



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJIRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 3, March 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423



9940 572 462



6381 907 438



ijirset@gmail.com



www.ijirset.com

A Machine Learning method with Hybrid Feature Selection for Improved Credit Card Fraud Detection

Mandula china pentu saheb^[1], Dhulipalla Vidhayini^[2], Gaddam Sharmila^[3], Bathula Munna^[4],
Divyakolu Vamsi^[5]

Asst. Professor of Computer Science and Engineering, Vasireddy Venkatadri Institute of Technology, Guntur, India^[1]

Undergraduate student of Computer Science and Engineering, Vasireddy Venkatadri Institute of Technology,
Guntur, India^[2,3,4,5]

ABSTRACT: This study addresses the burgeoning challenge of credit card fraud detection in the realm of electronic commerce and digital payments. Recognizing the surge in credit card transactions, the research focuses on optimizing machine learning (ML) classifiers by proposing a hybrid feature-selection technique. This method comprises filter and wrapper feature-selection steps, ensuring the utilization of only the most pertinent features for analysis. Various feature extraction approaches, including Full Feature, Information Gain (IG), Genetic Algorithm Wrapper (GAW), and an ensemble of IG-GAW, are employed. The study evaluates the performance of Extreme Learning Machine (ELM) and diverse ML models, such as AdaBoost, Logistic Regression, Random Forest, SVM, Decision Tree, and Voting Classifier. Notably, the extension of the research incorporates an ensemble method, demonstrating superior accuracy by combining predictions from multiple models. The Voting Classifier, in particular, attains a remarkable 100% accuracy. This research contributes significantly to the ongoing efforts in enhancing credit card fraud detection, providing valuable insights into feature selection and ensemble techniques for bolstering the robustness and accuracy of ML models in real-world scenarios.

KEYWORDS: credit card; feature selection; fraud detection; genetic algorithm; machine learning.

I. INTRODUCTION

In recent years, electronic payments (e-payments) have become ubiquitous, driven by technological advancements and the proliferation of electronic funding methods [1]. Among these, credit cards have emerged as a predominant means for conducting seamless and convenient e-payments [2]. The second quarter of 2021 witnessed a staggering issuance of 1131 million Mastercard and 1156 million Visa cards, underscoring the widespread adoption of credit cards globally [3]. However, the surge in credit card usage has also given rise to a parallel increase in fraud rates, impacting both consumers and merchants and causing substantial financial losses within the financial sector [4]. Recognizing this challenge, there is a pressing need to develop effective credit card fraud-detection systems to mitigate losses.

To address the complexity introduced by the advent of big data and the Internet of Things (IoT) in this context, machine learning algorithms have been pivotal [5–7]. Nevertheless, the high dimensionality of enormous datasets poses challenges, and leveraging feature-selection techniques becomes imperative for model accuracy and interpretability [11]. This paper explores the significance of feature selection in enhancing credit card fraud detection, categorizing techniques into filters, wrappers, and embedded methods [10,14]. Notably, filter methods, relying on attribute ranking, stand out for their independence from classifier bias, presenting a promising avenue for dimensionality reduction in fraud detection [15].

However, wrapper methods use an ML classifier's performance as the evaluation metric in selecting the most relevant feature set. Wrapper methods usually lead to better classification performance than filter techniques because the feature-selection procedure is optimized for the chosen classification algorithm [16,17]. Generally, wrapper methods employ a search strategy to identify the candidate subsets. The classifier's performance on the various feature subsets is measured, and the subset that leads to the highest performance is selected as the most informative subset. Examples of wrapper-based feature selection techniques include the Boruta algorithm, forward selection, backward elimination, and the genetic algorithm. Embedded methods select the features that enhance the model's performance during training. The feature selection is incorporated into the learning procedure [13]. Unlike wrapper methods, this type of feature selection aims to reduce the time used in training different subsets. Embedded methods include random forest, decision tree, gradient boosting, elastic net, and LASSO [10].

This study aims to optimize credit card fraud detection in electronic commerce using a hybrid feature-selection technique, combining filter and wrapper steps. Various feature extraction methods and machine learning models, including Extreme Learning Machine and ensemble techniques, are explored to enhance performance without presenting specific results.

