ISSN: 2754-6659

Journal of Artificial Intelligence & Cloud Computing

Review Article

Open Access

Artificial Intelligence-Powered Credit Card Fraud Detection: Feature Engineering and Machine Learning Approach's

Varun Bodepudi[1]*, Niharika Katnapally[2], Srinivasa Rao Maka[3], Gangadhar Sadaram[4], Manikanth Sakuru[5], and Laxmana Murthy Karaka[6]

[1]Applab Systems Inc, Computer Programmer, USA

[2]Amazon AWS, BI Developer, USA

[3]North Star Group Inc, Software Engineer, USA

[4]Bank of America, Sr DevOps/ Open Shift Admin Engineer, USA

[5]JP Morgan Chase, Lead Software Engineer, USA

[6]Microsoft, Senior Support Engineer, USA

ABSTRACT

The payment experience has been completely transformed by the use of cashless payment options including credit card purchases and web transactions, but it has also led to more sophisticated financial fraud, posing a significant challenge to payment system security. Accurately detecting fraudulent transactions while reducing false positives is a need for credit card fraud detection systems. use of a Convolutional Neural Network (CNN) model to detect fraudulent transactions is examined in this study using the Kaggle Credit Card Fraud Detection dataset. The CNN model performed quite well, with an F1 score of 79.52%, accuracy of 99.93%, precision of 80.8%, and recall of 78.29%. With a balanced trade-off between accuracy and recall, these findings demonstrate the model's capacity to detect fraud and manage unbalanced datasets. Further evidence of CNN's higher performance comes from comparison with other models, including k-Nearest Neighbours (k-NN) with Random Forest. This study demonstrates how advanced deep learning methods may be applied to effectively detect credit card fraud. Future research can explore hybrid models, advanced deep learning techniques, and domain-specific feature engineering to enhance model robustness and adapt to evolving fraud patterns.

***Corresponding author**

Varun Bodepudi, Applab Systems Inc, Computer Programmer, USA.

Received: July 07, 2022; **Accepted:** July 13, 2022; **Published:** July 20, 2022

Keywords: Credit Card Fraud Detection, Fraudsters, Fraud Detection, Digital Transactions, Online Payments, Machine Learning, CCFD Dataset

Introduction

In the quickly changing digital world of today, the expansion of online transactions has brought immense convenience but also significant risks, particularly in the realm of financial fraud. Fraud, defined as intentional deception for personal gain without the intent to repay, has long posed a serious threat across various industries [1]. As digital transactions continue to grow, the task of identifying and stopping fraud has grown more difficult [2]. In particular, fraud involving credit cards—especially in consumer-not-present (CNP) transactions, such as online payments—has reached alarming levels, affecting both merchants and consumers globally.

Credit card fraud is a serious issue as it undermines customer trust and harms organisations' reputations in addition to causing financial losses [3]. The fraudulent behaviour in credit card transactions often goes unnoticed for long periods, with fraudsters employing sophisticated methods to mimic legitimate user behaviour. This makes detection more challenging, particularly since fraudulent transactions are relatively rare compared to legitimate ones. The unbalanced nature of transaction datasets, with far fewer fraud cases, presents an additional obstacle, requiring specialised approaches to ensure accurate detection and minimise false positives [4].

Detecting credit card fraud in real time has become critical to reducing financial losses and mitigating risk. Conventional techniques, including manual inspection or rule-based systems, frequently fall behind the ever-evolving strategies of scammers [3]. Automated techniques have been developed to enhance the detection process, and ML and AI are two key players in this space. AI-powered systems may scan vast amounts of transaction data to identify subtle patterns and differences that could indicate fraud [5].

Credit card theft detection relies heavily on machine learning, A form of AI that creates models using past transaction data to forecast the probability of fraud in novel, unidentified transactions. These models continuously improve over time, adapting to new fraud patterns as fraudsters evolve their methods. The complexity of credit card fraud detection may be effectively addressed with machine learning (ML) due to its capacity to scan massive datasets, uncover hidden patterns, and generate predictions in real time [6].

