



**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**



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# 摘要

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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.

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# Acknowledgements

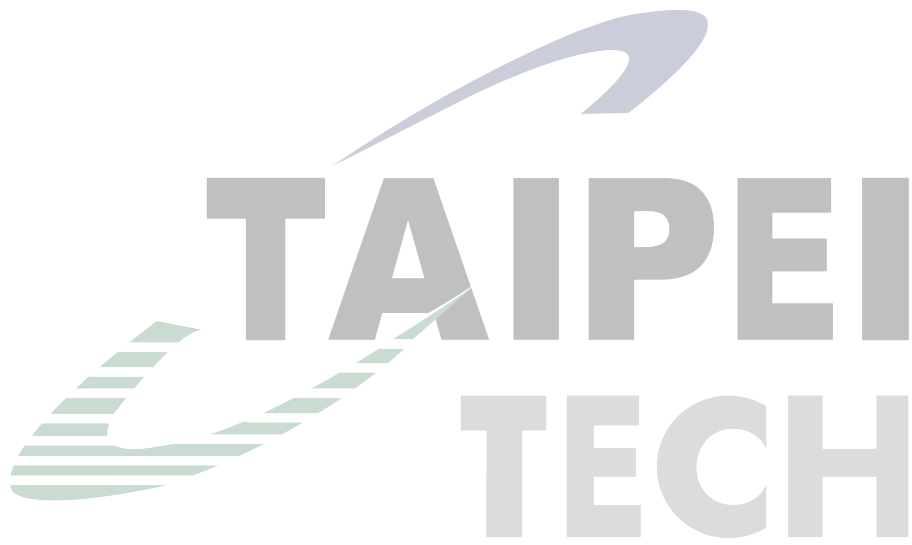
所有對於研究提供協助之人或機構，作者都可在誌謝中表達感謝之意。



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# 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.

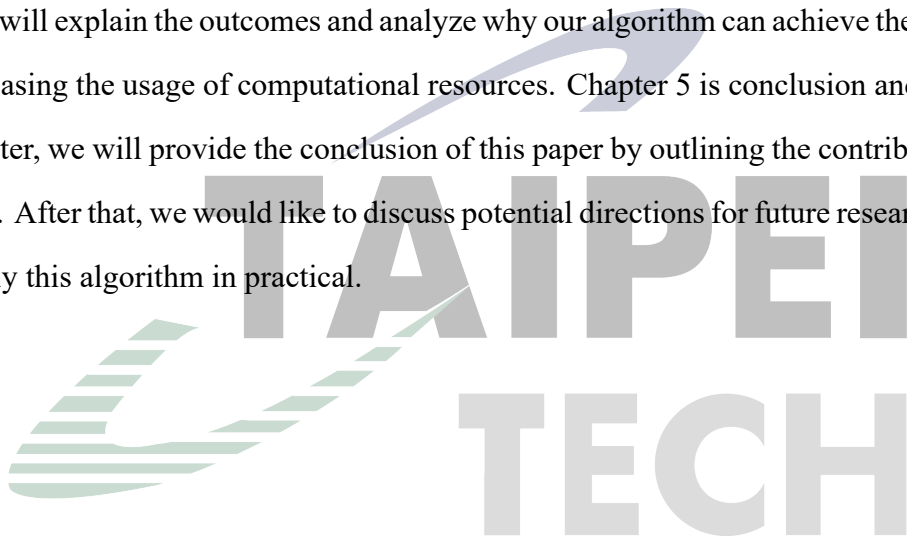
The model training process can be broadly divided into several key steps: collecting data and organizing it into datasets, partitioning the datasets into training and validation sets as needed, initializing model parameters, evaluating the performance of the model, adjusting the model parameters, and 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 algorithm (GA) [4] to automatically generate loss functions. Due to the domain-independent nature of GA, 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.

Given the rapid flow of information in today's society, we often need a quick way to find the necessary loss function to optimize the training process of the model. This paper proposes an efficiency-oriented GA, aiming to reduce the time required for GA 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 GA, the detailed description of the loss function and how they collaborate with deep learning model, and how loss functions are randomly generated via GA. 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 Loss Function**

### **2.2 Genetic Programming**

### **2.3 Learning to learn**



## **Chapter 3 Purposed Algorithm**

### **3.1 The Architecture of Algorithm**

### **3.2 Experimental Environment Setup**

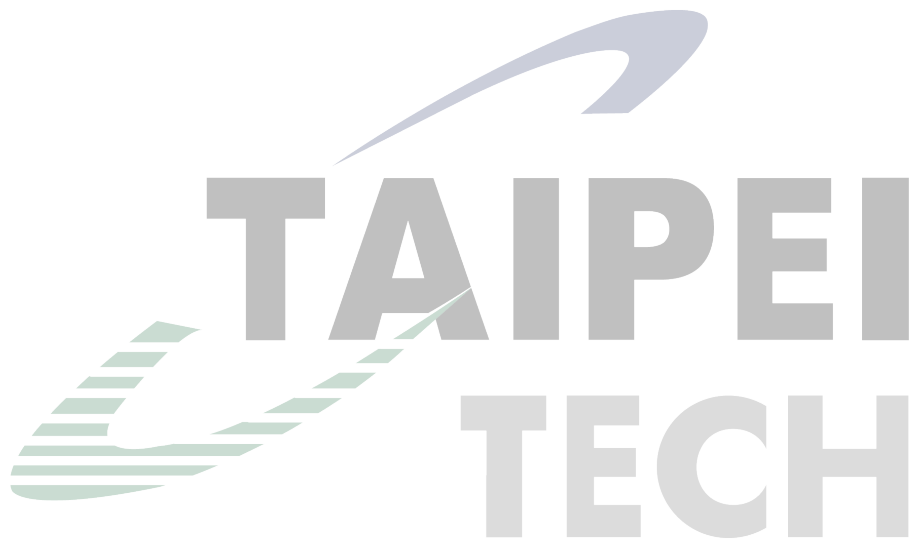
### **3.3 Main Method**



## **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] Manoj Kumar et al. “Genetic Algorithm: Review and Application”. In: *International Journal of Information Technology and Knowledge Management* 2.2 (2010), pp. 451–454.

