

***Enhancing Neural Network Training Through GA
& MCTS***

Course: optimization techniques

Spring semester 2025

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Abstract

In our following research, we discuss and implement a way to apply genetic algorithm (GA) and integrate it with Monte Carlo tree search (MCTS) to optimize the weights of the neural network. We build our research and implement on the (research), which originally introduced the idea of the combining the GA to MCTS. We extended the implementation of the paper and improved the performance of the model. We first start by applying the genetic algorithm which includes various steps that rely on to biological concepts such as mutation and crossover. Afterwards, MCTS is added to the algorithm to further enhance the performance by providing an optimized way to search in the solution space. All algorithms used were discussed with great detail and description of the dataset was also reviewed. The results that were achieved were quite satisfactory and showed great improvement in the performance and accuracy. We succeeded in achieving an accuracy of 79 which shows the great potential of the model. Further future work can be added to further enhance the performance of the optimization of neural network weights.

Introduction

Recently, several algorithms have been emerging to optimize various solutions of complex problems. These algorithms were based on several real-life concepts such as the genetic algorithm. The genetic algorithm follows the idea of natural selection and evolution. It is a heuristic algorithm that is commonly used in optimization and to solve complex problems. While the algorithm is not considered to be new discovery, it still withhold its reputation since it still quite used whether on its own or with other algorithms.

The genetic algorithm has 3 main components that it is built up on. It consists of selection which is the idea of selecting the individual which are the parents that has the most contribution of creating the next generation. The second step is crossover which is the idea of combining the genes of two patient to form children. Finally, we have mutation which applies some changes by inserting random genes to the parents to form new offsprings.

Several algorithms and concepts might be applied to GA to optimize its performance such as MCTS. MCTS has received various type of attention due to its ability to deal with complex problems using search areas. It workes by creating a

tree of the possible moves where it chooses the most move with highest potential while also exploiting other options. As it continues, it finds a way to balance both exploration and exploitation until it reaches the most optimal solution.

Overall, the combination of the following algorithms will increase the efficiency of the performance since the strengths of both algorithms will be combined to build a great model.

Problem Statement:

As technology grows, the usage of neural of neural networks becomes quite common. However, it soon became a problem that it is difficult to determine which neural network weights work with the stated problem. This problem is quite difficult to solve and several know algorithms can not properly solve this issue such as the gradient descent since it may require large computational resources.

To address this issue and solve it, research studies have proped a solution using the genetic algorithm integrated into the mcts to optimize the weights of the neural network. However, while it shows great results there are some room for improvement. Therefore, this research paper aims to further enhance and build upon the existing work done by the research and introduce several enhancements. The findings of this paper will greatly offer important insights into the field of AI and the optimization of neural networks.

Dataset Description:

The dataset used in this paper is the Pima Indians Diabetes Database. It contains medical records from 768 Pima Indian women patients who are at least 21 years old. Eight characteristics are included in each record: age, body mass index (BMI), diabetes pedigree function, triceps skinfold thickness, diastolic blood pressure, plasma glucose concentration after two hours, and the number of pregnancies. The outcome variable is binary and indicates whether diabetes is present or not according to WHO standards. Because the Pima Indian community is the focus of this dataset, it offers unique insights on the genetic and lifestyle factors impacting diabetes.

Methodologies:

A) Experimental set-up

The implementation of the research paper was done with the python programming language along with some of its known libraries such as tensor flow and sklearn. The following implementation was conducted on a personal computer. The following computer fit all the requirements needed to apply the impementating since it had all the resources required.

B) Dataset pre-processing

In the dataset that was used, several pre-processing steps were implemented to ensure correct and accurate results. The dataset was first checked to ensure that no missing values were present. Additionally, undersampling using the function 'RandomUnderSampler()' was implemented to ensure that the 2 outcome were equally represented without any biases. Scaling and normalizing was also implanted to ensure that the values and results are corrcet without any errors.

C) Model selection

The research was implemented using the artificial neural network (ANN) model since it can handle various problems and has a great performance. Additionally, it can be controlled by its layers to ensure that the model is the right was for this problem. The artificial neural network is made up of () to deal with the optimization of neural networks weight. The model was implemented in the genetic algorithm to ensure and increase its performance.

D) Genetic algorithm

The genetic algorithm was the main algorithm used in this research. Several steps were done to ensure that it was implemented properly which can be seen below:

- a) *Initial population*: the population was created based on the neural network model in which there were several version of it. Each version has the same structure but different weights were used to ensure it was fully optimized. Those version represents the population of the algorithm in which each model represents a solution to the problem.

- b) *The fitness score*: Each model is trained and then evaluated based on its performance. Then, the weights will adjust to ensure continuous optimization and will learn the data. Afterwards, comparison between the prediction and the real results will be done producing the accuracy score which represents the fitness score in our problem.
- c) *Selection*: the models that were created will be sorted to select the best models according to their fitness score to represent the parents of the algorithm and will then be used to produce offsprings.
- d) *Mutation*: the weights will slightly be changed sometimes to ensure that there is a wide and large range of solutions that are different from one another. The process will be repeated several times according to the number of iterations provided. Afterwards, it will be terminated and stopped so the best model can be chosen according to the fitness score.

E) *Monte Carlo Tree Search*:

The steps for implementing the MCTS is:

- a) *Intialization*: intialize the root node and the paramters needed,
- b) *Selection*: choose a node and continue along with it until a leaf node is reached. A selection strtegy can be used to control and balance between exploration and exploitation.
- c) *Expansion*: The leaf node will then create several children according to several action.
- d) *Rollout*: simulate the process of taking an action until the end is reached and to guess the possible outcomes.

