ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR961

Credit Card Fraud Detection

Shakuntala D. S.[1]; Shreyansh Kuchanur[2]; Smitha M. P.[3]; Sumanth J. M.[4]; Dr. Kavitha C.[5]
[1,2,3,4]Student; [5]Head of Department,
Department of Computer Science and Engineering,
Dayananda Sagar Academy of Technology and Management, Bangalore, Karnataka, India

Abstract:- While credit card fraud and abuse are the way becoming more common, the convenience using of there credit for the way online purchases has also improved. These fraudulent activities pose a severe financial danger to both credit the are card users and way they using it financial institutions. The first thinking aims to do of this research project is to recognize and put an end to these kinds of fraudulent activities. It addresses a broad range of subjects, including the frequency of false positives, imbalanced datasets, evolving fraud trends, and restricted public data access.

The literature now under publication offers a range of machine learning-based methods, including logistic regression, decision trees, random the forests, support to the vector of the +machines, and XG Boost, with the purpose of identifying credit card fraud. However, these methods often exhibit lower accuracy rates, highlighting the need for more advanced deep learning algorithms in order to effectively lower fraud losses. Therefore, the of way they primary thinks objective of this is to improve fraud detection abilities through which the way this application most be of state- of-the-art deep learning algorithms.

An assessment way it should be of the research project reveals better outcomes, including optimized AUC curves, precision, f1- score, and accuracy.

The ultimate objective there are is to create models that will greatly improve credit card fraud detection and prevention. This research focuses on advanced deep learning techniques in to the way it is order they provide the to more reliable and accurate fraud detection mechanisms, enhance security for credit card users, and lower financial risks for financial institutions when conducting online transactions.

Keywords:- *Transaction Data Analytics, Online Fraud, Credit Card Fraud, Deep Learning, Machine Learning, Fraud Detection.*

I. INTRODUCTION

A. An Overview of Credit Card Fraud Detection

Unauthorized transactions done by someone other than the cardholder using credit card information that has lost, stolen, or falsified are known as credit card fraud. Card-not-present fraud, in which credit card credentials are stolen and used to make online purchases, has increased in frequency due to the growth of internet shopping. Every year, fraudulent actions rise as of result of the thought widespread use these and of systems and e- banking, causing large financial losses.

The risk of credit way is card fraud has increased due to the widespread usage of credit way cards for l transactions, in age of digital commerce. Due to the possibility of identity theft and large financial losses, credit way card fraud is the a serious concern to financial individual cardholders.

The incorporation of machine way of learning algorithms for credit way card fraud detection has become a crucial tactic in response to issues.More complex way of conventional rule-based methods in the field of to the credit card fraud detection. Methods including support vector machines (SVMs), random forests, logistic regression trees, and neural networks have been extensively employed to develop predictive models that can differentiate between authentic and fraudulent By training models on past transaction data, machine of learning detect credit card fraud by teaching algorithms to recognize patterns that point to fraudulent activity. These models are more successful at identifying previously undetected fraudulent conduct because they are always changing and reacting to new fraud strategies. By reducing the amount of false positives, the integration of machine learning technologies helps minimize the disruption of valid transactions while simultaneously increasing the accuracy of fraud detection. To preserve their efficacy, machine learning models must be continuously developed and improved due to the ongoing growth of fraudulent techniques.

The in case use of several machine way they learning techniques and of the algorithms for credit fraud detection is examined way there are in this article. It covers the fundamentals of these methods, their benefits, drawbacks, and possible applications in the they are been area of credit the card for machine learning- based prevention of this enhanced security.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR961

II. BRIEF OVERVIEW OF CREDIT CARD FRAUD DETECTION USING MACHINE LEARNING TECHNIQUES

A. Machine Learning-Based Way for Credit Card Fraud Detection

Numerous number of the machine way of learning methods, such as the Extreme Learning way the Method, Decision, Random the Forest, Support Vector Machine, Logistic Regression, and XG Boost, have that been used to identify credit card fraud. The limited accuracy of current machine learning methodologies necessitates the development of cutting-edge deep way of things learning algo to minimize fraud losses.

B. A Comparative Way of Analysis of Machine the Learning and Deep Learning Algorithms

Convolutional a of neural network (CNN) architectures are implemented after machine learning methods have been applied empirically to detect fraud using a reference data set of European cards. This improves the performance of fraud detection. Evaluation of the study demonstrating enhanced AUC outcomes.