The surge in credit card transactions poses a challenge for fraud detection. This study addresses the issue of redundant and irrelevant features in credit card data, degrading machine learning classifier performance. A hybrid feature-selection technique is proposed to streamline feature relevance, optimizing fraud detection without presenting specific results.

II. LITERATURE REVIEW

Credit card fraud remains a significant challenge in the financial sector, necessitating the development of advanced fraud detection systems. Machine learning techniques have emerged as powerful tools for identifying fraudulent transactions, leveraging patterns and anomalies within large datasets. This literature survey aims to provide an overview of recent studies and advancements in credit card fraud detection using machine learning approaches.

In their work, Femila Roseline et al. [1] proposed an autonomous credit card fraud detection system employing a machine learning approach. They emphasized the importance of leveraging advanced algorithms to enhance fraud detection accuracy. By utilizing machine learning, their system aimed to adapt and evolve in response to changing fraud tactics, thereby improving overall detection performance.

Alharbi et al. [2] introduced a novel text2IMG mechanism for credit card fraud detection, utilizing deep learning techniques. Their approach involved converting textual data related to credit card transactions into images, which were then analyzed using convolutional neural networks (CNNs). This interdisciplinary approach demonstrated the potential of combining textual and image data to improve fraud detection accuracy significantly.

Bin Sulaiman et al. [3] conducted a comprehensive review of machine learning approaches for credit card fraud detection. Their study provided valuable insights into the strengths and limitations of different methodologies, aiding researchers and practitioners in selecting appropriate techniques for fraud detection systems. The review highlighted the importance of continuously evolving strategies to counter emerging fraud threats effectively.

Wang et al. [4] explored credit card fraud detection strategies incorporating consumer incentives. Their study investigated the effectiveness of offering incentives to consumers for reporting fraudulent activities promptly. By incentivizing consumer involvement, the proposed approach aimed to enhance fraud detection capabilities while promoting consumer vigilance in monitoring their transactions.

Nandi et al. [5] proposed a hierarchical behavior- knowledge space model for credit card fraud detection. Their approach integrated domain knowledge with machine learning algorithms to create a comprehensive fraud detection framework. By organizing transaction data into a hierarchical structure based on behavioral patterns and domain expertise, their model achieved improved detection accuracy.

Ileberi et al. [6] evaluated the performance of various machine learning methods for credit card fraud detection, incorporating techniques such as Synthetic Minority Over- sampling Technique (SMOTE) and AdaBoost. Their study highlighted the importance of preprocessing techniques and ensemble learning methods in improving fraud detection

accuracy, especially in imbalanced datasets.

Rtayli and Enneya [7] proposed an enhanced credit card fraud detection approach based on Support Vector Machine (SVM) with recursive feature elimination and hyperparameters optimization. Their method focused on refining feature selection and model optimization techniques to improve the overall performance of fraud detection systems.

Huebner et al. [9] explored the role of smartphones in assisting mental accounting and reducing consumer spending. Although not directly focused on fraud detection, their study highlighted the importance of transaction salience in influencing consumer behavior, which could indirectly impact fraud detection strategies and consumer awareness.

Ileberi et al. [19] presented a machine learning-based credit card fraud detection approach utilizing the Genetic Algorithm (GA) for feature selection. By employing GA for feature selection, their method aimed to identify the most informative features for improving fraud detection accuracy, thereby optimizing model performance.

Han et al. [23] introduced a competition-driven multimodal multiobjective optimization approach for feature selection in credit card fraud detection. Their method utilized a novel optimization framework to identify informative features from multiple modalities, enhancing the robustness and accuracy of fraud detection models.

Malik et al. [24] proposed a hybrid machine learning architecture for credit card fraud detection, combining multiple algorithms to leverage their complementary strengths. Their approach showcased the potential of hybrid models in enhancing fraud detection performance by integrating diverse learning techniques.

Zioviris et al. [25] developed a deep learning multistage model for credit card fraud detection, utilizing advanced neural network architectures. Their work demonstrated the efficacy of deep learning techniques in capturing complex patterns inherent in fraudulent transactions, showcasing the potential of deep learning in fraud detection applications.

The literature survey highlights the diverse approaches and methodologies employed in credit card fraud detection using machine learning techniques. From autonomous systems to hybrid architectures and deep learning models, researchers continue to innovate and refine fraud detection strategies to stay ahead of evolving fraud tactics. Future research directions may involve further exploration of interdisciplinary approaches, real-time data processing, and optimization techniques to enhance the efficacy and efficiency of fraud detection systems in safeguarding financial transactions.

