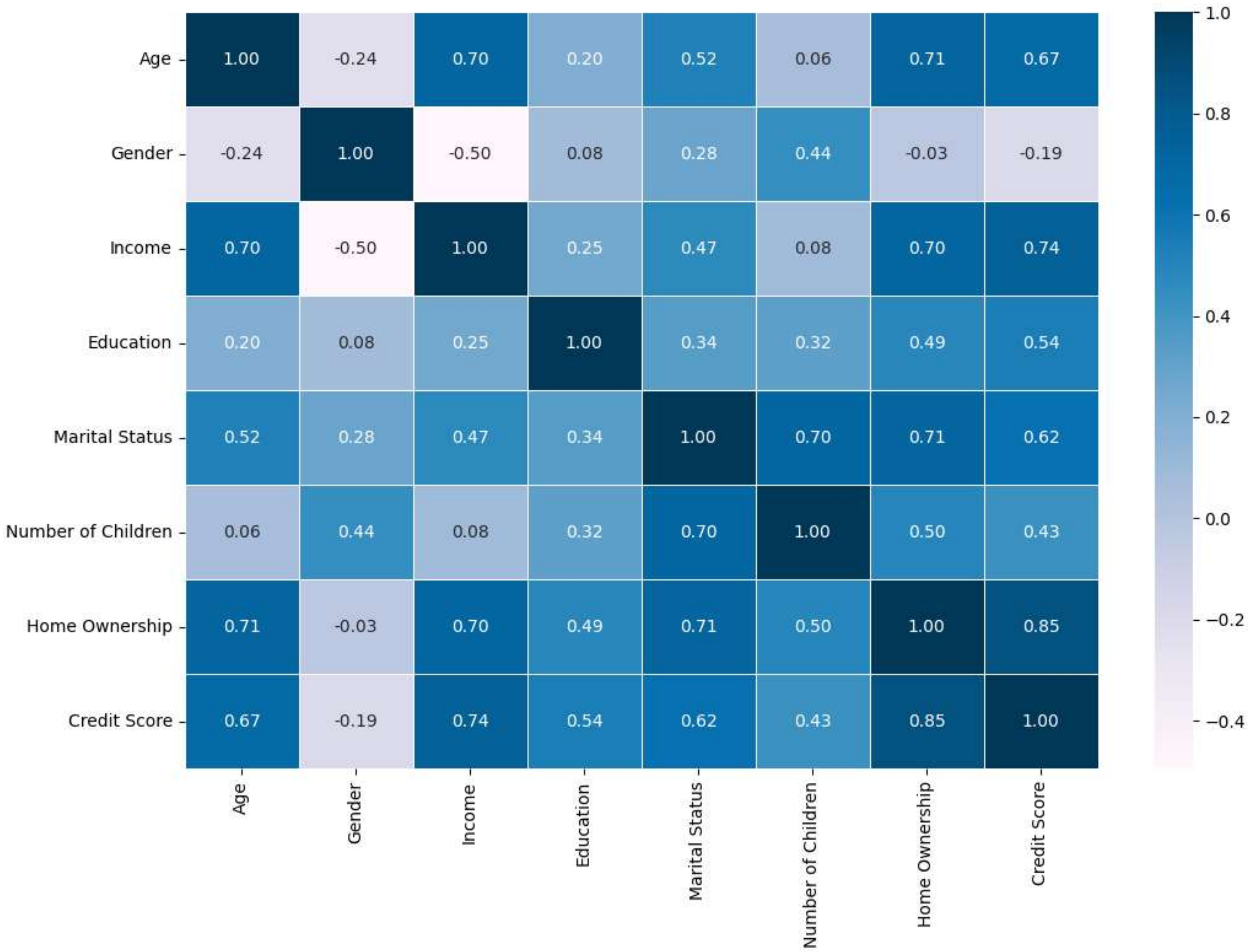

Figure 2: shows the heatmap of all features of the training dataset

As can be seen in Figure 2, some of our predictors do seem to be correlated with the Credit Score variable. Nonetheless, there seem to be relatively significant correlations for such variables. This can probably be attributed to the factor: class imbalance might distort the importance of certain correlations with regards to our Credit Score variable.

Furthermore, we have checked the negative correlation and positive correlation with Credit Score varible as can be seen in Figure 2.

It turned out that the features with positive correlation are: Home Ownership, Income, Age, Marital Status, Education, and Number of Children.

And the negative correlation is: Gender.