C. Description of the Way the Credit Card Data Set

During the course of two days, cardholder transactions totaling 284,807 were included in the credit card data set used for research. Of these, 492, or 0.172 percent, were fraudulent. Most of the dataset's features are subjected to principal of the component the way analysis (PCA), which reduces dimensionality, improves interpretability, and minimizes information loss.

D. Top 10 Machine Way they Learning Algorithms for Fraud Detection

To detect credit card fraud, various algorithms are used, including Linear Regression, Logistic Regression, Decision Tree, SVM, Naïve Bayes, CNN, K-Means, Random Forest, Dimension Reduction Algorithms, and Gradient Boosting Algorithms.

E. Model Confusing Metrics

The confusion metric, a representation of a classification model, shows how well the model is projected to the outcomes that were previously linked to the early ones. The confusion metrics can be visualized by using the association table as a heatmap.

F. Machine Learning Algorithms' Accuracy

There are six different types of structured classification models, including well-known models are the way like logistic regression, decision trees, and support vector machines. The accuracy which means the exact of the classifiers is shown by the reported things are results of applied machine learning techniques.

G. Data Distribution

One typical use of imbalanced binary classification is the identification of fraudulent way the credit card transactions, where the emphasis positive class (fraud) and negative class (non-fraud).By displaying the positive and negative distributions, the issue of class imbalance is better understood.

H. Machine Learning Algorithms

A Comparative Study Using accuracy and F1 measure metrics, a comparative analysis of applied ML algor for credit card fraud

III. REVIEW OF PAPER 1

A thorough investigation way the use of sophisticated machine of the learning (ML) and deep learning (DL) credit card of fraud (CCF) detection is presented in the paper "Credit Card Fraud detection is conducted to shed light how well various models work with an emphasis on fraudulent purchases. a summary of the assessment metrics, the dataset, and the results of tests conducted on an actual dataset. The study is broken up into several sections, including an analysis of pertinent literature, a detailed description of the proposed model and how it works, The paper also discusses the distribution of way the this credit card transaction of the data, the architecture of the suggested CNN model, and the range of training epochs[1]. Furthermore, the study highlights the effectiveness of deep learning algorithms for CCF categorization, including CNN and LSTM, and offers insights Exploring the significance of pre-processing data for machine learning[1]. Overall, the study provides a thorough which analysis of the use of sophisticated ML and DL algorithms for the detection means of credit way they card fraud, offering insightful information about the efficacy and performance they of the suggested CNN model relative to other methods.

A. Merits:

- **Comprehensive Analysis:** Using machine way of learning (ML) and deep way of learning (DL) algorithms, the paper offers a thorough credit card the way fraud detection. It also includes a thorough explanation of the various evaluation metrics and approaches.
- **Application of State-of-the-Art methods:** The study shows a dedication to utilizing cutting-edge technology for useful applications by applying state-of-the-art deep learning way of methods, such a way that as convolutional they are neural networks (CNN), to increase fraud detection performance.
- **Comparative Analysis:** In addition to comparing the performance of the suggested CNN model to other methods, the publication also offers a comparative analysis of both ML and DL algorithms, offering insightful information about the subject of credit card the fraud detection.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR961

B. *Demerits:*

- **Lack of Data Disclosure:** The topic of concealment is brought up in the document, which may limit the transparency and repeatability of the research findings by preventing the publication of the structures and background. Detection Using State-of-the-Art Machine Learning and Deep Learning Algorithms"[1]. The study compares a convolutional of the neural network (CNN) model's performance analysis to that of other ML and DL techniques already in use. The study places a strong emphasis on evaluating the efficacy of the classifiers using performance evaluation metrics like accuracy, precision, and recall[1]. The experimental transactions made by cardholders across Europe,
- **Ethical and Privacy Considerations:** The use of credit card transaction data the for research purposes may have ethical ramifications and raise privacy concerns, which the study does not specifically address. This is a crucial point to take into account when discussing data security and privacy.
- **Real-World Implementation Challenges:** The document may not address the potential challenges associated with the real-world.

