# AUT Report 2023

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#### Abstract

This research paper presents a study on the classification of Graphics Processing Units based on graphics memory type. The motivation for this study arose from personal experience as a tech enthusiast, where I recognized the challenge of providing accurate recommendations for technology products in light of the complexity and rapid evolution of the technology domain. The study aims to automate this process by using machine learning algorithms to classify GPUs based on memory type. Three different machine learning algorithms were employed in this study. The performance of these algorithms was evaluated using a confusion matrix and cross-validation. The results of this study demonstrate the effectiveness of using these algorithms for classifying GPUs based on memory type and provide insights into which algorithm is the best fit for this task.

#### **Index Terms**

classifier, model, random forest (RFC), decision tree (DTC), support vector machine (SVM), Graphics processing unit (GPU), machine learning (ML)

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#### I. Introduction

[1]Classification is a powerful technique that allows for faster and more efficient processing of large amounts of data. For technology experts, the ability to quickly and accurately classify data can open up new possibilities for research and experimentation. With the increasing amount of data being generated by devices and applications, the ability to process this data in real-time is becoming increasingly important. GPU classification allows for the creation of more sophisticated models and algorithms, enabling new insights and discoveries. Additionally, the use of GPU classification can significantly reduce the time and resources required for data processing, allowing for more efficient use of resources and cost savings. Overall, GPU classification is a valuable tool for anyone looking to push the boundaries of what is possible with data analysis and machine learning.

The current study was motivated by the desire to address the challenge of providing technology recommendations based on multiple factors. I noticed that family members, friends and colleagues often sought advice on technology products, particularly in the realm of computer technology. The complexity of the technology domain, as well as the increasing number of products being released, makes it difficult to keep track of all options and determine the best fit for individual needs.

To address this challenge, I proposed a classification solution that utilizes computer processing to classify technology products based on relevant features. The initial focus was the classification of the Graphics Processing Units based on memory type. However, the goal is to not only classify GPUs but also to expand this solution to other technology products.

The study aimed to classify GPUs based on memory type, as memory plays a crucial role in the performance of a GPU. Different types of memory, such as DDR3, DDR4, GDDR5 and GDDR6, have different characteristics and can impact the overall performance of a GPU. Three Machine Learning algorithms were employed and the script was written in Python programming language. By classifying GPUs based on memory type, the study aimed to provide a more accurate and comprehensive evaluation of the products available in the market.

#### II. DATASET SELECTION AND DESCRIPTION

- III. TASK SOLUTION BY STATE-OF-THE-ART CLASSIFICATION METHODS
- IV. TASK SOLUTION BY STATE-OF-THE-ART CLASSIFICATION METHODS

#### A. What is ML?

Machine learning is a subfield of computer science that aims to allow computers to "learn" without being explicitly programmed [1]. It has its roots in the 1950s artificial intelligence movement and emphasises practical goals and applications, particularly prediction and optimization. In machine learning, computers "learn" by improving their performance at tasks through "experience" [2].

## B. Why ML?

A branch of computing algorithms called machine learning is constantly developing and aims to replicate human intelligence by learning from the environment. In the new era of 'big data,' they are regarded as the workhorse. Machine learning methods have been effectively used in a variety of industries, including banking, entertainment, biomedicine, pattern recognition, computer vision, spacecraft engineering and computational biology. In addition, it has readily available libraries to perform tasks like clustering, classification etc. Hence, ML is the perfect solution to classification.

## C. Machine Learning Overview

Here is a brief overview of some of the most popular machine learning algorithms [3].

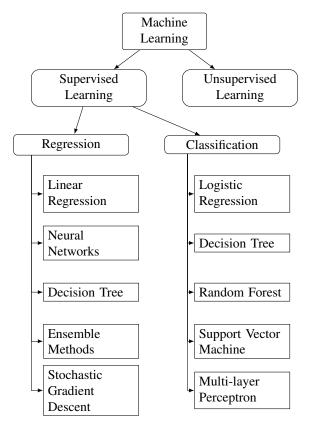


Fig. 1: Machine learning classification tree diagram

Machine learning is classified into Supervised Learning and Unsupervised Learning along with others like Semi-Supervised Learning, Reinforcement Learning, Multi-task Learning, Ensemble Learning, Neural Networks and Instance-Based Learning [3].

Unsupervised learning is a form of machine learning technique that unearths obscure patterns or data clusters without the assistance of a human [4].

In this paper, supervised learning was studied. It is machine learning algorithm that can develop broad patterns and hypotheses by using examples from outside sources to predict the results of incoming examples. The goal of supervised machine learning classification algorithms is to classify data based on existing knowledge (Labelled data) [5]. Supervised Learning is further categorised into two parts i.e. Regression and Classification.

Regression is frequently used for forecasting and prediction, two areas where machine learning and their application have a lot in common.

Supervised classification is one of the functions that so-called intelligent systems carry out most frequently [6]. The goal of supervised learning is to create a precise model of the distribution of class labels in terms of predictor features. When the values of the predictor characteristics are known but the value of the class label is unknown, the resulting classifier is used to give class labels to the testing cases. In this paper, we focus on the classification of GPU based on memory type (Target variable).