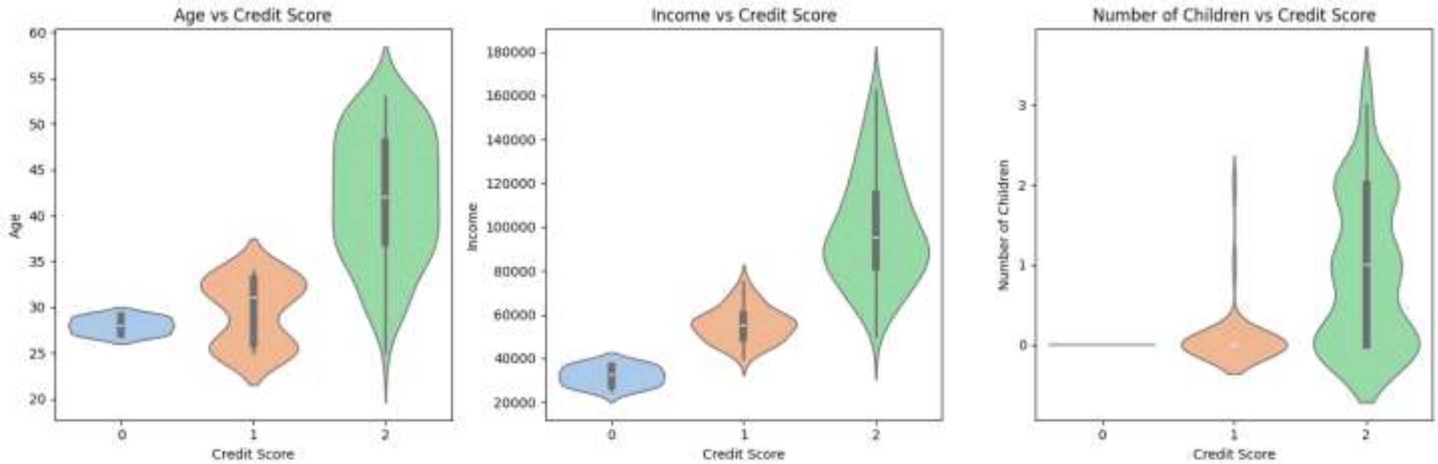

Figure 3: shows the violin plot of numerical features of the training dataset

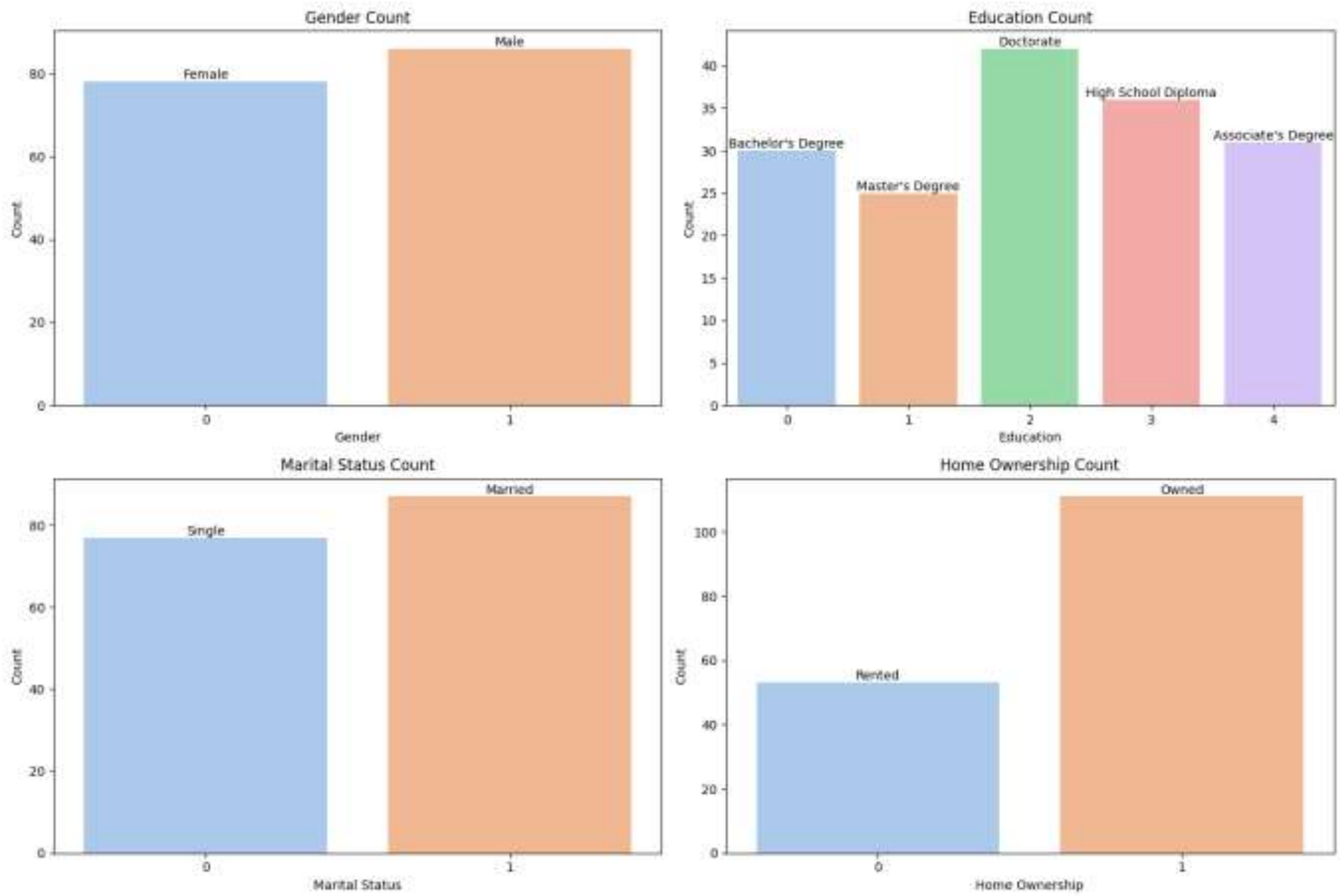

Figure 4: shows the bar chart of numerical features of the training dataset

3.3 First Experiment:

We have used the dataset as is (unbalanced). We have split the dataset into three datasets: training, validating and testing. The ratio of the splitting was (60 x 20 x 20). We have trained and tested each model and recorded the results (accuracy, Precision, Recall, F1- score and time required for the training process in seconds) as can be seen in Table 2.