III. METHODOLOGY

i) Proposed Work:

The proposed system aims to enhance credit card fraud detection in the context of burgeoning electronic commerce and digital payments. To address the challenge of suboptimal machine learning (ML) classifier performance caused by redundant and irrelevant features in credit card data, a hybrid feature-selection technique is introduced. This technique integrates both filter and wrapper feature-selection steps, ensuring that only the most pertinent features are utilized for analysis. Various feature extraction methods, including Full Feature, Information Gain (IG), Genetic Algorithm Wrapper (GAW), and an ensemble of IG-GAW, are explored. The study evaluates the effectiveness of Extreme Learning Machine (ELM) alongside diverse ML models, such as AdaBoost, Logistic Regression, Random Forest, SVM, Decision Tree, and the Voting Classifier. Additionally, an ensemble approach is employed to combine predictions from multiple models for a more robust and accurate final prediction. This comprehensive system contributes valuable insights to the field, aiming to bolster the efficiency of credit card fraud detection in real-world scenarios.

ii) System Architecture:

The credit card fraud detection system architecture consists of several key components. Firstly, the dataset containing credit card transaction data is processed, including preprocessing steps such as cleaning and normalization. Feature extraction techniques such as Information Gain (IG) and Genetic Algorithm Wrapper (GAW) are then applied to extract relevant features from the dataset.

Next, the dataset is split into training and testing subsets for model evaluation. Various machine learning models including Extreme Learning Machine (ELM), AdaBoost, Logistic Regression, Random Forest, Support Vector Machine (SVM), Decision Tree, and Voting Classifier are trained on different feature sets.

Finally, the trained models make predictions on new transactions to determine whether they are fraudulent or non-fraudulent. The system outputs the final prediction, providing insights into potential fraudulent activities, thereby assisting in fraud detection and prevention efforts.

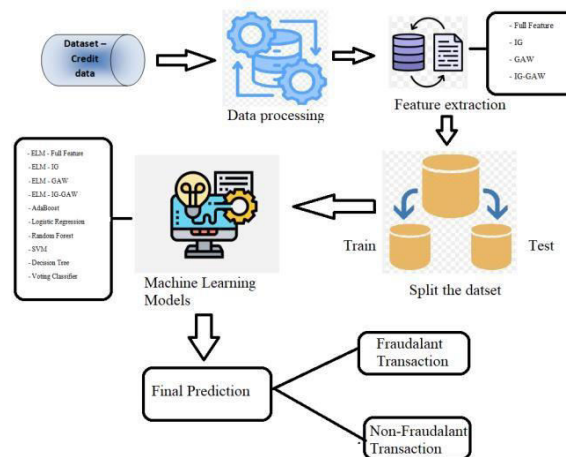


Fig 1 System Architecture

iii) Dataset Collection:

The dataset used in this study for credit card fraud detection comprises transactions made by European cardholders in September 2013, publicly available and widely utilized in various research endeavors in fraud detection. It consists of 284,807 transactions, among which 492 are labeled as fraudulent, making up only 0.17% of the dataset. The majority class consists of legitimate transactions, accounting for 99.83% of the dataset. This class imbalance presents a significant challenge for conventional machine learning algorithms.

To address privacy concerns, features in the dataset were anonymized and labeled as V1 to V28, except for the "Time" and "Amount" features. The "Time" feature denotes the seconds elapsed between a transaction and the first transaction in the dataset, while the "Amount" feature represents the monetary value of each transaction. The "Class" attribute serves as the response variable, distinguishing between legitimate (labeled as 0) and fraudulent (labeled as 1) transactions. This dataset provides a realistic and challenging scenario for evaluating the performance of fraud detection algorithms.

iv) Exploratory Data Analysis:

Data processing:

Data processing begins with loading the dataset into a pandas dataframe, a powerful Python library for data manipulation and analysis. This step facilitates efficient handling of the dataset, allowing for various operations such as filtering, sorting, and summarizing. Once loaded, the dataset undergoes preprocessing, which includes identifying and handling missing values, converting data types if necessary, and encoding categorical variables.

