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Fraud Detection Using Multi-layer Heterogeneous EnsembleMethod

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ABSTRACT

Fraudulent detection is a large number of exercises that try to keep cash or property out of the way. Fraud surveillance is used in many businesses such as banking or security. At the bank, misrepresentation may involve producing checks or using a Credit Card taken. Different types of robberies can include misfortune or create a problem with the expectation of only a paid Layer Ensemble Method running other AI fields including collecting learning. Recently, there have been one deep group models deployed with a large number of classifiers in each layer. These models, as a result, require a much larger calculation. In addition, the deep integration models are available that use all the separating elements including the unnecessary ones that can reduce the accuracy of the group. In this experiment, we propose a multi-layered learning structure called the Two-Layer Ensemble System to address the issue of definition. The proposed framework is working with a number of weird filters to get the troupe jumper sity, in these lines being a technology in the use of equipment.

KEYWORDS: *Credit Card Fraud, MULES, gcForest*

I. Introduction

A credit card is a statement issued to a client to allow a cardholder to pay a merchant in transaction with a cardholder guarantee to the payer in order to pay it in spite of the following approved total amount. The sponsor of the card is usually a bank, The cardholder can get money from the merchant or as a forward share.

As credit card exchange rates increase, cash-related frauds each year as a result of fraudulent use of credit cards are increasing dramatically. It has changed into an important problem-based measurement problem. Visa impulse has cost about $ 21 billion worldwide and will look to move to $ 31 billion by 2020. There are various ways to deal with creating a Credit cardexchange. At the time when the card actually appears to make a Most ecommerce companies part, withdraw, or exchange. The following is the point where the card is lost, especially for purchases or divisions made to (requires certain tricks such as card verification value, cardholder name, PIN, security question). Credit card misconduct occurs when credit card data or a certain number of consent is taken and used without allowing them to defraud money, objects and organizations. Cybercriminals are basically not giving credit card fraud, they are constantly advancing sophisticated methods, so there is a real need to make advanced and dynamic systems designed to adapt to the clever flow of trading model distortions will be fraudulently monitored if the system detects customer deviations. A few data mining techniques are used to identify the problem of credit card fraud. This paper aims to design an effective classification-based study program that is inspired by representation reading using layer analysis by DNNs. To achieve this goal, the following objectives are explained:

• Create a compilation of a novel model that involves the storage of multiple layers with different partitions in each layer (called MULES). By combining the benefits of learning together with in-depth learning, the proposed system is expected to perform well in many classification tasks.

• Investigate how to simultaneously select subdivision elements and features in each layer. The proposed method therefore can overcome the limit of the existing algorithm for data mining

II. PROPOSED SYSTEM

Integration algorithm then trains in prediction. In fact, this model is based on the concept of DNNs where data is transferred to several components in a learning, and Development have researched on Two new, process. However, it is different from DNNs since the data in MULES is processed under a forwarding system where the information is transmitted only from one layer to the next layer and does not include back transmission as neural network channels. In addition, different learning algorithms will be used for each layer, while DNNs only work with layers of neurons. Image of MULES with 3 layer Architecture as shown in figure1. The results of the Decision Tree, Naïve Bayes, and Random Forest classifier in the first layer are combined with the actual training data to produce the second layer. The same scheme is applied in the second layer with two dividers (SVM and Decision Tree) and in the third layer with two dividers (LDA and SVM), before the release of the third layer combined with the final prediction.In integrated components, an algorithm is used to integrate the prediction of shared prediction dividers. In this study, we used the Sum Rule method of integration. The Sum Rule summarizes the predictions of each situation in relation to each class label and provides an example of a class label We show an example of the foundations of MULES found in the credit card database. For each layer, MULES has selected the appropriate dividers and their characteristics to produce input in the next layer. In detail, in the first layer