Table2: shows the result of the 12 models without SMOTE (unbalanced dataset)

Model Name	Accuracy	Precision	Recall	F1_score	Time in Sec
LogisticRegressionCV	100.00%	100.00%	100.0%	100.00%	1.05
ExtraTreeClassifier	100.00%	100.00%	100.0%	100.00%	0.01
LGBMClassifier	96.00%	96.57%	96.0%	95.49%	0.20
AdaBoostClassifier	96.00%	96.57%	96.0%	95.49%	0.20
GradientBoostingClassifier	96.00%	96.57%	96.0%	95.49%	0.37
Perceptron	76.00%	70.00%	76.0%	71.20%	0.02
RandomForestClassifier	100.00%	100.00%	100.0%	100.00%	0.26
KNeighborsClassifier	100.00%	100.00%	100.0%	100.00%	0.01
BaggingClassifier	96.00%	96.57%	96.0%	95.49%	0.04
DecisionTreeClassifier	96.00%	96.57%	96.00	95.49%	0.01
CalibratedClassifierCV	76.00%	70.00%	76.0%	71.20%	0.07
LabelPropagation	100.00%	100.00%	100.0%	100.00%	0.01
Deep Learning	100.00%	100.00%	100.0%	100.00%	0.10

This dataset is severely imbalanced (most of the Credit Score High). So, the algorithms are much more likely to classify new observations to the majority class and high accuracy won't tell us anything. To address the problem of imbalanced dataset we can use undersampling and oversampling data approach techniques. Oversampling increases the number of minority class members in the training set. The advantage of oversampling is that no information from the original training set is lost unlike in undersampling, as all observations from the minority and majority classes are kept. On the other hand, it is prone to overfitting. There is a type of oversampling called SMOTE (Synthetic Minority oversampling Technique), which we are going to use to make our dataset balanced. It creates synthetic points from the minority class.

Also we shouldn't use accuracy score as a metric with imbalanced datasets (will be usually high and misleading), instead we should use f1-score, precision/recall score and confusion matrix

- **Recall of fraud cases (sensitivity)** summarizes true positive rate (True positive/True positive + False Negative) - how many cases we got correct out of all the positive ones
- **Recall of non-fraud (specificity)** summarizes true negative rate (True negative/True negative + False positive) - how many cases we got correct out of all the negative ones
- **Precision of fraud cases** (True positive/True positive + False positive) summarizes the accuracy of fraud cases detected - out of all predicted as fraud, how many are correct
- **Precision of non-fraud cases** (True negative/True negative + False negative) summarizes the accuracy of non-fraud cases detected - out of all predicted as non-fraud, how many are correct
- **F1-score** is the harmonic mean of recall and precision.

3.4 Second Experiment:

We have balanced the dataset using SMOTE technique. The class feature (credit score) now is balanced (50% for fraud transaction and 50% for non-fraud transaction) as in Figure 5. Then we have split the dataset for three datasets: training, validating and testing as in the first experiment. The ratio of splitting was (60 x 20 x 20). We have trained and tested each model and recorded the results (accuracy, Precision, Recall, F1-score and time required for the training process in seconds) as can be seen in Table 3.

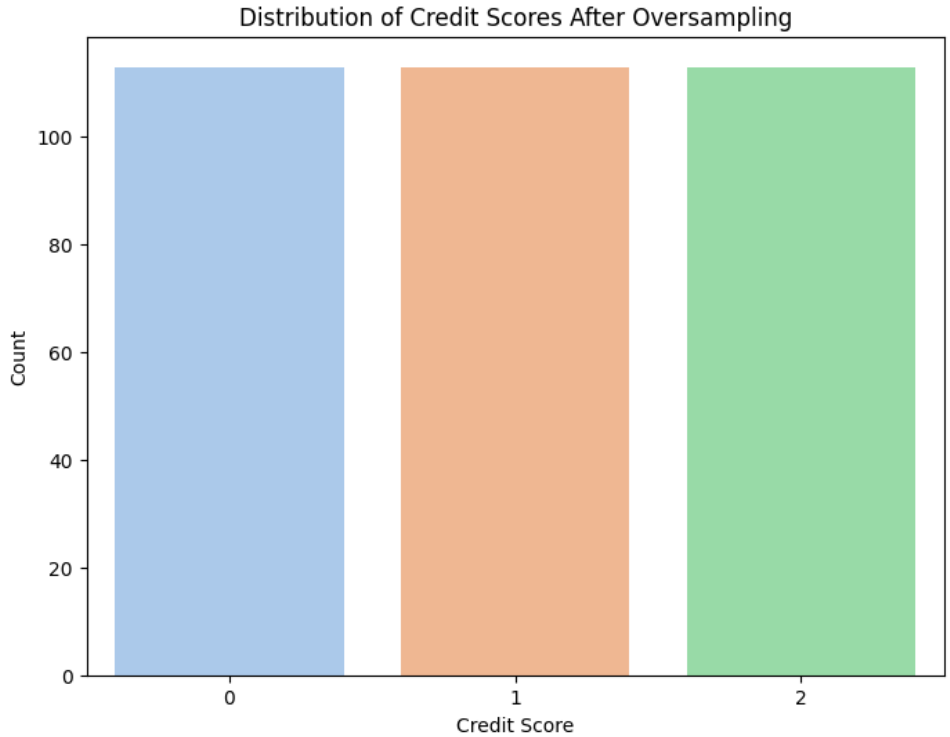

Figure 5: credit score feature (credit score) is balanced

Table3: shows the result of the 12 models with SMOTE (balanced dataset)