Motivation and Contributions

The identification of credit card theft is becoming more difficult for financial organisations as fraudsters continuously develop new techniques to bypass traditional detection systems. As the use of cashless payment methods increases, ensuring the security of these transactions becomes critical. This work was motivated by the desire to improve the use of ML techniques to identify fraudulent credit card transactions, which have shown great potential in identifying complex patterns in imbalanced datasets. The primary contributions of this study include:

- Using the Kaggle Credit Card Fraud Detection dataset, which offers an extensive and unbalanced dataset for studies on fraud detection.
- Making use of effective data preparation methods, such Principal Component Analysis (PCA), Z-score normalisation, and random oversampling, to alleviate the class imbalance and maximise computing performance.
- Use and create ML and DL models for credit card fraud detection, such as CNN, RF, and KNN.
- To ensure a comprehensive assessment of model performance and its applicability in fraud detection scenarios, evaluation metrics such as F1-score, recall, accuracy, and precision are used.

Organization of the Paper

The structure of the paper is as follows: The current knowledge of credit card detection is discussed in section II. Section III then provides this means in turn. Following that, Section IV showcases the result and discussion. Section V gives the conclusion and recommendation.

Literature Review

The primary focus of this section is the literature estimation of previous ML techniques for detecting credit card fraud.

This study, Sethia, Patel and Raut used the standard implementation of GANs, including Margin Adaptive, Relaxed Wasserstein, Least Squares, and Wasserstein. Analysis is done on the empirical comparison with the data generated are then plotted against the actual fraud data, accuracy of the classifier, convergence of every model, as well as the number of generations to the optimal model. This data is then evaluated and optimised by an ANN model with an authorised recall increase of 12.86% for a dataset classified with an initial class disparity of 579:1 [7].

In this research, Zamini and Montazer suggested an autoencoder-based clustering approach for unsupervised fraud detection. 284807 transactions from European banks were used to evaluate k-means clustering and three hidden layers in an autoencoder. According to the findings, this approach surpasses previous methods with an accuracy of 98.9% and a TPR of 81% [8].

In this study, Mubalaike and Adali aimed to comprehend the potential benefits of using DL models to precisely detect fraudulent transactions. Over six million transactions are included in the dataset, which was extracted from an actual set of data brought from an African mobile money service provider for one-month operation. To execute this, the most effective machine learning algorithms, including the EDT, and deep learning techniques, including SAE and RBM classifiers, are used once data is preprocessed. The performance of the developed classifier models is evaluated using the confusion matrix, ROC scores, accuracy, sensitivity, specificity, and precision. The corresponding ideal accuracy results are 90.49%, 80.52%, and 91.53% [9].

This research, Awoyemi, Adetunmbi and Oluwadare investigated the impact of NB, LR, an KNN algorithm on highly imbalanced credit card fraud data. The sample data includes 284,807 credit card transactions from cardholders across Europe. On the over-sampled skewed data, a combined under-sampling and over-sampling method is employed. All these three techniques are employed on both raw and processed data. The work is realised in the Python language. The approaches' performance is evaluated using the following metrics: They are the balanced classification rate, Matthew's correlation coefficient, Accuracy, sensitivity, specificity and precision. It is shown that the performance of the categories of classifiers used notably range in accuracy in the following order: the LR, KNN and NB classifiers with accuracies of 54.86%, 97.69%, and 97.92%, respectively [10].

This study, Van Vlasselaer et al. Provided APATE, an advanced method in order to identify credit card frauds occurred in Internet merchants. Our method use the network of merchants and credit card holders to calculate time dependent suspiciousness score of each network object It incorporates inherent characteristics of the incoming transactions and customer spending profile and network characteristics. It actually uses the RFM, which stands for approach to Internet advertisement. These results show that both the intrinsic and the network-based characteristics of the same theory are two different and dependent concepts. Thus, while the two mentioned feature categories are combined, the high-performing mark recognised by AUC-score is above 0.98 [11].

Table 1 summarises previous studies evaluating ML methods for predicting credit card fraud, emphasising the differences between the effectiveness of deep learning and ML methods.

Table 1: Summary of the Related Work on Credit Card Fraud Detection using Machine Learning Techniques

References	Dataset	Methodology	Performance	Limitations & Future Work
Sethia, Patel, and Raut	Fraud data with class imbalance (579:1)	There are several GAN implementations, including Margin Adaptive, Relaxed Wasserstein, Least Squares, and Vanilla. Testing and data augmentation with an artificial neural network (ANN).	Recall for ANN with enriched data increased by 12.86%.	Focus on optimising GAN convergence, determining the optimal number of generations, and improving recall further.