Next, unwanted columns are dropped from the dataframe. These columns may contain redundant or irrelevant information that does not contribute to the analysis or modeling process. By removing unnecessary columns, the dataset is streamlined, reducing computational overhead and improving model performance.

Data Normalization:

Data normalization is crucial for ensuring that features are on a similar scale, preventing certain features from dominating others during the training of machine learning models. Normalization involves transforming numerical features to a standard range, typically between 0 and 1 or following a standard distribution.

Common normalization techniques include Min-Max scaling and Standardization (Z-score normalization). Min-Max scaling scales the features to a specified range, while Standardization transforms the data to have a mean of 0 and a standard deviation of 1. These techniques help improve the convergence of optimization algorithms and enhance the stability of machine learning models.

Visualization using seaborn & matplotlib:

Visualization plays a vital role in understanding the underlying patterns and relationships within the data. Seaborn and Matplotlib, two popular Python libraries for data visualization, are employed for this purpose.

Various types of plots are generated, including histograms, scatter plots, box plots, and heatmaps, to visualize the distribution of features, relationships between variables, and correlations among them. These visualizations aid in identifying outliers, understanding data distributions, detecting patterns, and gaining insights into the dataset's characteristics.

Feature Extraction:

Feature extraction involves selecting the most relevant features from the dataset to improve model performance and reduce computational complexity. Four feature extraction techniques are employed in this study:

Full Feature: All available features in the dataset are retained for analysis without any feature selection or extraction.

Information Gain (IG): Features with the highest information gain regarding the target variable (fraudulent or legitimate transactions) are selected. Information gain measures the reduction in uncertainty about the target variable achieved by including a particular feature.

Genetic Algorithm Wrapper (GAW): A genetic algorithm is applied to search for the optimal subset of features that maximize the performance of the classification model. The genetic algorithm iteratively selects and evaluates feature subsets based on their contribution to model accuracy.

IG-GAW: A combination of Information Gain and Genetic Algorithm Wrapper is utilized to select features, leveraging the strengths of both techniques. Information gain is first used to identify informative features, which are then further optimized using the genetic algorithm to enhance model performance. This hybrid approach aims to improve feature selection effectiveness and model generalization.

v) Training & Testing:

In splitting the dataset, the goal is to divide the data into separate subsets for training and testing the machine learning model. This process is crucial for evaluating the model's performance on unseen data and assessing its ability to generalize to new observations.

The dataset is randomly partitioned into two subsets: the training set and the testing set. The training set comprises a majority portion of the data, typically around 70-80%, and is used to train the machine learning model. This subset allows the model to learn patterns and relationships within the data.

Conversely, the testing set constitutes the remaining portion of the data and is kept separate from the training set. This subset is used to evaluate the trained model's performance by assessing its predictive accuracy on unseen data.

It's essential to ensure that the distribution of classes (fraudulent and legitimate transactions) is preserved in both the training and testing sets to prevent biased evaluations. Cross-validation techniques can also be employed to further

validate the model's performance.

vi) Algorithms:

ELM - Full Feature: Extreme Learning Machine (ELM) with Full Feature utilizes all available features for credit card fraud detection. This algorithm is chosen for its ability to efficiently process high-dimensional data, providing a swift and effective solution for fraud pattern recognition without the need for feature selection.

ELM - IG: ELM with Information Gain (IG) selects features based on their information gain, optimizing model performance. This approach is employed to enhance the efficiency of credit card fraud detection by focusing on the most informative features, thereby improving the algorithm's predictive accuracy.

ELM - GAW: In ELM with Genetic Algorithm Wrapper (GAW), a genetic algorithm is applied to select features, optimizing model efficiency. This technique is chosen to address the challenge of high dimensionality, ensuring that only the most relevant features are considered, leading to improved fraud detection accuracy.

ELM - IG-GAW: ELM with an ensemble of Information Gain and Genetic Algorithm Wrapper combines both feature selection methods. This dual approach is implemented to leverage the strengths of both techniques, providing a comprehensive solution for optimizing feature relevance and enhancing credit card fraud detection accuracy.

AdaBoost: AdaBoost is employed in this project to create an ensemble of weak learners, boosting the overall model's performance. By combining multiple classifiers, AdaBoost improves the detection of fraudulent patterns, making it a suitable choice for enhancing the accuracy and robustness of credit card fraud detection models.