Model Name	**Accuracy**	**Precision**	**Recall**	**F1_score**	**Time in Sec**
LogisticRegressionCV	100.00%	100.00%	100.0%	100.00%	1.21
ExtraTreeClassifier	100.00%	100.00%	100.0%	100.00%	0.02
LGBMClassifier	100.00%	100.00%	100.0%	100.00%	0.25
AdaBoostClassifier	100.00%	100.00%	100.0%	100.00%	0.19
GradientBoostingClassifier	100.00%	100.00%	100.0%	100.00%	0.46
Perceptron	98.04%	98.15%	98.04%	98.02%	0.02
RandomForestClassifier	98.04%	98.15%	98.04%	98.02%	0.30
KNeighborsClassifier	98.04%	98.15%	98.04%	98.02%	0.02
BaggingClassifier	98.04%	98.15%	98.04%	98.02%	0.04
DecisionTreeClassifier	98.04%	98.15%	98.04%	98.02%	0.01
CalibratedClassifierCV	94.12%	94.32%	94.12%	94.07%	0.13
LabelPropagation	94.12%	94.32%	94.12%	94.07%	0.02
Deep Learning	98.04%	98.15%	97.22%	97.60%	0.09

As can be seen from table 2 and table 3 the followings:

- In the unbalanced dataset, the Recall and F1-Score is low for most models.
- The only models with unbalanced dataset and have very high Recall and F1-Score are: LogisticRegressionCV, ExtraTreeClassifier, RandomForestClassifier, KNeighborsClassifier and LabelPropagation only.
- In the balanced dataset, the Recall and F1-Score is very high for all models.

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- The top two highest models are LogisticRegressionCV and ExtraTreeClassifier.
- Some models can give high recall and F1-Score regardless of the dataset balanced or unbalanced.

After finishing the training of the 13 models we determined the best features in the dataset by Plotting Feature Importance using Bagging Classifier because it is the best classifier as in Figure 5.

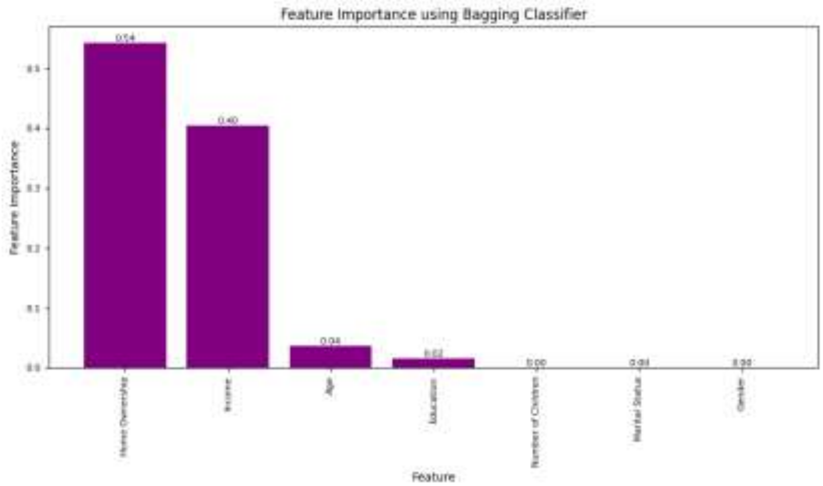

Figure 6: Feature Importance

4. Conclusions

Good prediction results can be achieved with imbalanced datasets as well as with balanced ones. LogisticRegressionCV ,ExtraTreeClassifier,and LGBMClassifier gave us the best results being able to detect 100.0% Credit Score. There is no perfect model and there will always be a trade-off between precision and recall. It is up to the company and its objectives to decide which approach is the best in each particular situation.