IV. REVIEW OF PAPER 2

A neural way the learning network the way ensemble of classifier method its are and a hybrid data technique are used in the collection study "A Neural Network Ensemble With Feature Engineering for Improved Credit way of the Card the Fraud Detection" to provide an effective method of credit that are card fraud detection[2]. The paper tackles the problems of unbalanced credit card datasets and the static mapping of input vectors to output vectors that renders traditional machine of they learning methods ineffective for detecting fraud. The suggested way of the approach makes usecase way they of the edited nearest neighbor (SMOTE-ENN) method for data resampling and the synthetic minority oversampling methodology and long s network as the base learner in the adaptive boosting (AdaBoost) technique[2]. The experimental findings show that LSTM ensemble performs better than alternative benchmark techniques, reaching a high way understanding level of specificity and sensitivity[2]. The way it is suggested method's higher effectiveness is demonstrated by a comparison with current way of credit way of card fraud detection learning techniques in the paper[2]. Furthermore, the study shows the robustness of the suggested method in identifying means fraudulent way of things which are transactions and proves its efficacy using real-world credit way of card transaction datasets[2]. The that was employed, the adaptive boosting algorithm, and the classifiers' performance both with and without data resampling are all covered in the study. It offers a thorough which they are been analysis of the current approaches to dealing with unbalanced data in credit card fraud the way detection and emphasizes the of deep way learning methods, especially recurrent neural networks, to solve fraud detection problems.

A. *Merits:*

- **Superior Performance:** Comparing the suggested LSTM ensemble with SMOTE-ENN to other cutting-edge techniques, the ensemble performed exceptionally well, demonstrating the method's resilience.
- **Effective Data Resampling:** The of the SMOTE-ENN data resampling technique was demonstrated by the study, which also revealed that the resampled data considerably improved the performance of the different classifiers, including the suggested ensemble.
- **Robust Solution:** An important advancement in the way these field is the creation of a reliable technique way these are been for detecting credit card fraud utilizing an LSTM neural network ensemble, in addition to efficient feature engineering through the resampling of unbalanced data.
- **Adaptation to Dynamic Shopping Behavior:** By adjusting to the changing shopping habits of credit card customers, the AdaBoost methodology, which creates strong classifiers less prone to overfit, and the LSTM algorithm, a reliable method for modeling sequential data, combine to provide an efficient way to detect credit way of finding card fraud.
- **High Predictive Ability:** With a ROC curve that is to the upper-left corner and a higher AUC value than other classifiers, the suggested LSTM ensemble performed well in identifying both way leaning fraudulent and valid transactions.

B. *Demerits:*

- **Poor Sensitivity without Data Resampling:** When trained with the original, un resampled data, the classifiers including the suggested ensemble obtained low sensitivity scores, demonstrating the effective way they of class imbalance on performance.
- **Class Imbalance Challenge:** Conventional machine of the way learning methods are challenged by the inherent class imbalance in credit way finding card the transaction datasets, which results in poor sensitivity and misclassifications.
- **Complexity of Data Resampling:** Despite its effectiveness, the SMOTE-ENN data resampling technique may complicate the fraud way they are detection system's preprocessing step, necessitating cautious adoption and oversight.
- **Limited Comparison Metrics:** The study may have ignored other crucial measurements like precision, accuracy, and F1 score by concentrating mostly on sensitivity, specificity, and AUC as performance evaluation metrics.
- **Dataset Limitations:** The research employed publicly accessible real-world credit the way card transaction datasets, which might not accurately capture the variety and intricacy of credit card transactions in various locations or

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR961

situations, there by restricting the applicability of the suggested methodology.

V. REVIEW OF PAPER 3

The usage of adaptive enhancement (Adaboost) models for fraud detection and the rising incidence of credit card fraud occurrences in online transactions are covered in the document. It the way how we solves the classic Adaboost algorithm's lack of resilience, which is mostly caused by the basic classifier selection strategy's exclusive focus on error rate[3]. In order to improve the Adaboost algorithm's objective function, the study suggests D- AMWSPLAdaboost, an enhanced Adaboost algorithm that combines an adaptive hybrid weighted self-paced learning technique. It also integrates a double-fault metric into the computation of weak learners' weight and introduces it as a way to measure variation among base categories[3]. AUC value and F1 theway which think suggested through the algorithm performs better than previous Adaboost enhancement algorithms when tested on credit card fraud datasets[3].The significance of performance evaluation measures in unbalanced classification problems—specifically, credit card fraud detection—is also covered in the research, including AUC and F1. According to experimental results, D-AMWSPL Adaboost performs better overall and converges mostly the quickly than other algorithms in terms of AUC and F1 values[3]. The suggested way of the algorithm offers a more reliable and efficient method way they for identifying credit card fraud, and it has the potential to be put to good use in actual situations.

