



國立臺北科技大學

資訊工程系碩士班

碩士學位論文

**Use Efficiency-based Genetic Programming
to Create Loss Function for Image
Classification**

研究生：周子榆

指導教授：陳香君博士

中華民國一百一十四年五月



國立臺北科技大學

資訊工程系碩士班

碩士學位論文

**Use Efficiency-based Genetic Programming
to Create Loss Function for Image
Classification**

研究生：周子榆

指導教授：陳香君博士

中華民國一百一十四年五月

「學位論文口試委員會審定書」掃描檔

審定書填寫方式以系所規定為準，但檢附在電子論文內的掃描檔須具備以下條件：

1. 含指導教授、口試委員及系所主管的完整簽名。
2. 口試委員人數正確，碩士口試委員至少 3 人、博士口試委員至少 5 人。
3. 若此頁有論文題目，題目應和書背、封面、書名頁、摘要頁的題目相符。
4. 此頁有無浮水印皆可。

Abstract

Title: Use Efficiency-based Genetic Programming to Create Loss Function for Image Classification

Pages: (Fill it)

School: National Taipei University of Technology

Department: Computer Science and Information Engineering

Time: May, 2025

Degree: Master of Science

Researcher: Tzu-Yu Chou

Advisor: Shiang-Jiun Chen, Ph.D.

Keyword: Image Classification, Genetic Programming, Loss Function, Deep Learning

In the past five years, with the rapid rise of deep learning, image classification models have quickly become one of the most popular and widely known models. When training such models, the steps are broadly divided into the following: preparing image datasets, dividing them into training, validation and testing sets as needed, training the model, evaluating the model, and repeating these steps until the ideal result is met or the computational resources are exhausted.

A crucial function during the process of training a model is called the loss function, which calculate the difference between the predicted values and the ground-truth values. The results of the loss function can significantly influence the effectiveness of the model's training because it simply decide the direction of the adjustment to the model. However, designing a loss function often requires the assistance of experts in the related field, leading to a resource-intensive design process. Recent research has proposed using Genetic Programming (GP) to generate loss functions to avoid the necessity of hiring numerous domain experts for assistance. Nevertheless, using GP typically results in decreased computational efficiency. This paper aims to improve the method of using GP to generate loss functions by modifying certain genetic operations and introducing the concept of tournament selection.

Acknowledgements

所有對於研究提供協助之人或機構，作者都可在誌謝中表達感謝之意。



Table of Contents

Abstract	i
Acknowledgements	ii
Table of Contents	iii
Chapter 1 Introduction	1
Chapter 2 Related Work	3
2.1 Metaheuristic	3
2.1.1 Evolving Algorithm	3
2.1.2 Genetic Algorithm	3
2.1.3 Genetic Programming	3
2.2 Loss Function	3
2.2.1 Deep Learning Model	3
2.2.2 Importance of Loss Function	3
2.3 Image Classification	3
Chapter 3 Purposed Algorithm	4
3.1 The Architecture of Algorithm	4
3.2 Experimental Environment Setup	5
3.2.1 Software Setup	5
3.2.2 Hardware Setup	5
3.3 Main Method	5
Chapter 4 Result and Analysis	6
4.1 Parameter settings	6
4.2 Figures	6
Chapter 5 Conclusion and Future Work	7
5.1 Conclusion	7
5.2 Future Work	7
References	8

List of Figures

3.1	FlowChart for Efficiency-based GP	4
-----	---	---



List of Tables



Chapter 1 Introduction

After several decades of development, deep learning [1] technology has achieved significant breakthroughs in the last ten years, largely due to the remarkable improvements in GPU computational power. Consequently, the predictive and analytical capabilities of models have achieved substantial advancements. Numerous models have been launched by major companies and applied in practical scenarios, leading to significant changes in our daily lives.