Classification is a data mining technique used to predict data instance group membership [7]

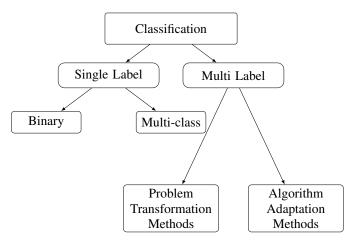


Fig. 2: Types of classification techniques

Most classification problems assign a single class to each example or instance [8]. However, there are many classification tasks in which each instance can be assigned to one or more classes. This set of problems falls under the category of multi-label classification [9]. Multi-label classification is further categorised into two types, Problem Transformation Methods and Algorithm Adaptation Methods.

Part of single label classification technique, binary classification is a supervised learning algorithm that categorizes new observations into one of two classes [10].

A multiclass classification task is a machine learning classification task with more than two classes or outputs [11]. It assumes that each sample has only one label and employs the Bayes theorem to predict the class of unknown datasets [11].

A study presents a network kernel function called Multi-field packet classification, which classifies and routes packets on a GPU using a set of rules [12]. Another study utilizes a shapelet discovery algorithm for time series classification, which identifies useful subsequences from a set of time series [13]. The study notes that with recent advancements in high-performance computing techniques, such as GPU, large-scale deep learning models are now possible for machine learning applications [14]. However, there is a lack of research on CPU classification. To address this gap, the study conducts GPU classification using different types of graphics memory and evaluates and compares three classification algorithms (Random Forest, Support Vector Classification and Decision Tree classifier).

V. INCREASING CLASSIFICATION PERFORMANCE: FEATURE EXTRACTION AND FEATURE SELECTION

VI. ADVANCED CLASSIFICATION METHODS

VII. REDUCTION COMPLEXITY AND EXECUTION TIME

### VIII. CONCLUSION

The results of the study showed that the Random Forest algorithm had the highest accuracy in classifying the GPU based on memory type, followed by Decision Tree and Support Vector Machine. The study also evaluated the performance of the algorithms based on precision, recall and F1-score, which are commonly used metrics for evaluating the performance of classification models. However, it should be noted that the study did not include any parameter optimization and the performance could potentially be improved through hypermeter tuning.

The study concludes that the proposed classification solution, which utilizes computer processing and machine learning algorithms, can effectively classify GPUs based on memory type. The results of this study can be used to provide more accurate recommendations for technology products and can be extended to other technology products as well. This research can be used as a foundation for further research in the field of technology product classification and it can be useful for consumers, manufacturers and retailers.

## APPENDIX

| Item | Mean | Variance | Std. Dev. | No. | Left            | Right              | Scale          |
|------|------|----------|-----------|-----|-----------------|--------------------|----------------|
| 1    | 1,8  | 0,2      | 0,4       | 5   | annoying        | enjoyable          | Attractiveness |
| 2    | 2,2  | 0,2      | 0,4       | 5   | not             | understandable     | understandable |
| 3    | 0,6  | 2,3      | 1,5       | 5   | creative        | dull               | Novelty        |
| 4    | 3,0  | 0,0      | 0,0       | 5   | easy to learn   | difficult to learn | Perspicuity    |
| 5    | 2,2  | 0,2      | 0,4       | 5   | valuable        | inferior           | Stimulation    |
| 6    | 0,8  | 1,7      | 1,3       | 5   | boring          | exciting           | Stimulation    |
| 7    | 1,8  | 0,7      | 0,8       | 5   | not interesting | interesting        | Stimulation    |
| 8    | 2,2  | 1,2      | 1,1       | 5   | unpredictable   | predictable        | Dependability  |
| 9    | 2,2  | 1,7      | 1,3       | 5   | fast            | slow               | Efficiency     |
| 10   | -1,4 | 2,3      | 1,5       | 5   | inventive       | conventional       | Novelty        |
| 11   | 2,4  | 0,3      | 0,5       | 5   | obstructive     | supportive         | Dependability  |
| 12   | 2,2  | 0,7      | 0,8       | 5   | good            | bad                | Attractiveness |
| 13   | 1,2  | 5,7      | 2,4       | 5   | complicated     | easy               | Perspicuity    |
| 14   | 2,0  | 1,0      | 1,0       | 5   | unlikable       | pleasing           | Attractiveness |
| 15   | -1,2 | 2,7      | 1,6       | 5   | usual           | leading edge       | Novelty        |
| 16   | 2,0  | 0,5      | 0,7       | 5   | unpleasant      | pleasant           | Attractiveness |
| 17   | 2,4  | 0,8      | 0,9       | 5   | secure          | not secure         | Dependability  |
| 18   | 1,8  | 0,2      | 0,4       | 5   | motivating      | demotivating       | Stimulation    |
| 19   | 2,2  | 1,7      | 1,3       | 5   | meets           | does not meet      | Dependability  |
| 20   | 2,6  | 0,3      | 0,5       | 5   | inefficient     | efficient          | Efficiency     |
| 21   | 1,8  | 0,7      | 0,8       | 5   | clear           | confusing          | Perspicuity    |
| 22   | 2,2  | 0,7      | 0,8       | 5   | impractical     | practical          | Efficiency     |
| 23   | 2,0  | 1,0      | 1,0       | 5   | organized       | cluttered          | Efficiency     |
| 24   | 2,0  | 1,5      | 1,2       | 5   | attractive      | unattractive       | Attractiveness |
| 25   | 2,2  | 0,7      | 0,8       | 5   | friendly        | unfriendly         | Attractiveness |
| 26   | -1,4 | 2,3      | 1,5       | 5   | conservative    | innovative         | Novelty        |

TABLE I: Mean value per item

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