A. Merits:

- **Enhanced Robustness:** The adaptive hybrid weighted selfpaced learning technique included in the suggested AMWSPLAdaboost algorithm solves the weak robustness of the conventional Adaboost algorithm. This improves the classifier's overall performance and convergence speed, increasing its efficacy in detecting credit way they card fraud.
- **Improved Performance Metrics**: As assessment metrics, the method makes use of AUC and F1 values, which are especially well-suited for unbalanced classification issues such as credit way thinking card fraud detection. This makes it possible to evaluate the model's performance in-depth, producing outcomes that are more accurate and trustworthy.
- **Effective Handling of Imbalanced Data:** In order to produce more accurate and superior findings, the research focuses on processing imbalanced data by utilizing undersampling strategies and other machine learning methods. This method is essential for detecting from credit way the card fraud since it helps identify fraudulent transactions, which can be difficult to distinguish from authentic ones.
- **Incorporation of Diversity Measure**: The approach takes into account the variety among weak classifiers, calculating diversity by introducing a double-fault measure and adding it to the weak learners' weight computation. This improves the model's ability to generalize and increases its efficacy in detecting fraud.
- **Practical Applicability:** It is demonstrated algorithm of the way performs better than alternative Adaboost improvement techniques in of the terms of F1 value and AUC value, indicating its usefulness in practical settings. This implies that the technique can be applied successfully in the detection of credit of the card fraud and possibly in other fields with related problems.

B. Demerits:

- **Underfitting Concerns:** Accordingway they are to the research, underfitting may occur in the suggested AMWSPL Adaboost algorithm when the number maximum way of iterations is low. This implies that selecting the number which it means of iterations for practical application requires significant thought.
- **Complexity:** The algorithm becomes more sophisticated with the team addition of diversity metrics and adaptive hybrid weighted self-paced learning. Although these improvements lead to better performance, there's a chance that they also make understanding and implementation more difficult.
- **Limited Comparison:** The suggested approach is compared in the paper to previous Adaboost improvement algorithms, but more comparisons with a wider variety of fraud detection techniques would be beneficial to give a more thorough evaluation of its efficacy.
- **Lack of Real-world Implementation Results:** Although the approach performs well in experimental conditions, the publication lacks case studies or detailed real-world implementation findings that could further support the algorithm's applicability.
- **Algorithm-Specific Limitations:** Certain restrictions or constraints, like as computational efficiency, scalability to bigger datasets, or adaptability to emerging fraud trends, may apply to the things proposed approach and are not completely addressed in the work. These factors ought to be taken into account for a more thorough assessment of the algorithm's suitability.

VI. REVIEW OF PAPER 4

The paper "Performance Evaluation of way Machine Learning Methods for Credit Card Fraud Detection Using SMOTE and AdaBoost" provides a comprehensive analysis of the use case of the of ML algorithms for credit way which card fraud detection[4]. The study addresses the issue of class imbalance in real-world datasets and evaluates the effectiveness of various machine learning techniques, including the combination of Decision Tree, Extra Tree, Support Vector

Machine, Random Forest, Extreme Gradient Boosting, and Adaptive Boosting (AdaBoost)[4]. The work focuses on using the method may be Syntheticis is the Minority Over-sampling Technique (SMOTE) to address class imbalance and combines machine way the learning (ML) techniques with AdaBoost to increase performance[4]. The framework is validated using a highly skewed synthetic credit way of card fraud dataset, results demonstrate that AdaBoost improves such a way learning the performance of the ML approaches. In way terms of accuracy, recall, precision, Matthews Correlation Coefficient (MCC), and Area of the Under the Curve (AUC), applying AdaBoost enhances the trial findings. Additionally, the study demonstrates that the which are been proposed framework outperforms existing ML-based credit way of the card fraud detection algorithms in terms of fraud detection accuracy[4]. In-depth examination of past research using machine way the learning techniques to identify credit The report also covers card fraud, which provides insight into the field's current state.Taking everything into consideration, the research contributes to the creation of a scalable framework that effectively corrects class imbalance and enhances classification quality by utilizing AdaBoost in credit way it is card fraud identification[4]. The results show that there is room for improvement in accuracy and validate the value of thesuch way proposed framework.