References

1. Abu Ghali, M. J., et al. (2018). "An Intelligent Tutoring System for Teaching English Grammar." International Journal of Academic Engineering Research (IJAER) 2(2): 1-6.
2. Abu Nada, A. M., et al. (2020). "Age and Gender Prediction and Validation Through Single User Images Using CNN." International Journal of Academic Engineering Research (IJAER) 4(8): 21-24.
3. Abu Nada, A. M., et al. (2020). "Arabic Text Summarization Using AraBERT Model Using Extractive Text Summarization Approach." International Journal of Academic Information Systems Research (IJAISR) 4(8): 6-9.
4. Abu Naser, S. (2008). "An Agent Based Intelligent Tutoring System For Parameter Passing In Java Programming." Journal of Theoretical & Applied Information Technology 4(7).
5. Abu Naser, S. S. (2001). "A comparative study between animated intelligent tutoring systems AITS and video-based intelligent tutoring systems VITS." Al-Aqsa Univ. J 5(1): 72-96.
6. Abu Naser, S. S. (2008). "Developing visualization tool for teaching AI searching algorithms." Information Technology Journal, Scialert 7(2): 350-355.
7. Abu Naser, S. S. (2012). "A Qualitative Study of LP-ITS: Linear Programming Intelligent Tutoring System." International Journal of Computer Science & Information Technology 4(1): 209.
8. Abu Naser, S. S. and M. J. Al Shobaki (2016). "Enhancing the use of Decision Support Systems for Re-engineering of Operations and Business-Applied Study on the Palestinian Universities." Journal of Multidisciplinary Engineering Science Studies (JMESS) 2(5): 505-512.
9. Abu Naser, S. S. and M. J. Al Shobaki (2016). The Impact of Management Requirements and Operations of Computerized Management Information Systems to Improve Performance (Practical Study on the employees of the company of Gaza Electricity Distribution). First Scientific Conference for Community Development.
10. Abu Naser, S. S. and M. J. Al Shobaki (2017). "Organizational Excellence and the Extent of Its Clarity in the Palestinian Universities from the Perspective of Academic Staff." International Journal of Information Technology and Electrical Engineering 6(2): 47-59.
11. Abu Naser, S. S. and M. J. Al Shobaki (2017). "The Impact of Senior Management Support in the Success of the e-DMS." International Journal of Engineering and Information Systems (IJEAIS) 1(4): 47-63.
12. Abu Naser, S. S. and M. Shobaki (2016). "Requirements of using Decision Support Systems as an Entry Point for Operations of Re-engineering in the Universities (Applied study on the Palestinian universities in Gaza Strip)." World Wide Journal of Multidisciplinary Research and Development 2(4): 32-40.
13. Abu Naser, S. S., et al. (2016). "KM Factor Affecting High Performance in Intermediate Colleges and its Impact on High Performance-Comparative Study." Computational Research Progress in Applied Science & Engineering 2(4): 158-167.
14. Abu Naser, S. S., et al. (2017). "Impact of Communication and Information on the Internal Control Environment in Palestinian Universities." International Journal of Hybrid Information Technology 10(11): 41-60.
15. Abu Naser, S. S., et al. (2017). "The Reality of Electronic Human Resources Management in Palestinian Universities from the Perspective of the Staff in IT Centers." International Journal of Engineering and Information Systems (IJEAIS) 1(2): 74-96.
16. Abu Naser, S. S., et al. (2017). "Trends of Palestinian Higher Educational Institutions in Gaza Strip as Learning Organizations." International Journal of Digital Publication Technology 1(1): 1-42.
17. Abu Naser, S., et al. (2011). "Human Computer Interaction Design of the LP-ITS: Linear Programming Intelligent Tutoring Systems." International Journal of Artificial Intelligence & Applications (IJAIA) 2(3): 60-70.
18. AbuEloun, N. N. and S. S. Abu Naser (2017). "Mathematics intelligent tutoring system." International Journal of Advanced Scientific Research 2(1): 11-16.
19. Abu-Naser, S. S. (2008). "JEE-Tutor: An Intelligent Tutoring System for Java Expression Evaluation." Information Technology Journal 7(3): 528-532.
20. Abu-Naser, S. S. (2015). "Sl5 Object: Simpler Level 5 Object Expert System Language." International Journal of Soft Computing, Mathematics and Control (IJSCMC) 4(4): 25-37.
21. Abu-Naser, S. S. and I. A. El Haddad (2016). "An Expert System for Genital Problems in Infants." WWJMRD 2(5): 20-26.
22. Abu-Naser, S. S. and I. S. Zaqout (2016). "Knowledge-based systems that determine the appropriate students major: In the faculty of engineering and information technology." World Wide Journal of Multidisciplinary Research and Development 2(10): 26-34.
23. Abu-Naser, S. S. and M. A. Al-Nakhal (2016). "A Ruled Based System for Ear Problem Diagnosis and Treatment." World Wide Journal of Multidisciplinary Research and Development 2(4): 25-31.
24. Abu-Naser, S. S. and M. H. Al-Bayed (2016). "Detecting Health Problems Related to Addiction of Video Game Playing Using an Expert System." World Wide Journal of Multidisciplinary Research and Development 2(9): 7-12.
25. Abu-Naser, S. S. and M. J. Al Shobaki (2016). "Computerized Management Information Systems Resources and their Relationship to the Development of Performance in the Electricity Distribution Company in Gaza." EUROPEAN ACADEMIC RESEARCH 6(8): 6969-7002.
26. Abu-Naser, S. S. and M. M. Hilles (2016). "An expert system for shoulder problems using CLIPS." World Wide Journal of Multidisciplinary Research and Development 2(5): 1-8.
27. Abu-Naser, S. S., et al. (2011). "An intelligent tutoring system for learning java objects." International Journal of Artificial Intelligence & Applications (IJAIA) 2(2): 86-77.
28. Abu-Naser, S. S., et al. (2016). "Promoting Knowledge Management Components in the Palestinian Higher Education Institutions-A Comparative Study." International Letters of Social and Humanistic Sciences 73: 42-53.
29. Abu-Nasser, B. S. and S. S. Abu Naser (2018). "Rule-Based System for Watermelon Diseases and Treatment." International Journal of Academic Information Systems Research (IJAISR) 2(7): 1-7.
30. Abunasser, B. S., et al. (2022). "Breast Cancer Detection and Classification using Deep Learning Xception Algorithm." International Journal of Advanced Computer Science and Applications 13(7).
31. Abu-Saqer, M. M. and S. S. Abu-Naser (2019). "Knowledge Based System for Uveitis Disease Diagnosis." International Journal of Academic Information Systems Research (IJAISR) 3(5): 18-25.
32. Afana, M., et al. (2018). "Artificial Neural Network for Forecasting Car Mileage per Gallon in the City." International Journal of Advanced Science and Technology 124: 51-59.
33. Ahmad, H. R., et al. (2018). "Information Technology Role in Determining Communication Style Prevalent Among Al-Azhar University Administrative Staff." International Journal of Information Technology and Electrical Engineering ` 7(4): 21-43.