Logistic Regression: Logistic Regression is utilized in this project due to its simplicity and effectiveness in binary classification tasks. It provides a probabilistic output, making it suitable for predicting the likelihood of credit card fraud. Its interpretability and efficiency contribute to the overall model diversity and performance.

Random Forest: Random Forest is selected for its ability to handle high-dimensional data and reduce overfitting. By constructing a multitude of decision trees, it enhances the model's accuracy and generalization, making it a robust choice for credit card fraud detection in complex datasets.

SVM: Support Vector Machines (SVM) are employed for their capacity to handle high-dimensional data and effectively classify patterns. SVM's ability to find the optimal hyperplane in feature space contributes to improved credit card fraud detection accuracy, making it a valuable algorithm in this project.

Decision Tree: Decision Trees are chosen for their simplicity and interpretability. In this project, they are employed for credit card fraud detection due to their ability to capture non-linear relationships and hierarchical patterns in the data, contributing to the overall model diversity and effectiveness.

Voting Classifier: A Voting Classifier is implemented to combine predictions from multiple individual models, including ELM, AdaBoost, and others. This ensemble approach aims to enhance overall predictive accuracy and robustness, making it a strategic choice for improving the effectiveness of credit card fraud detection in diverse scenarios.

IV. EXPERIMENTAL RESULTS



Fig 2 Home page



Fig 3 About page

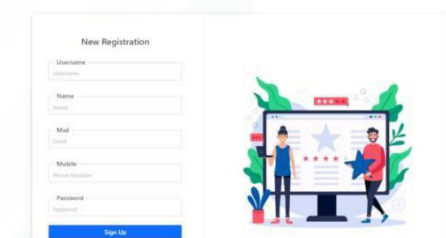


Fig 4 Registration page

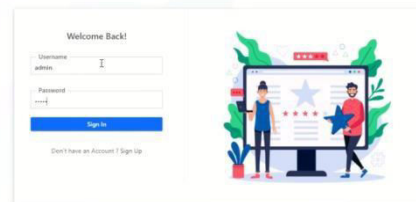


Fig 5 Login page

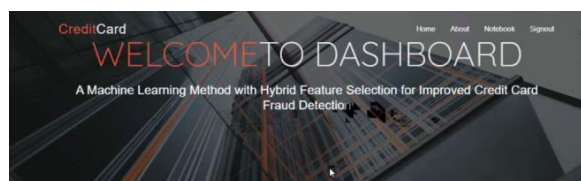


Fig 6 Main page

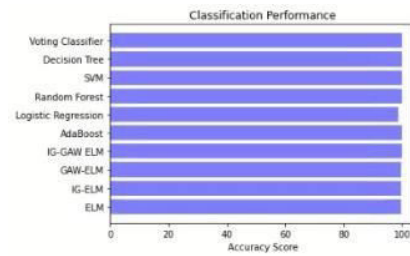
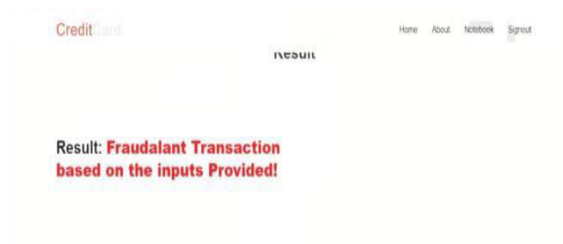


Fig 7 Accuracy comparison graph



Credit card input form with fields for V4, V5, V8, V10, V14, V16, V17, V21, V27, and V28. Each field contains a numerical value. A 'Predict' button is located at the bottom.

Fig 8 Upload input values



Result display showing 'Result: Fraudulant Transaction based on the inputs Provided!'.