A. Merits:

- **Scalable Fraud Detection Framework:** In to they are they order to detect fraudulent activity in credit of they card transactions, the research offers a scalable methodology for detecting credit way card fraud that effectively solves class such that imbalance in real-world datasets.
- **Implementation of SMOTE Technique:** In way they are been order to solve such way of the the problem of class are totally imbalance in credit way of card fraud datasets, the study uses the Synthetic Minority Over-sampling Technique (SMOTE), which shows how to handle skewed data distributions in an aggressive manner.
- **Ada Boost Method Integration:** The study combines various machine learning techniques with the Adaptive Boosting (Ada Boost) algorithm to improve classification quality and performance, demonstrating a thorough strategy for boosting fraud are the were detection model efficacy.
- **Comparative Analysis of ML Methods:** Using a publicly accessible dataset of actual credit card transactions, the study compares and contrasts a number they are been used of machine learning techniques, offering insightful information about the efficiency and performance of various fraud detection systems.
- **Validation on Synthetic Dataset:** The suggested structure is verified using an extremely unbalanced artificial credit way of the card fraud dataset, verifying the efficacy of the study findings and showcasing its potential for practical implementation.

B. Demerits:

- **Limited Real-World Dataset Validation:** Although the suggested framework is validated on a synthetic dataset by the research, it has not been validated on a large-scale real-world credit card fraud dataset, which could limit the findings' applicability in real-world scenarios.
- **Focus on Specific ML Methods:** The study's primary focus is on assessing particular machine learning techniques, which may restrict the investigation of other algorithms that could enhance the efficacy of credit way the card fraud detection.
- **Lack of Exploration of Additional Performance Metrics:** The study mainly concentrates on the performance parameters of accuracy, recall, precision, Matthews Correlation Coefficient (MCC),possibly ignoring other pertinent indications that could offer a more thorough assessment of fraud detection models.
- **Limited Discussion on Model Interpretability:** The interpretability of the way the such machine way the are learning models used for fraud detection is not sufficiently covered in the study, despite the fact that it is crucial to comprehending the decision-making process and guaranteeing openness in credit way card the way fraud detection systems.
- **Overemphasis on Synthetic Dataset Validation:** Although the synthetic dataset validation is useful, a more thorough investigation of real-world data validation would help the research to assure the robustness and practical application of the suggested methodology.

VII. REVIEW OF PAPER 5

The difficulty of imbalanced datasets in credit of the card fraud detection is addressed in a novel way in the research "Credit Card Fraud Detection Based on Improved Variational Autoencoder Generative Adversarial Network"[5]. The work suggests an enhanced VAEGAN model for data augmentation and evaluates the effectiveness of several oversampling techniques, such as SMOTE, GAN, VAE, and VAEGAN. The experimental results show that the modified VAEGAN technique is useful for improving the classification model's precision, recall, and F1_score—especially when handling such an are imbalanced data classification issues.'Time' and 'Amount' features, together with numerical features that have undergone PCA dimensionality reduction, are among the 30 features in the credit way that card fraud dataset that the study uses from the Kaggle platform[5]. The dataset presents a typical imbalanced classification problem because it is severely imbalanced, with only 492 fraudulent transactions out of 284,807 total transactions. To solve this problem, the authors rebalance the training set by using oversampling techniques and normalizing the transaction amount[5]. Based on its superior performance, the XGBoost classification algorithm is chosen as the baseline model for fraud detection, according to the experimental results. The study shows how well the suggested oversampling strategy works to improve the classification model's F1_score and precision by contrasting the performance of the XGBoost algorithm with that of other machine way of the learning and deep way of learning techniques[5]. The study concludes with a thorough analysis of oversampling techniques and how they affect the identification of credit way card fraud. The suggested enhanced VAEGAN approach provides a dependable and efficient solution for real-world fraud detection applications by demonstrating encouraging outcomes in strengthening the resilience and efficacy of the classification model[5]. The paper makes a significant contribution to the fields of information security and machine of which learning by offering insightful solutions for dealing with unbalanced datasets in fraud way detection.

