國立臺北科技大學

資訊工程系碩士班

碩士學位論文

待訂

To be decide

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

待訂

To be decide

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。

審定書不用頁碼

摘要

論文名稱：待訂

頁數：(請自己填) 頁

校所別：國立臺北科技大學 資訊工程系碩士班

畢業時間：一百一十三學年度 第二學期

學位：碩士

研究生：周子榆

指導教授：陳香君博士

關鍵詞：(請自己填)

摘要為論文或報告的精簡概要, 其目的是透過簡短的敘述使讀者大致瞭解整篇報告的內容。摘要的內容通常須包括問題的描述以及所得到的結果, 但以不超過 500 字或一頁為原則, 且不得有參考文獻或引用圖表等。以中文撰寫之論文除中文摘要外，得於中文摘要後另附英文摘要。標題使用 20pt 粗標楷體並於上、下方各空一行（1.5 倍行高，字型 12pt 空行）後鍵入摘要內容。摘要頁須編頁碼（小寫羅馬數字表示頁碼)。

Abstract

Title: To be decide

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: (Fill it)

Start writing abstract from here. Start writing abstract from here. Start writing abstract from here. Start writing abstract from here. Start writing abstract from here. Start writing abstract from here. Start writing abstract from here. Start writing abstract from here. Start writing abstract from here.

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

摘要 i

Abstract ii

Acknowledgements iii

Table of Contents iv

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 Loss Functions Make Differences 3

2.3 Image Classification 3

2.3.1 Overview of Image Classification 3

2.3.2 Previous Study 3

Chapter 3 Purposed Algorithm 4

3.1 The Architecture of Algorithm 4

3.2 Experimental Environment Setup 4

3.3 Main Method 4

Chapter 4 Result and Analysis 5

4.1 Parameter settings 5

4.2 Figures 5

Chapter 5 Conclusion and Future Work 6

5.1 Conclusion 6

5.2 Future Work 6

References 7

List of Figures

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. Therefore, in this paper, 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. The steps are as follows: 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. By employing these two concepts, we proposes an efficiency-oriented GP algorithm, aiming 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.

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

2.2 Loss Function

2.2.1 Deep Learning Model

2.2.2 Loss Functions Make Differences

2.3 Image Classification

2.3.1 Overview of Image Classification

2.3.2 Previous Study

Chapter 3 Purposed Algorithm

3.1 The Architecture of Algorithm

3.2 Experimental Environment Setup

3.3 Main Method

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.