Zamini and Montazer	284,807 transactions from European banks	Unsupervised autoencoder-based clustering Using k-means clustering and three hidden layers.	98.9% accuracy and 81% TPR.	Applicability to other datasets and scenarios with different characteristics.
Mubalaike and Adali	Financial logs from mobile money service (6+ million transactions).	Deep learning models include Ensemble Decision Trees (EDT), Restricted Boltzmann Machines (RBM), and Stacked Auto-Encoders (SAE).	Accuracy: 90.49% (SAE), 80.52% (RBM), 91.53% (EDT).	Addressing dataset variability and extending models for real-time fraud detection
Awoyemi, Adetunmbi, and Oluwadare	284,807 transactions (European cardholders)	LR, NB, and KNN. Hybrid sampling (under-sampling and oversampling) for class imbalance correction.	Accuracy: 97.92% (Naïve Bayes), 97.69% (KNN), 54.86% (Logistic Regression).	Exploring other algorithms to improve Logistic Regression results; broader application to dynamic fraud patterns.
Van Vlasselaer et al.	Online retailers' credit card transactions	The APATE method for time-dependent suspiciousness score calculation combines network-based and RFM-based characteristics (Recency–Frequency–Monetary).	AUC-score > 0.98.	Expanding feature space and improving real-time detection in diverse transaction scenarios.

Methodology

The use of credit card details for purchase in an unlawful way is known as credit card fraud. They consist of direct credit card sales and online credit card sales. The main process of the credit card fraud detection approach is as follows and begins with the data acquisition from a suitable fraud detection dataset. This is then followed by data preprocessing, where missing values are first handled, and something known as Z-score normalisation is done to bring the values of the variables around the global mean of zero. Random oversampling is also used to deal with class imbalance to go further. There is then the use of PCA, a dimensionality reduction technique from which the most important characteristics can be retrieved. The data that is generated after analysis is then split into 80% training data and only 20% testing data. A CNN is utilised for the identification of frauds. These are precision, recall F1 score, and accuracy, and the results are presented show. Figure 1 shows the whole research design strategy.

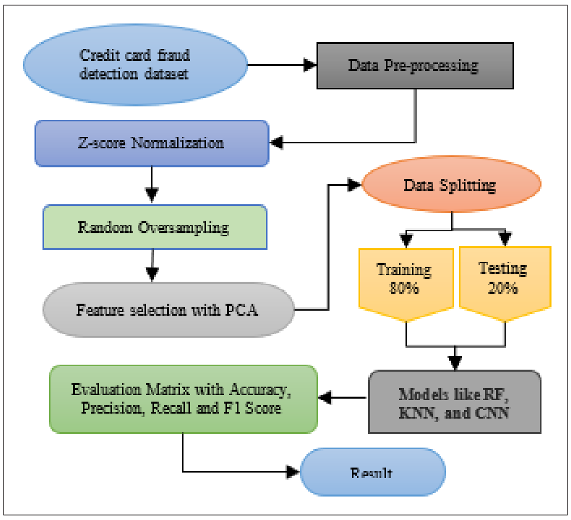

Figure 1: Flowchart for Credit Card Fraud Detection

Figure 1's flowchart's subsequent phases are explained in detail below:

Data Collection

For credit card fraud detection, the extracted Kaggle dataset of credit card fraud data is used. The dataset consists of 284807 credit card transaction records generated by the EU cardholders in two days in September 2013. The following statistical chart is displayed in Figure 2.

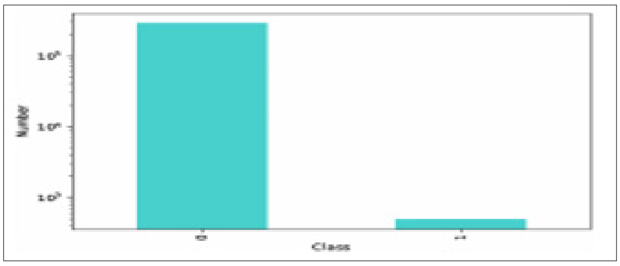

Figure 2: Statistical Chart for Positive and Negative Samples

The data sample's schematic design is displayed in Figure 2. Every transaction furthermore includes a collection of "Class" tags: 1 for fraudulent data and 0 for valid transaction data. The total number of fraudulent transactions among them is just 492, making about 0.172% of the dataset. The numbers of positive and negative samples in this dataset differ significantly, as seen in Figure 2.