34. Ahmed, A. A., et al. (2018). "The Impact of Information Technology Used on the Nature of Administrators Work at Al-Azhar University in Gaza." International Journal of Academic Information Systems Research (IJAISR) 2(6): 1-20.
35. Akkila, A. N. and S. S. Abu Naser (2017). "Teaching the right letter pronunciation in reciting the holy Quran using intelligent tutoring system." International Journal of Advanced Research and Development 2(1): 64-68.
36. Akkila, A. N., et al. (2019). "Survey of Intelligent Tutoring Systems up to the end of 2017." International Journal of Academic Information Systems Research (IJAISR) 3(4): 36-49.
37. Al Barsh, Y. I., et al. (2020). "MPG Prediction Using Artificial Neural Network." International Journal of Academic Information Systems Research (IJAISR) 4(11): 7-16.
38. Al Hila, A. A., et al. (2017). "Organizational Excellence in Palestinian Universities of Gaza Strip." International Journal of Information Technology and Electrical Engineering 6(4): 20-30.
39. Al Shobaki, M. J. and S. S. Abu Naser (2016). "Performance development and its relationship to demographic variables among users of computerized management information systems in Gaza electricity Distribution Company." International Journal of Humanities and Social Science Research 2(10): 21-30.
40. Al Shobaki, M. J. and S. S. Abu Naser (2016). "The reality of modern methods applied in process of performance assessments of employees in the municipalities in Gaza Strip." International Journal of Advanced Scientific Research 1(7): 14-23.
41. Al Shobaki, M. J. and S. S. Abu-Naser (2016). "The Dimensions Of Organizational Excellence In The Palestinian Higher Education Institutions From The Perspective Of The Students." GLOBAL JOURNAL OF MULTIDISCIPLINARY STUDIES 5(11): 66-100.
42. Al Shobaki, M. J. and S. S. Abu-Naser (2017). "The Requirements of Computerized Management Information Systems and Their Role in Improving the Quality of Administrative Decisions in the Palestinian Ministry of Education and Higher Education." International Journal of Academic Pedagogical Research (IJAPR) 6(6): 7-35.
43. Al Shobaki, M. J., et al. (2017). "Strategic and Operational Planning As Approach for Crises Management Field Study on UNRWA." International Journal of Information Technology and Electrical Engineering 5(6): 43-47.
44. Al Shobaki, M. J., et al. (2018). "The Role of Measuring and Evaluating Performance in Achieving Control Objectives-Case Study of" Islamic University"." International Journal of Engineering and Information Systems (IJEAIS) 2(1): 106-118.
45. Al Shobaki, M. M., et al. (2017). "The Efficiency of Information Technology and its Role of e-HRM in the Palestinian Universities." International Journal of Engineering and Information Systems (IJEAIS) 1(6): 36-55.
46. Al Shobaki, M., et al. (2018). "Performance Reality of Administrative Staff in Palestinian Universities." International Journal of Academic Information Systems Research (IJAISR) 2(4): 1-17.
47. Alajrami, E., et al. (2019). "Blood Donation Prediction using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 3(10): 1-7.
48. Alamawi, W. W., et al. (2016). "Rule Based System for Diagnosing Wireless Connection Problems Using SL5 Object." International Journal of Information Technology and Electrical Engineering 5(6): 26-33.
49. Alawar, M. W. and S. S. Abu Naser (2017). "CSS-Tutor: An intelligent tutoring system for CSS and HTML." International Journal of Academic Research and Development 2(1): 94-98.
50. Al-Bastami, B. G. and S. S. Abu Naser (2017). "Design and Development of an Intelligent Tutoring System for C# Language." EUROPEAN ACADEMIC RESEARCH 6(10): 8795.
51. Albatish, I. M. and S. S. Abu-Naser (2019). Modeling and controlling smart traffic light system using a rule based system. 2019 International Conference on Promising Electronic Technologies (ICPET), IEEE.
52. Aldahdooh, R. and S. S. Abu Naser (2017). "Development and Evaluation of the Oracle Intelligent Tutoring System (OITS)." EUROPEAN ACADEMIC RESEARCH 6(10): 8711-8721.
53. Al-Daour, A. F., et al. (2020). "Banana Classification Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 3(12): 6-11.
54. Al-Habil, W. I., et al. (2017). "The Impact of the Quality of Banking Services on Improving the Marketing Performance of Banks in Gaza Governorates from the Point of View of Their Employees." International Journal of Engineering and Information Systems (IJEAIS) 1(7): 197-217.
55. Al-Hanjori, M. M., et al. (2017). "Learning computer networks using intelligent tutoring system." International Journal of Advanced Research and Development(2): 1.
56. Al-Hila, A. A., et al. (2017). "The Impact of Applying the Dimensions of IT Governance in Improving e-training-Case Study of the Ministry of Telecommunications and Information Technology in Gaza Governorates." International Journal of Engineering and Information Systems (IJEAIS) 1(7): 194-219.
57. Al-Kahlout, M. M., et al. (2020). "Neural Network Approach to Predict Forest Fires using Meteorological Data." International Journal of Academic Engineering Research (IJAER) 4(9): 68-72.
58. Al-Masri, A., et al. (2011). "A prototype decision support system for optimizing the effectiveness of elearning in educational institutions." International Journal of Data Mining & Knowledge Management Process (IJDKP) 1: 1-13.
59. Almasri, A., et al. (2019). "Intelligent Tutoring Systems Survey for the Period 2000-2018." International Journal of Academic Engineering Research (IJAER) 3(5): 21-37.
60. Almurshidi, S. H. and S. S. Abu-Naser (2018). Expert System For Diagnosing Breast Cancer, Al-Azhar University, Gaza, Palestine.
61. Al-Nakhal, M. A. and S. S. Abu Naser (2017). "Adaptive Intelligent Tutoring System for learning Computer Theory." EUROPEAN ACADEMIC RESEARCH 6(10): 8770-8782.
62. Al-Qumboz, M. N. A. and S. S. Abu-Naser (2019). "Spinach Expert System: Diseases and Symptoms." International Journal of Academic Information Systems Research (IJAISR) 3(3): 16-22.
63. Alshawwa, I. A., et al. (2019). "An Expert System for Coconut Diseases Diagnosis." International Journal of Academic Engineering Research (IJAER) 3(4): 8-13.
64. Alshawwa, I. A., et al. (2019). "An Expert System for Depression Diagnosis." International Journal of Academic Health and Medical Research (IJAHMR) 3(4): 20-27.
65. Al-Shawwa, M. and S. S. Abu-Naser (2019). "Knowledge Based System for Apple Problems Using CLIPS." International Journal of Academic Engineering Research (IJAER) 3(3): 1-11.
66. Al-Shawwa, M. and S. S. Abu-Naser (2019). "Predicting Birth Weight Using Artificial Neural Network." International Journal of Academic Health and Medical Research (IJAHMR) 3(1): 9-14.