Fig 9 Predict result as fraudalant transaction



Form

V2: 0.7669405

V4: 0.01666045

V5: 0.54108391

V8: 0.02010946

V10: 0.002201208

V14: 0.014764073

V16: 0.176000083

V17: 0.434076798

V21: 0.00146794

V27: 0.073404751

V28: 0.00110908

Predict

Fig 10 Upload another input values

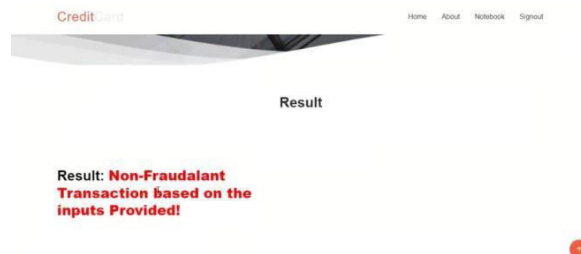


Fig 11 Final outcome as Non-fraudulent transaction based on given input values

V. CONCLUSION

In conclusion, the study addresses the intricate challenge of detecting fraudulent credit card transactions by proposing a novel hybrid approach. Leveraging the strengths of various feature-selection methods and machine learning (ML) techniques, including information gain, genetic algorithms, and extreme learning machines, the proposed system offers a comprehensive solution. The hybrid feature-selection technique, integrating both filter and wrapper steps, ensures the utilization of pertinent features, addressing the issue of suboptimal classifier performance attributed to redundant and irrelevant data. The evaluation of diverse ML models, such as AdaBoost, Logistic Regression, Random Forest, SVM, Decision Tree, and the Voting Classifier, in conjunction with the ensemble approach, highlights the system's adaptability and robustness. The exploration of feature extraction methods, including Full Feature, IG, GAW, and IG-GAW, further contributes to the system's efficiency in credit card fraud detection. By combining cutting-edge methodologies and embracing a holistic perspective, the proposed system stands as a valuable contribution to the field. The study's findings offer insights that can significantly enhance the detection rate of fraudulent activities in electronic commerce, providing a reliable and adaptable solution for real-world scenarios in the dynamic landscape of digital payments.

VI. FUTURE SCOPE

The future scope involves expanding research by exploring additional combinations of evolutionary algorithms and machine learning-based feature selection techniques to advance credit card fraud detection capabilities. Further efforts will focus on incorporating novel aspects and refining the proposed hybrid approach. Obtaining more recent and diverse datasets will be a priority to ensure ML models are trained on up-to-date information, enhancing their adaptability to evolving fraud patterns and strengthening the overall effectiveness of fraud detection systems in real-world scenarios.