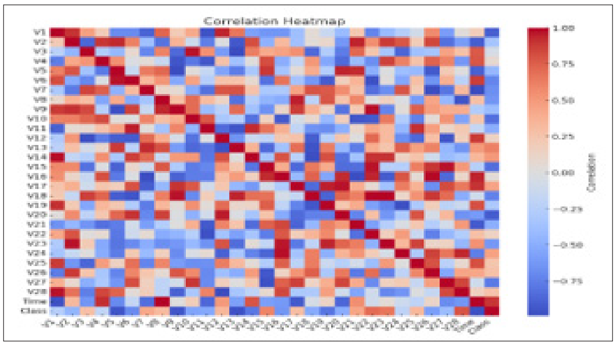

Figure 3: Correlation Matrix for Attributes

The dataset's correlation matrix is displayed in Figure 3. This matrix illustrates how attribute class is unaffected by the transaction's size and timing. The matrix even makes it evident that the PCA-applied qualities determine the transaction's class.

Data Preprocessing
The first process which is the data acquisition phase as in data preparation phase involves the processing of credit card fraud detection dataset for analysis. Below is the list of the pre-processing processes:

Z-score Normalization
Data normalisation is an indispensable part of training a model. The dataset is converted to a Gaussian distribution using Z-score normalisation [12]. As a result, the likelihood of an event taking place inside the bounds of a Gaussian distribution may be understood. This is how this phrase is utilised (Equation (1)).

$$Z = \frac{X-\mu}{\sigma} \quad (1)$$

The output, feature value, mean, and standard deviation of the variable values are denoted by Z, X, μ, and σ, respectively.

Random Oversampling
A sampling approach called oversampling, often referred to as upsampling, replicates the minority class samples in order to balance the dataset. The Smote method works effectively when the dataset is small. The creation of synthetic data points will take longer and perform less effectively when dealing with sufficiently large datasets [13]. The Smote approach was used to construct the new synthetic data point, A, which has the following definition:

$$\boxed{A = X + c(X_R - X)} \quad (2)$$

where c ($0 \le c \le 1$) is a constant, X_R is the data point chosen at random from among X is K closest neighbours, and X is a data point in the dataset.

Feature Selection with Principal Component Analysis
A data preparation method called feature selection keeps the most important characteristics while reducing the dimensionality of the dataset, improving model performance, and minimising computation time. To enhance efficiency and ensure data security, The principle component analysis (PCA) approach is used to choose features [14]. PCA generates a principal component formula (FF) where the coefficients of each index serve as initial weights. The dataset is analysed alongside its principal components, deriving an expression based on FF. These coefficients are then utilised as initial weights for the iterative classifier, streamlining the modelling process.

Data Splitting
The technique of breaking data into two or more groups is known as data splitting. This study uses an 80:20 ratio to divide the information into groups for testing and training.

Fraud Detection with CNN (Convolutional Neural Networks)
CNNs are thought to be the fundamental architecture of deep learning. The architecture of a CNN consists of one or more successive convolution layers and a pooling layer. These layers are supplemented with a categorisation layer and a fully connected layer, respectively. In this study, the CNN model proposed by Kim was used [15]. The architecture of this model is a slight adaptation of Collobert's CNN design [16]. These attributes are used to establish the input data categories.

Each of the n inputs in the input layer has a dense vector with k values [17]. Therefore, the input x is signified by a $d\ x\ k$ dimensional feature map. Let $x_i \in R^k$ can be a k-dimensional word vector which related to the i-th word of the input sentence. Thus length of a sentence is represented by n and a sentence by the symbol (3):

$$x_{1:n} = x_1 \oplus x_2 \oplus \dots \dots . \oplus x_n \quad (3)$$

where the operator for concatenation is $\oplus$. A convolution operation creates a new feature by applying a $w \in R^{hk}$ filter on an h-word window. A new property $ccii$ feature, for example, is made utilising a window of $x_{i:i+h-1}$words.

$$c_i = f(w.x_{i:i+h-1} + b) \quad (4)$$

In Eq. (4), b∈R is A constant and an odd function like tanh can be added as a form of incorporation of bias, are represented by ff. This convolution filter is applied to all potential word windows in the phrase$x_{1:h}$, $x_{2:h+1,\dots\dots}$, $x_{n-h+1:n}$. for making a feature map, Eq. (4) is used.

$$c = [c_1, c_{12} \dots \dots, c_{n-h+1}] \quad (5)$$

In Eq. (5), Here $c \in R^{n-h+1}$ A max-overtime pooling procedure is then performed on the feature map to get the maximum response of each filter [18]. Capturing the most noticeable characteristics in feature maps is the aim of this procedure. Using many Using different window sizes and filters, the model looks for different characteristics [19]. The outputs of the layer with these qualities are sent to the final layer, which is a fully connected layer [20]. It should be noted that the probability distribution of the labels is done through fully linked softmax layer.