67. AlZamily, J. Y. and S. S. Abu-Naser (2018). "A Cognitive System for Diagnosing Musa Acuminata Disorders." International Journal of Academic Information Systems Research (IJAISR) 2(8): 1-8.
68. Anderson, J., et al. (2005). "Adaptation of Problem Presentation and Feedback in an Intelligent Mathematics Tutor." Information Technology Journal 5(5): 167-207.
69. Ashqar, B. A. M. and S. S. Abu-Naser (2019). "Identifying Images of Invasive Hydrangea Using Pre-Trained Deep Convolutional Neural Networks." International Journal of Academic Engineering Research (IJAER) 3(3): 28-36.
70. Bakr, M. A. H. A., et al. (2020). "Breast Cancer Prediction using JNN." International Journal of Academic Information Systems Research (IJAISR) 4(10): 1-8.
71. Barhoom, A. M., et al. (2019). "Predicting Titanic Survivors using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 3(9): 8-12.
72. Dheir, I. M., et al. (2019). "Knowledge Based System for Diabetes Diagnosis Using SL5 Object." International Journal of Academic Pedagogical Research (IJAPR) 3(4): 1-10.
73. El Kahlout, M. I. and S. S. Abu-Naser (2019). "An Expert System for Citrus Diseases Diagnosis." International Journal of Academic Engineering Research (IJAER) 3(4): 1-7.
74. El Talla, S. A., et al. (2018). "The Nature of the Organizational Structure in the Palestinian Governmental Universities-Al-Aqsa University as A Model." International Journal of Academic Multidisciplinary Research (IJAMR) 2(5): 15-31.
75. El-Mashharawi, H. Q. and S. S. Abu-Naser (2019). "An Expert System for Sesame Diseases Diagnosis Using CLIPS." International Journal of Academic Engineering Research (IJAER) 3(4): 22-29.
76. El-Mashharawi, H. Q., et al. (2019). "An Expert System for Arthritis Diseases Diagnosis Using SL5 Object." International Journal of Academic Health and Medical Research (IJAHMR) 3(4): 28-35.
77. Elnajjar, A. E. A. and S. S. Abu Naser (2017). "DES-Tutor: An Intelligent Tutoring System for Teaching DES Information Security Algorithm." International Journal of Advanced Research and Development 2(1): 69-73.
78. Elsharif, A. A., et al. (2020). "Potato Classification Using Deep Learning." International Journal of Academic Pedagogical Research (IJAPR) 3(12): 1-8.
79. Elzamly, A., et al. (2015). "Predicting Software Analysis Process Risks Using Linear Stepwise Discriminant Analysis: Statistical Methods." Int. J. Adv. Inf. Sci. Technol 38(38): 108-115.
80. FarajAllah, A. M., et al. (2018). "The Impact of the Leadership Standard in International Quality Models on Improving University Performance through the Intermediate Role of the Strategy Standard." International Journal of Engineering and Information Systems (IJEAIS) 2(9): 21-32.
81. Hamed, M. A. and S. S. Abu Naser (2017). "An intelligent tutoring system for teaching the 7 characteristics for living things." International Journal of Advanced Research and Development 2(1): 31-45.
82. Harz, H. H., et al. (2020). "Artificial Neural Network for Predicting Diabetes Using JNN." International Journal of Academic Engineering Research (IJAER) 4(10): 14-22.
83. Jamala, M. N. and S. S. Abu-Naser (2018). "Predicting MPG for Automobile Using Artificial Neural Network Analysis." International Journal of Academic Information Systems Research (IJAISR) 2(10): 5-21.
84. Kashkash, K., et al. (2005). "Expert system methodologies and applications-a decade review from 1995 to 2004." Journal of Artificial Intelligence 1(2): 9-26.
85. Khalil, A. J., et al. (2019). "Apple Trees Knowledge Based System." International Journal of Academic Engineering Research (IJAER) 3(9): 1-7.
86. Madi, S. A., et al. (2018). "The dominant pattern of leadership and Its Relation to the Extent of Participation of Administrative Staff in Decision-Making in Palestinian Universities." International Journal of Academic Management Science Research (IJAMSR) 2(7): 20-43.
87. Mahdi, A. O., et al. (2016). "An intelligent tutoring system for teaching advanced topics in information security." World Wide Journal of Multidisciplinary Research and Development 2(12): 1-9.
88. Marouf, A. and S. S. Abu-Naser (2018). "Predicting Antibiotic Susceptibility Using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 2(10): 1-5.
89. Mettleq, A. S. A., et al. (2019). "Expert System for the Diagnosis of Seventh Nerve Inflammation (Bell's palsy) Disease." International Journal of Academic Information Systems Research (IJAISR) 3(4): 27-35.
90. Nasser, I. M. and S. S. Abu-Naser (2019). "Artificial Neural Network for Predicting Animals Category." International Journal of Academic and Applied Research (IJAAR) 3(2): 18-24.
91. Nasser, I. M. and S. S. Abu-Naser (2019). "Predicting Tumor Category Using Artificial Neural Networks." International Journal of Academic Health and Medical Research (IJAHMR) 3(2): 1-7.
92. Qwaider, S. R., et al. (2020). "Artificial Neural Network Prediction of the Academic Warning of Students in the Faculty of Engineering and Information Technology in Al-Azhar University-Gaza." International Journal of Academic Information Systems Research (IJAISR) 4(8): 16-22.
93. Salama, A. A., et al. (2017). "The Relationship between Performance Standards and Achieving the Objectives of Supervision at the Islamic University in Gaza." International Journal of Engineering and Information Systems (IJEAIS) 1(10): 89-101.
94. Salama, A. A., et al. (2018). "The Role of Administrative Procedures and Regulations in Enhancing the Performance of The Educational Institutions-The Islamic University in Gaza is A Model." International Journal of Academic Multidisciplinary Research (IJAMR) 2(2): 14-27.
95. Salman, F. M. and S. S. Abu-Naser (2020). "Expert System for COVID-19 Diagnosis." International Journal of Academic Information Systems Research (IJAISR) 4(3): 1-13.
96. Shamia, M. J., et al. (2018). "Using the Asian Knowledge Model "APO" as a Determinant for Performance Excellence in Universities-Empirical Study at Al-Azhar University-Gaza." International Journal of Information Technology and Electrical Engineering 7(1): 1-19.
97. Sultan, Y. S. A., et al. (2018). "Effect of the Dominant Pattern of Leadership on the Nature of the Work of Administrative Staff at Al-Aqsa University." International Journal of Academic Information Systems Research (IJAISR) 2(7): 8-29.
98. Sultan, Y. S. A., et al. (2018). "The Style of Leadership and Its Role in Determining the Pattern of Administrative Communication in Universities-Islamic University of Gaza as a Model." International Journal of Academic Management Science Research (IJAMSR) 2(6): 26-42.
99. Zaqout, I., et al. (2018). "Information Technology used and it's Impact on the Participation of Administrative Staff in Decision-Making in Palestinian Universities." International Journal of Academic Multidisciplinary Research (IJAMR) 2(8): 7-26.