When it comes to training deep learning model, we usually refer to the following steps: collecting relevant data and organizing it into datasets, partitioning the datasets into training and validation sets as needed, initializing model parameters, training the model, evaluating the performance of the model, adjusting the model parameters, and repeating the training until the target is achieved or computational resources are exhausted. During the evaluation of the model's performance, we use a function called the loss function [2]. Its purpose is to calculate the difference between the model's predicted results and the ground truth, which helps model adjust its parameter to better fit the target. Therefore, different loss functions can influence the direction of model adjustments, significantly impacting the final outcomes of the model.

However, the design of a loss function is often closely related to the propose of the model [3]. In other words, different models may require experts from specific fields to assist in designing the loss function to enhance the speed and effectiveness of model training. Nevertheless, recent research has shown that it's feasible to use genetic programming (GP) [4] to automatically generate loss functions. Due to the domain-independent nature of GP, it allows us to develop an algorithm that can automatically create the required loss function without needing specialized knowledge in that particular field. However, this method typically requires a significant amount of time and computational resources.

The operation mode of GP can be simply divided into the following steps: Representing the solution we hope to find (which may be a value or a function) in an encoded form, then forming these solutions into a population. After evaluating the whole population, we perform genetic operations (e.g., mutation or crossover) on the population's solutions, reevaluate them, and repeat the above steps until the target is achieved or computational resources are exhausted.

Although the computational power of GPUs today is far superior to that of the past, both training models and using GP to find solutions still require substantial computational resources and time to achieve a decent result. In this paper, an efficiency-oriented GP algorithm is proposed to reduce the computational resources and the time to train the model required for GP to search for the optimal algorithm while maintaining the same level of effectiveness. We aim to improve the genetic operation part of the existing GP framework by referencing the concept that offspring in a better living environment can usually receive better care. We modify the GP's genetic operation such that only a certain number of high-scoring populations can execute it. Here's what we want to do: Select a certain proportion of high-scoring offspring from the population, then randomly select a fixed number from these offspring to perform genetic operations. The randomized selection can avoid always using the same population for genetic operations, giving more excellent offspring the opportunity to improve.

The structure of this paper is as follows: Chapter 2 is related work. This chapter provides a detailed illustration to the development and history of GP, the detailed description of the loss function and how they collaborate with deep learning model, and how loss functions are randomly generated via GP. Chapter 3 is proposed algorithm and main methodology. In this chapter, we will explain the architecture of the algorithm implemented in this paper. After that, we will then describe the experimental environment setup and the initial parameter values. Finally, we will present the methods and procedures used in this paper. Chapter 4 is results analysis. This section will show the detail parameter settings among all compared peer-algorithm. After that, we will present the analysis of the results by organizing the experimental results into charts and figures. Finally, we will explain the outcomes and analyze why our algorithm can achieve the similar result while decreasing the usage of computational resources. Chapter 5 is conclusion and future work. In this chapter, we will provide the conclusion of this paper by outlining the contribution we have made so far. After that, we would like to discuss potential directions for future research or possible way to apply this algorithm in practical.

Chapter 2 Related Work

2.1 Metaheuristic

2.1.1 Evolving Algorithm

2.1.2 Genetic Algorithm

2.1.3 Genetic Programming

In [5], a genetic programming

2.2 Loss Function

2.2.1 Deep Learning Model

2.2.2 Importance of Loss Function

In [6], a loss function meet genetic programming is proposed

2.3 Image Classification

Chapter 3 Purposed Algorithm

This section will provide a brief overview of the contents that will be discussed in this chapter: Section 3.1 will introduce the architecture of our algorithm and use a simple flowchart to provide a basic introduction to the proposed algorithm. Section 3.2 will provide a detailed description of our software and hardware specifications, as well as the setup procedures. Section 3.3 will provide an in-depth explanation of our proposed algorithm, including the underlying concepts and the rationale behind our approach.