Model Evaluation
The performance is evaluated metric of recall, accuracy, precision, and f1 score. Because they are helpful in evaluating circumstances involving imbalanced binary categorisation, certain assessment metrics are requested. For the performance of the model, if they have to compare it with the actual values, confusion matrix is used based on TP, TN, FP, and FN. These numbers provide information on the efficacy of categorisation by assisting in the calculation of metrics like recall, precision, and accuracy.

Accuracy: The forecasted accuracy of the proposed model on the database is validated by accuracy. The model's total classification accuracy may be inferred from the accuracy rate. It can be written as (6):

$$Accuracy = \frac{(True\ Positive + True\ Negative)}{(Total\ Number\ of\ Predictions)} \quad (6)$$

Precision: Precision, which may be written as (7), quantifies the percentage of samples that the classification model accurately recognised as positive—that is, cases that are identified as diabetic among patients with diabetes:

$$Precision = \frac{TP}{(TP+FP)} \quad (7)$$

Recall: In a classification model, it calculates the proportion of properly predicted positive examples to genuine positive examples—that is, cases that are accurately classified as diabetes patients. It may be written like this (8):

$$Recall = \frac{TP}{(TP+FN)} \quad (8)$$

F1 Score: The F1-Score, which may be written as (9), is a more thorough performance assessment in the event of class imbalance:

$$\boxed{F1 - score = 2 \times \frac{precision \times recall}{(+recall)}} \quad 9)$$

The classification outcomes of the variants employed in this article are evaluated using these performance metrics.

Result Analysis and Discussion

This section pertains to the examination and clarification of the results, as well as the subsequent discussion. Use ML models like RFand KNN, to detect credit card fraud. Use the Kaggle dataset to compare these models (see Table III) to the CNN model. The CNN model performance, as summarised in Table 2, indicates impressive performance across key classification metrics.

Table 2: Results of the CNN model for Credit Card Fraud Detection

Evaluation Parameters	Convolutional Neural network (CNN)
Accuracy	99.93
Precision	80.8
Recall	78.29
F1-Score	79.52

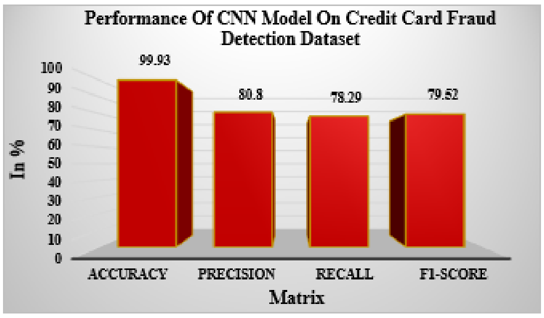

Figure 4: CNN Model Performance

Table 2 and Figure 4 summarise the performance of a CNN model across various classification metrics, showcasing outstanding results. With an impressive accuracy of 99.93%, the model demonstrates an exceptional ability to correctly classify outcomes in nearly all instances. Its precision of 80.8% indicates effectiveness in minimising false positives, while the recall of 78.29% reflects its ability to identify most relevant instances. To demonstrate the model's reliability, its F1-Score is 79.52% and represents the golden mean between the precision and recalling of results.

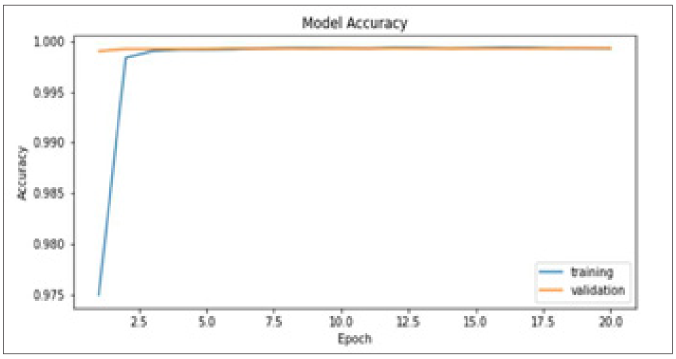

Figure 5: Accuracy Curve of Training and Validation Data

The performance of the model for both training and validation data and current epoch up to 20 epochs is depicted below in Figure 5. Initially, training accuracy increases rapidly and converges near 100%, indicating the model learns the training data's patterns efficiently. Additionally, validation accuracy stays close to 100%, demonstrating how effectively the model generalises to new data. The overlap between training and validation accuracy curves suggests minimal overfitting, demonstrating robust model performance.