100. M. Khedmati, M. Erfani, and M. GhasemiGol, “Applying support vector data description for fraud detection,” arXiv, pp. 1–6, 2020.
101. K. R. Seeja and M. Zareapoor, “FraudMiner: A novel credit card fraud detection model based on frequent itemset mining,” Sci. World J., vol. 2014, 2014, doi: 10.1155/2014/252797.
102. L. S. V S S and S. Deepthi Kavila, “Machine Learning For Credit Card Fraud Detection System,” Int. J. Appl. Eng. Res., vol. 13, no. 24, pp. 16819–16824, 2018.
103. Y. Lucas et al., “Towards automated feature engineering for credit card fraud detection using multi-perspective HMMs,” Futur. Gener. Comput. Syst., vol. 102, pp. 393–402, 2020, doi: 10.1016/j.future.2019.08.029.
104. N. Carneiro, G. Figueira, and M. Costa, “A data mining based system for credit-card fraud detection in e-tail,” Decis. Support Syst., vol. 95, pp. 91–101, 2017, doi: 10.1016/j.dss.2017.01.002.
105. V. N. Dornadula and S. Geetha, “Credit Card Fraud Detection using Machine Learning Algorithms,” Procedia Comput. Sci., vol. 165, no. 20, pp. 631–641, 2019, doi: 10.1016/j.procs.2020.01.057.
106. A. Thennakoon, C. Bhagyani, S. Premadasa, S. Mihiranga, and N. Kuruwitaarachchi, “Real-time credit card fraud detection using machine learning,” Proc. 9th Int. Conf. Cloud Comput. Data Sci. Eng. Conflu. 2019, pp. 488–493, 2019, doi: 10.1109/CONFLUENCE.2019.8776942.
107. X. Yu, X. Li, Y. Dong, and R. Zheng, “A Deep Neural Network Algorithm for Detecting Credit Card Fraud,” Proc. - 2020 Int. Conf. Big Data, Artif. Intell. Internet Things Eng. ICBAIE 2020, pp. 181–183, 2020, doi: 10.1109/ICBAIE49996.2020.00045.
108. R. Jain, B. Gour, and S. Dubey, “A Hybrid Approach for Credit Card Fraud Detection using Rough Set and Decision Tree Technique,” Int. J. Comput. Appl., vol. 139, no. 10, pp. 1–6, 2016, doi: 10.5120/ijca2016909325.
109. D. Ge, J. Gu, S. Chang, and J. H. Cai, “Credit card fraud detection using lightgbm model,” Proc. - 2020 Int. Conf. E-Commerce Internet Technol. ECIT 2020, pp. 232–236, 2020, doi: 10.1109/ECIT50008.2020.00060.