A. Merits:

- **Enhanced Precision and F1_Score:** In particular, the enhanced VAEGAN oversampling approach outperforms the original one in improving the classification model's accuracy and F1_score while handling unbalanced data classification issues.
- **Effective Classification Results:** The efficacy of the suggested strategy is demonstrated by the experimental findings, which show that the XGBoost classifier combined with the enhanced VAEGAN algorithm produces superior classification results than other classifiers.
- **Comprehensive Assessment:** The paper offers a thorough analysis of resampling techniques and how they affect credit card fraud detection, providing insightful information for dealing with unbalanced data sets in fraud detection.
- **Efficiency and Robustness of the Model:** The suggested resampling technique offers a dependable and effective solution for real-world fraud detection applications while also significantly enhancing the classification model's robustness and efficiency.
- **Benchmarking Analysis:** The work presents a thorough grasp of the efficacy of resampling techniques by comparing the performance of several approaches, such as GAN, VAE, and SMOTE, and shows that the enhanced VAEGAN method performs better in terms of accuracy, F1_score, and other metrics. the method.

B. Demerits

- **Shortcomings:** Recall reduction possibility: In certain instances, the enhanced VAEGAN method's recall is marginally lower than that of alternative approaches, suggesting a possible accuracy vs. recall trade-off that should be carefully evaluated.
- **Model Training Complexity:** Resampling techniques and ensemble learning classification algorithms can complicate model installation and training, necessitating careful consideration of training time and computer resources.
- **Limited Generalizability:** Although the study shows that the suggested strategy works, more testing and validation may be necessary before applying it to other fraud detection datasets and real-world applications.
- **Impact of Data Imbalance:** The study draws attention to the issue of imbalanced way data sets in credit which card fraud detection and makes the case for the necessity of ongoing investigation and the creation of reliable remedies.
- **Potential Trade-Offs:** The findings of the experiments suggest possible trade-offs between various resampling techniques and classification performance indicators, necessitating careful evaluation of particular needs and objectives in fraud most detection applications.

VIII. CONCLUSION

To sum up, creating and putting into place reliable mechanisms for detecting credit way of the card fraud is essential to safeguarding financial transactions. Sophisticated technologies like machine learning, data analysis, and pattern recognition significantly enhance the speed at which fraudulent activity can be detected. To keep abreast of developing fraud strategies, detection systems must be continuously improved and adjusted. Financial institutions, academics, and regulators must work together to promote innovation and successfully counter new dangers. The adoption of a proactive strategy that incorporates advanced detection methods is necessary in which they order to reduce risk, preserve trust in financial institutions, and guarantee secure transactions for all stakeholders.

REFERENCES

[1]. Raj S.B.E., Portia A.A., An Analysis of Credit Card Fraud Detection Methods, International Conference on Computer, Communication and Electrical Technology (ICCCET) (2011), 152-156.
[2]. Jain R., Gour B., Dubey S., A hybrid approach to credit card fraud detection using rough set and decision tree techniques, International Journal of Computer Applications 139(10) (2016).
[3]. Dermala N., Agrawal A.N., Credit card fraud detection using SVM and false alarm reduction, International Journal of Innovations in Engineering and Technology (IJIET) 7(2) (2016).
[4]. Hafiz K.T, Aghili S, Zavarsky P, Using predictive analytics technology to detect credit card fraud, 11th Iberian Conference on Information Systems and Technologies (CISTI) (2016), 1.
[5]. Sonepat H.C.E Survey Paper on Credit Card Fraud Detection, International Journal of Advanced Research in Computer Engineering & Technology (2014).
[6]. R. Wheeler, S. Aitken, "Multiple algorithms for fraud detection" in Knowledge-Based Systems, Elsevier, vol. 13, no. 2, pp. 93-99, 2018.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR961

[7]. S. Patil, H. Somavanshi, J. Gaikwad, A. Deshmane, R. Badgujar, "Credit Card Fraud Detection Using Decision Tree Induction Algorithm", International Journal of Computer Science and Mobile Computing (IJCSMC), vol. 4, no. 4, pp. 92- 95, 2020, ISSN ISSN: 2320-088X.