3.1 The Architecture of Algorithm

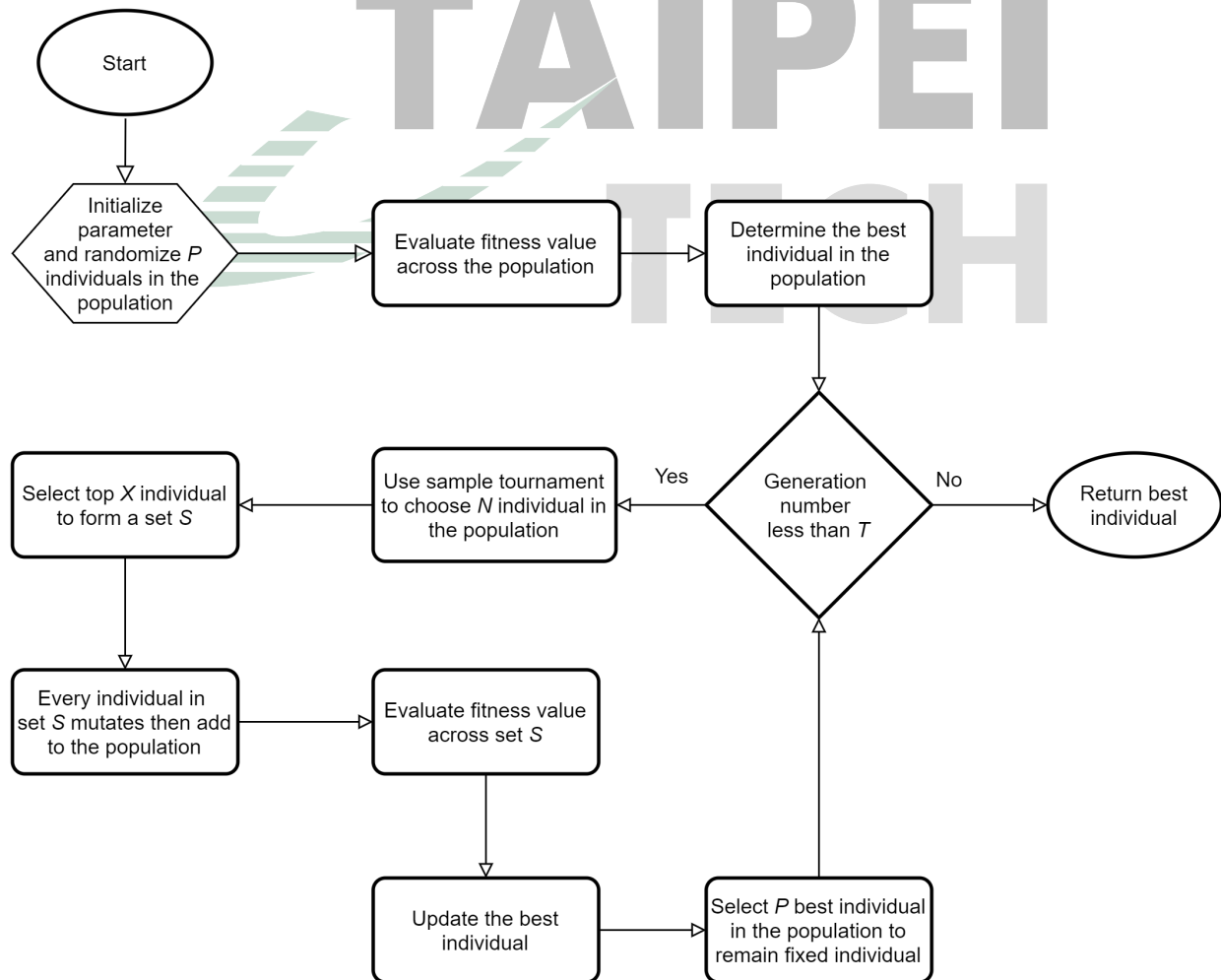


Figure 3.1 FlowChart for Efficiency-based GP

3.2 Experimental Environment Setup

3.2.1 Software Setup

In our software setup, we run our code in Ubuntu 24.04. The Python version we employ is 3.8, and the Pytorch version is X. Within Python and Pytorch, we utilize the following packages: Some package.

3.2.2 Hardware Setup

In our hardware setup, we run our code on an AMD Ryzen 5 5600X 6-Core Processor. The system is equipped with 32GB of memory, operating at a frequency of DDR4-3600MHz. Additionally, we utilize an NVIDIA GeForce RTX 3060 Ti GPU for our computational needs.