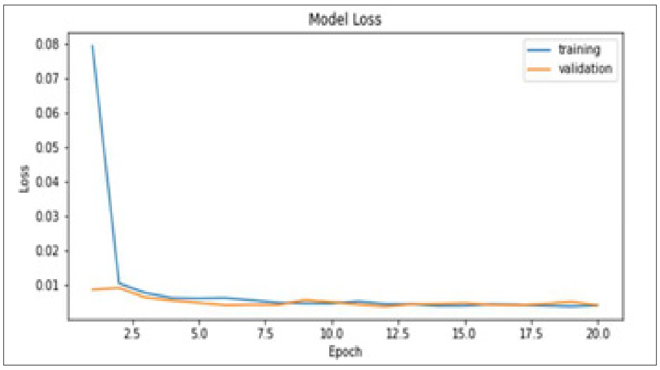

Figure 6: Loss Curve of Training and Validation Data

The model's training and validation losses are displayed in Figure 6. data over 20 epochs. Initially, the training loss decreases sharply, indicating rapid learning In order to reduce error, the model modifies its weights. The validation loss also declines quickly and stabilises at a very low value, demonstrating the model's ability to generalise effectively. Both curves remain close throughout the epochs, reflecting minimal overfitting and a well-optimized model. The consistent low loss suggests strong predictive performance.

Comparative Analysis Results on Kaggle Credit Card Fraud Detection Dataset

Models	Accuracy	Precision	Recall	F1 score
RF [21]	96.96	90.27	67.89	78.11
KNN[10]	97.15	99.9	82.85	90.66
CNN	99.93	80.8	78.29	79.52

The comparative analysis of the models reveals varying strengths and weaknesses in their performance metrics. The CNN model demonstrated its better ability to accurately identify instances overall, achieving the greatest accuracy of 99.93%. However, its precision 80.8%, recall 78.29%, and F1 score 79.52% were lower compared to other models, indicating room for improvement in handling imbalanced data. KNN exhibited excellent precision (99.9%) and balanced performance with an F1 score of 90.66, despite a slightly lower accuracy, 97.15%, than CNN. RF demonstrated robust accuracy 96.96% but lagged significantly in recall at 67.89%, resulting in the lowest F1 score of 78.11. Overall, CNN excels in accuracy, while KNN offers a more balanced performance in terms of all metrics.

Conclusion and Future Scope

Given that scammers are always developing new strategies to evade detection systems, credit card fraud is becoming a bigger danger to financial institutions. One of the main goals of an efficient fraud detection system is to accurately forecast fraudulent situations and minimise false positives. Using a CNN model and machine learning techniques, this study offers a thorough framework for detecting credit card fraud. This study shows how well a CNN model works to detect credit card fraud, achieving an impressive accuracy of 99.93%, thereby outperforming traditional machine learning models like KNN and RF in classification accuracy. However, the CNN model exhibits lower precision, recall, and F1 scores compared to KNN, highlighting limitations in handling class imbalance and reducing both false negatives and false positives. In order to improve accuracy and recall, future research might concentrate on investigating cutting-edge methods like hybrid models or attention processes. Additionally, incorporating real-time fraud detection systems and testing the model on larger, more diverse datasets could further validate its applicability and scalability in dynamic environments [21-38].