REFERENCES

- [1] Femila Roseline, J.; Naidu, G.; Samuthira Pandi, V.; Alamelu alias Rajasree, S.; Mageswari, N. Autonomous credit card fraud detection using machine learning approach. *Comput. Electr. Eng.* 2022, 102, 108132. [CrossRef]
- [2] Alharbi, A.; Alshammari, M.; Okon, O.D.; Alabrah, A.; Rauf, H.T.; Alyami, H.; Meraj, T. A Novel text2IMG Mechanism of Credit Card Fraud Detection: A Deep Learning Approach. *Electronics* 2022, 11, 756. [CrossRef]
- [3] Bin Sulaiman, R.; Schetinin, V.; Sant, P. Review of Machine Learning Approach on Credit Card Fraud Detection. *Hum.-Centric Intell. Syst.* 2022, 2, 55–68. [CrossRef]
- [4] Wang, D.; Chen, B.; Chen, J. Credit card fraud detection strategies with consumer incentives. *Omega* 2019, 88, 179–195. [CrossRef]
- [5] Nandi, A.K.; Randhawa, K.K.; Chua, H.S.; Seera, M.; Lim, C.P. Credit card fraud detection using a hierarchical behavior-knowledge space model. *PLoS ONE* 2022, 17, e0260579. [CrossRef]
- [6] Ileberi, E.; Sun, Y.; Wang, Z. Performance Evaluation of Machine Learning Methods for Credit Card Fraud Detection Using SMOTE and AdaBoost. *IEEE Access* 2021, 9, 165286–165294. [CrossRef]
- [7] Rtayli, N.; Enneya, N. Enhanced credit card fraud detection based on SVM-recursive feature elimination and hyper-parameters optimization. *J. Inf. Secur. Appl.* 2020, 55, 102596. [CrossRef]
- [8] Oo, M.C.M.; Thein, T. An efficient predictive analytics system for high dimensional big data. *J. King Saud Univ. - Comput. Inf. Sci.* 2022, 34, 1521–1532. [CrossRef]
- [9] Huebner, J.; Fleisch, E.; Ilic, A. Assisting mental accounting using smartphones: Increasing the salience of credit card transactions helps consumer reduce their spending. *Comput. Hum. Behav.* 2020, 113, 106504. [CrossRef]
- [10] Pudjihartono, N.; Fadason, T.; Kempa-Liehr, A.W.; O'Sullivan, J.M. A Review of Feature Selection Methods for Machine Learning-Based Disease Risk Prediction. *Front. Bioinform.* 2022, 2, 927312. [CrossRef]
- [11] de-la-Bandera, I.; Palacios, D.; Mendoza, J.; Barco, R. Feature Extraction for Dimensionality Reduction in Cellular Networks Performance Analysis. *Sensors* 2020, 20, 6944. [CrossRef]
- [12] Bouaguel, W. A New Approach for Wrapper Feature Selection Using Genetic Algorithm for Big Data. In *Intelligent and Evolutionary Systems*; Springer : Cham, Switzerland, 2016; pp. 75–83. [CrossRef]
- [13] Chandrashekar, G.; Sahin, F. A survey on feature selection methods. *Comput. Electr. Eng.* 2014, 40, 16–28. [CrossRef]
- [14] Bashir, S.; Khattak, I.U.; Khan, A.; Khan, F.H.; Gani, A.; Shiraz, M. A Novel Feature Selection Method for Classification of Medical Data Using Filters, Wrappers, and Embedded Approaches. *Complexity* 2022, 2022, e8190814. [CrossRef]
- [15] Kumar, A.; Bhatia, M.P.S.; Sangwan, S.R. Rumour detection using deep learning and filter-wrapper feature selection in benchmark twitter dataset. *Multimed. Tools Appl.* 2022, 81, 34615–34632. [CrossRef]
- [16] Wang, F.; Lu, X.; Chang, X.; Cao, X.; Yan, S.; Li, K.; Dui'c, N.; Shafie-khah, M.; Catalão, J.P. Household profile identification for behavioral demand response: A semi-supervised learning approach using smart meter data. *Energy* 2022, 238, 121728. [CrossRef]
- [17] Wang, Z.; Gao, S.; Zhou, M.; Sato, S.; Cheng, J.; Wang, J. Information-Theory-based Nondominated Sorting Ant Colony Optimization for Multiobjective Feature Selection in Classification. *IEEE Trans. Cybern.* 2022, 1–14. [CrossRef]
- [18] Rasool, A.; Tao, R.; Kamyab, M.; Hayat, S. GAWA—A Feature Selection Method for Hybrid Sentiment Classification. *IEEE Access* 2020, 8, 191850–191861. [CrossRef]
- [19] Ileberi, E.; Sun, Y.; Wang, Z. A machine learning based credit card fraud detection using the GA algorithm for feature selection. *J. Big Data* 2022, 9, 24. [CrossRef]
- [20] Al-Ahmad, B.; Al-Zoubi, A.M.; Abu Khurma, R.; Aljarah, I. An Evolutionary Fake News Detection Method for COVID-19 Pandemic Information. *Symmetry* 2021, 13, 1091. [CrossRef]
- [21] Soumaya, Z.; Drissi Taoufiq, B.; Benayad, N.; Yunus, K.; Abdelkrim, A. The detection of Parkinson disease using the genetic algorithm and SVM classifier. *Appl. Acoust.* 2021, 171, 107528. [CrossRef]



- [22] Huang, G.-B.; Zhu, Q.-Y.; Siew, C.-K. Extreme learning machine: A new learning scheme of feedforward neural networks. In Proceedings of the 2004 IEEE International Joint Conference on Neural Networks (IEEE Cat. No.04CH37541), Budapest, Hungary, 25–29 July 2004; Volume 2, pp. 985–990. [CrossRef]
- [23] Han, S.; Zhu, K.; Zhou, M.; Cai, X. Competition- Driven Multimodal Multiobjective Optimization and Its Application to Feature Selection for Credit Card Fraud Detection. IEEE Trans. Syst. Man Cybern. Syst. 2022, 52, 7845–7857. [CrossRef]
- [24] Malik, E.F.; Khaw, K.W.; Belaton, B.; Wong, W.P.; Chew, X. Credit Card Fraud Detection Using a New Hybrid Machine Learning Architecture. Mathematics 2022, 10, 1480. [CrossRef]
- [25] Zioviris, G.; Kolomvatsos, K.; Stamoulis, G. Credit card fraud detection using a deep learning multistage model. J. Supercomput. 2022, 78, 14571–14596. [CrossRef]



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details