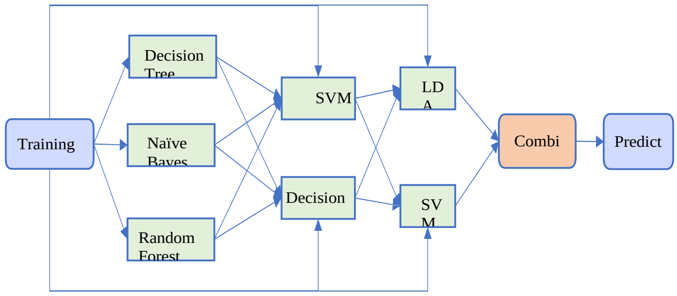


Fig 1:Flow chart of Proposed Model

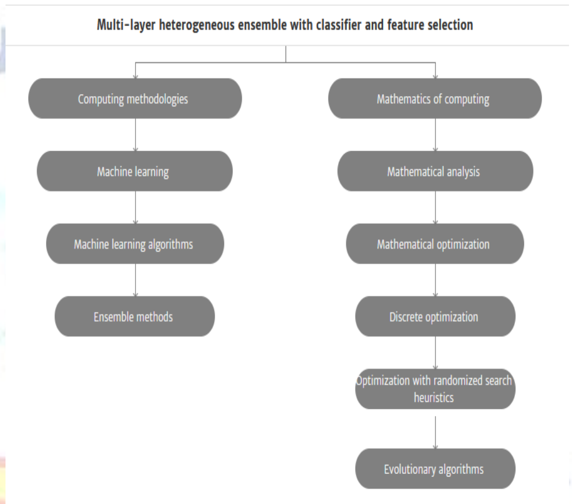
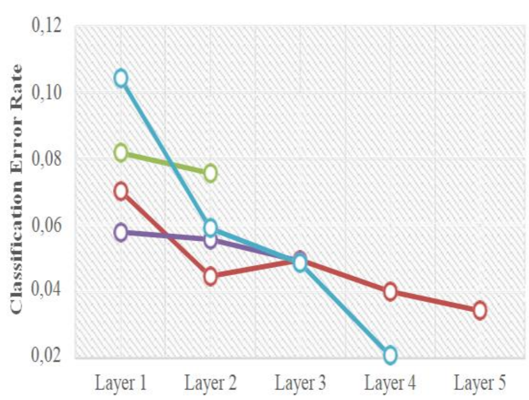


Fig2:Multi –layer heterogeneous ensemble with classifier and feature selection

In detail, in the first layer, MULES selected 3 divisions: Rands Rango, Decision Tree, and KNN. Each separator has used its selected features in the original features. In the second layer, classifiers outside the Decision Tree were selected with sets of various features found in the first and predictable features. In the third and fourth layers, two categories of KNN and Logistic Regression were selected with sets of various features. By selecting the appropriate subdivisions for each layer and the appropriate characteristics for each subdivision, MULES can achieve high predictive accuracy and efficiency in resource utilization depending on memory and computational requirement.



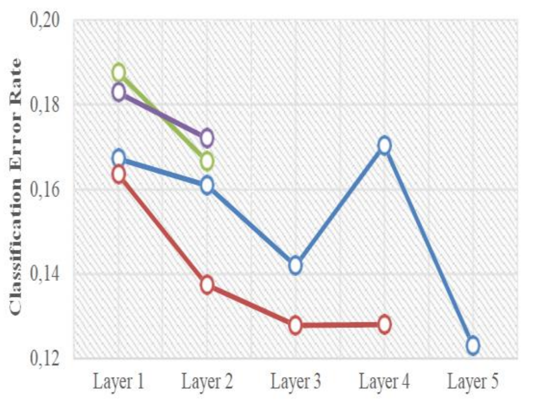


Fig3:The changes of classification error rate in each layer

III. Experimental Result

Classification time: Although MULES takes much higher train-ing time than gcForest, the classification time of MULES is lowerthan gcForest. On Credit card dataset, for example, MULES used3154.86 second for training process compared to only 311.78 ofgcForest. Meanwhile, gcForest used 0.62 second to classify all testinstances while MULES only used 0.26 second.

IV. Conclusion

In summary, we have introduced the Multi-Layer Heterogeneous Ensemble System (MULES) that is a layer-by-layer processing of DNNs. MULES incorporates several layers of a separate divider group where the sections train one train into new training details created by the previous layer. The new single-layer training data is the integration of the divider specs in the previous layer with the actual training data. . In the credit card database, for example, MULES spent 3154.86 seconds on the training process compared to only 311.78 gcForest. Meanwhile, gcForest used 0.62 seconds to separate all test conditions while MULES used only 0.26 seconds.

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