References

1. Kumar V, Chan FTS (2011) A superiority search and optimisation algorithm to solve RFID and an environmental factor embedded closed loop logistics model. Int J Prod Res 49.
2. Montague D (2010) Essentials of Online Payment Security and Fraud Prevention. Wiley https://onlinelibrary.wiley.com/doi/book/10.1002/9781118386750.
3. Hasan MZ, Fink R, Suyambu MR, Baskaran MK (2012) Assessment and improvement of intelligent controllers for elevator energy efficiency. IEEE International Conference on Electro Information Technology https://ieeexplore.ieee.org/document/6220727.
4. Quah JTS, Sriganesh M (2008) Real-time credit card fraud detection using computational intelligence. Expert Syst Appl 35: 1721-1732.
5. Li XL, Zhong Y (2012) An Overview of Personal Credit Scoring: Techniques and Future Work. Int. J. Intell. Sci https://www.scirp.org/journal/paperinformation?paperid=24193.
6. Abakarim Y, Lahby M, Attioui A (2018) An Efficient Real-Time Model For Credit Card Fraud Detection Based On Deep Learning. Proceedings of the 12th International Conference on Intelligent Systems: Theories and Applications, in SITA'18. New York, NY, USA: Association for Computing Machinery https://dl.acm.org/doi/10.1145/3289402.3289530.
7. Sethia A, Patel R, Raut P (2018) Data augmentation using generative models for credit card fraud detection. 4th International Conference on Computing Communication and Automation, ICCCA https://ieeexplore.ieee.org/document/8777628.
8. Zamini M, Montazer (2018) Credit Card Fraud Detection using autoencoder based clustering. 9th International Symposium on Telecommunication: With Emphasis on Information and Communication Technology https://ieeexplore.ieee.org/document/8661129.
9. Mubalaike AM, Adali E (2018) Deep Learning Approach for Intelligent Financial Fraud Detection System. 3rd International Conference on Computer Science and Engineering https://ieeexplore.ieee.org/document/8566574.
10. Awoyemi JO, Adetunmbi AO, Oluwadare SA (2017) Credit card fraud detection using machine learning techniques: A comparative analysis. International Conference on Computing Networking and Informatics (ICCNI) 1-9.
11. Véronique Van Vlasselaer, Cristián Bravo, Olivier Caelen, Tina Eliassi-Rad, Leman Akoglu, et al. (2015) APATE: A novel approach for automated credit card transaction fraud detection using network-based extensions. Decis Support Syst https://www.sciencedirect.com/science/article/abs/pii/S0167923615000846.
12. Kumar VV, Liou FW, Balakrishnan SN, Kumar V (2015) Economical impact of RFID implementation in remanufacturing: a Chaos-based Interactive Artificial Bee Colony approach. J Intell Manuf 26: 815 - 830.
13. Kumar VV, Tripathi M, Pandey MK, Tiwari MK (2009) Physical programming and conjoint analysis-based redundancy allocation in multistate systems: A Taguchi embedded algorithm selection and control (TAS&C) approach. Proc Inst Mech Eng Part O J Risk Reliab 223: 215-232.
14. Kumar V, Kumar VV, Mishra N, Chan FTS, Gnanasekar B (2010) Warranty failure analysis in service supply Chain a multi-agent framework. Proceedings of 2010 8th International Conference on Supply Chain Management and Information Systems: Logistics Systems and Engineering https://ieeexplore.ieee.org/document/5681777.
15. Kim Y (2014) Convolutional neural networks for sentence classification. EMNLP 2014 - 2014 Conference on Empirical Methods in Natural Language Processing, Proceedings of the Conference 1746-1751.
16. Collobert R, Weston J, Bottou L, Karlen M, Kavukcuoglu K, et al. (2011) Natural language processing (almost) from scratch. J Mach Learn Res 2493-2537.
17. Kumar VV (2014) An interactive product development model in remanufacturing environment : a chaos-based artificial bee colony approach. Missouri University of Science and Technology https://scholarsmine.mst.edu/cgi/viewcontent.cgi?article=8243&context=masters_theses.
18. Hasan MZ, Fink R, Suyambu MR, Baskaran MK, James D, et al. (2015) Performance evaluation of energy efficient intelligent elevator controllers. IEEE International Conference on Electro Information Technology https://ieeexplore.ieee.org/document/7293320.
19. Kumar VV, Yadav SR, Liou FW, Balakrishnan SN (2013) A digital interface for the part designers and the fixture designers for a reconfigurable assembly system. Math Probl Eng https://onlinelibrary.wiley.com/doi/10.1155/2013/943702.
20. Kumar VV, Pandey MK, Tiwari MK, Ben-Arieh D (2010) Simultaneous optimization of parts and operations sequences in SSMS: A chaos embedded Taguchi particle swarm optimization approach. J Intell Manuf 21: 335-353.
21. Xuan S, Liu G, Li Z, Zheng L, Wang S, et al. (2018) Random forest for credit card fraud detection. ICNSC 15th IEEE International Conference on Networking, Sensing and Control https://ieeexplore.ieee.org/document/8361343.
22. Gagan Kumar Patra, Shravan Kumar Rajaram, Venkata Nagesh Boddapati (2019) Ai And Big Data In Digital Payments: A Comprehensive Model For Secure Biometric Authentication. Educational Administration: Theory and Practice 25: 773-781.
23. Chandrababu Kuraku, Hemanth Kumar Gollangi, Janardhana Rao Sunkara (2020) Biometric Authentication In Digital Payments: Utilizing AI And Big Data For Real-Time Security And Efficiency. Educational Administration: Theory and Practice 26: 954-964.