3.3 Main Method

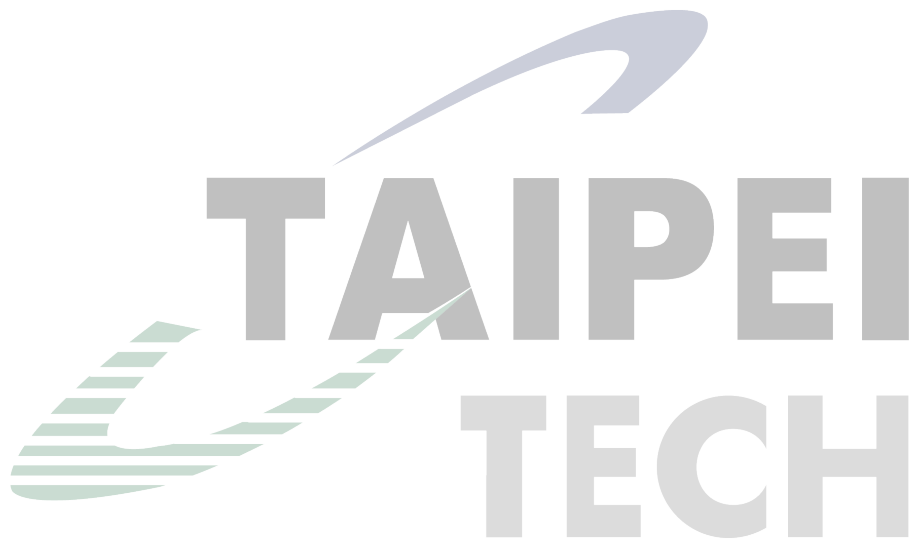
Algorithm 1 Efficiency-based GP to generate loss function

```
Initialize:  $P = x$ ,  $T = x$ ,  $N = x$ ,  $M_{ST} = 0.5$ 
Randomly initialize population which include  $P$  trees
Evaluate GP fitness function  $F$  for each individual in the population
Determine the best individual
while generation number  $< T$  do
    Sample tournament  $G \sim \text{Uniform}(P)$ 
    Select top  $N$  trees from  $G$  to form a set  $S$ 
    for Individual in  $S$  do
        if  $\text{rand}_1 < M_{ST}$  then
            Apply subtree mutation to the generated child
        else
            Apply one-point mutation to the individual
        end if
        if Functional_check() is true then
            add individual to population
        end if
    end for
    Evaluate GP fitness function  $F$  for each generated child individual
    Update the best individual
    Select  $P$  best trees from population to form a new population containing  $P$  trees
end while
```

Chapter 4 Result and Analysis

4.1 Parameter settings

4.2 Figures



Chapter 5 Conclusion and Future Work

5.1 Conclusion

5.2 Future Work



References

- [1] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. “Deep learning”. In: *Nature* 521.7553 (2015), pp. 436–444.
- [2] Katarzyna Janocha and Wojciech Marian Czarnecki. *On Loss Functions for Deep Neural Networks in Classification*. 2017. arXiv: 1702.05659 [cs.LG]. URL: <https://arxiv.org/abs/1702.05659>.
- [3] Lorenzo Rosasco et al. “Are Loss Functions All the Same?” In: *Neural Computation* 16.5 (2004), pp. 1063–1076. DOI: 10.1162/089976604773135104.
- [4] Michael O’ Neill. “Riccardo Poli, William B. Langdon, Nicholas F. McPhee: A Field Guide to Genetic Programming”. In: *Genetic Programming and Evolvable Machines* 10.2 (2009), pp. 229–230.
- [5] Shakhnaz Akhmedova and Nils Körber. *Next Generation Loss Function for Image Classification*. 2024. arXiv: 2404.12948 [cs.CV]. URL: <https://arxiv.org/abs/2404.12948>.
- [6] Santiago Gonzalez and Risto Miikkulainen. *Improved Training Speed, Accuracy, and Data Utilization Through Loss Function Optimization*. 2020. arXiv: 1905.11528 [cs.LG]. URL: <https://arxiv.org/abs/1905.11528>.