24. Eswar Prasad Galla, Chandrakanth Rao Madhavaram, Venkata Nagesh Boddapati (2021) Big Data And AI Innovations In Biometric Authentication For Secure Digital Transactions. Educational Administration: Theory and Practice 27: 1228-1236.
25. Janardhana Rao Sunkara, Sanjay Ramdas Bauskar, Chandrakanth Rao Madhavaram, Eswar Prasad Galla, Hemanth Kumar Gollangi (2021) Data-Driven Management: The Impact of Visualization Tools on Business Performance, International Journal of Management (IJM) 12: 1290-1298.
26. Mohit Surender Reddy, Manikanth Sarisa, Siddharth Konkimalla, Sanjay Ramdas Bauskar, Hemanth Kumar Gollangi, et al. (2021) Predicting tomorrow's Ailments: How AI/ML Is Transforming Disease Forecasting. ESP Journal of Engineering & Technology Advancements 1: 188-200.
27. Gollangi K, Bauskar SR, Madhavaram CR, Galla P, Sunkara JR, et al. (2020) Echoes In Pixels : The Intersection Of Image Processing And Sound Open Access Echoes In Pixels : The Intersection Of Image Processing And Sound Detection. Int J Dev Res 10: 39735-39743.
28. Gollangi HK, Bauskar SR, Madhavaram CR, Galla EP, Sunkara JR, et al. (2020) Unveiling the Hidden Patterns: AI-Driven Innovations in Image Processing and Acoustic Signal Detection. JRTCSE 8: 25-45.
29. Gollangi HK, Bauskar SR, Madhavaram CR, Galla EP, Sunkara JR, et al. (2020) Exploring AI Algorithms for Cancer Classification and Prediction Using Electronic Health Records. Journal of Artificial Intelligence and Big Data 1: 65-74.
30. Chandrakanth RM, Eswar PG, Mohit SR, Manikanth S, Venkata NB, et al. (2021) Predicting Diabetes Mellitus in Healthcare: A Comparative Analysis of Machine Learning Algorithms on Big Dataset. In Global Journal of Research in Engineering & Computer Sciences 1: 1-11.
31. Krutthika HK (2019) Modelling of data delivery modes of next-generation SOC-NOC router. IEEE Global Conference for Advancement in Technology (GCAT) https://ieeexplore.ieee.org/document/8978290.
32. Pavitha US, Nikhila S, Krutthika HK (2012) Design and implementation of image dithering engine on a spartan 3AN FPGA. Intern J Future Compt Comm 1: 361.
33. Nikhila S, Pavitha US, Krutthika HK (2014) Face recognition using wavelet transforms. International Journal of Advanced Research in Electrical Electronics and Instrumentation Engineering 3: 6740-6746.
34. Krutthika HK, Rajashekhara (2019) Modeling of Data Delivery Modes of Next Generation SOC-NOC Router. Global Conference for Advancement in Technology (GCAT) 1-6.
35. Kalla D, Kuraku DS, Samaah F (2021) Enhancing cyber security by predicting malwares using supervised machine learning models. International Journal of Computing and Artificial Intelligence 2: 55-62.
36. Kalla D, Smith N, Samaah F, Polimetla K (2021) Facial Emotion and Sentiment Detection Using Convolutional Neural Network. Indian Journal of Artificial Intelligence Research (INDJAIR) 1: 1-13.
37. Kuraku S, Kalla D (2020) Emotet malware- A banking credentials stealer. Iosr J Comput Eng 22: 31-41.
38. Kalla D, Samiuddin V (2020) Chatbot for medical treatment using NLTK Lib. IOSR J Comput Eng 22: 12.