Afterwards, backprobagation is implemented and the search is consintued and until the best child is chosen.

F) *Training procedure*

The training of the following models were done by using the Adam optimizer with a learning rate of 0.001 and a loss function of () which was appropriate and useful to use in our project. Each model was trained for 10 epochs to ensure that the evaluation was done without high computational time and resources. Afterwards, the fitness score was calculated each time until the best model was chosen.

G) Evaluation metrics

The evaluation metrics that were used were mainly the accuracy to ensure that the predicted value is close the really outcome in the diabetes dataset.

Result:

several visualization were implemented to analyze the resultd and the dataset that we used. We performed the correlation matrix to view the association of the features between each other as seen below:

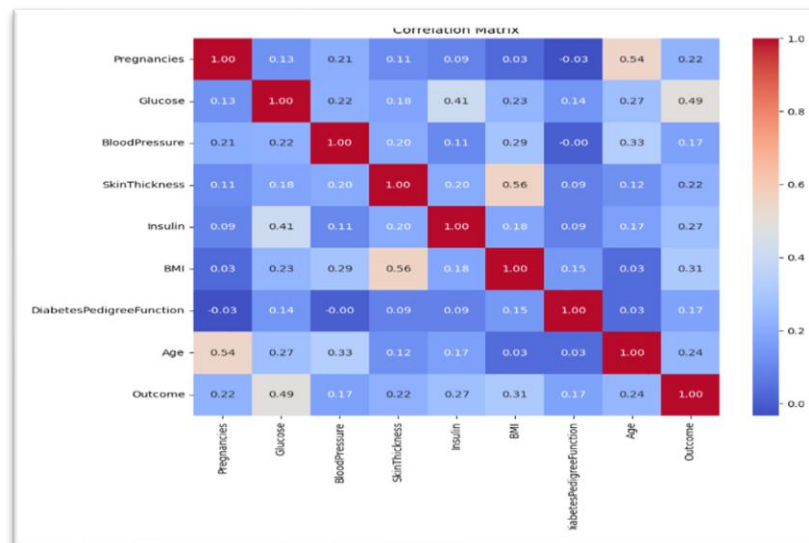


Figure 1:Correlation Heatmap

After performing several models on the dataset we were able to produce the following results:

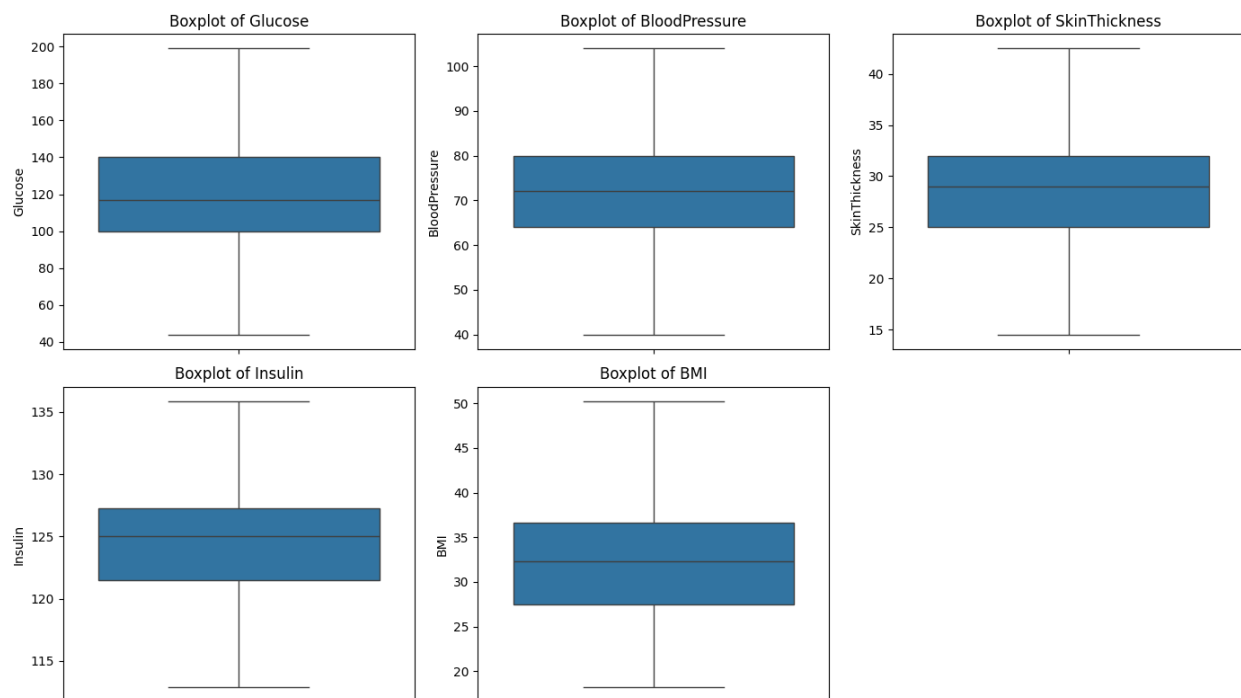
	Accuracy		
Artificial NN		loss	accuracy
	Adagrad	0.483285	0.769481
	Nadam	0.493560	0.759740
	Adam	0.502485	0.750000
	RMSprop	0.502819	0.740260
Genetic Algorithm	0.91		
GA+MCTS	0.8950		

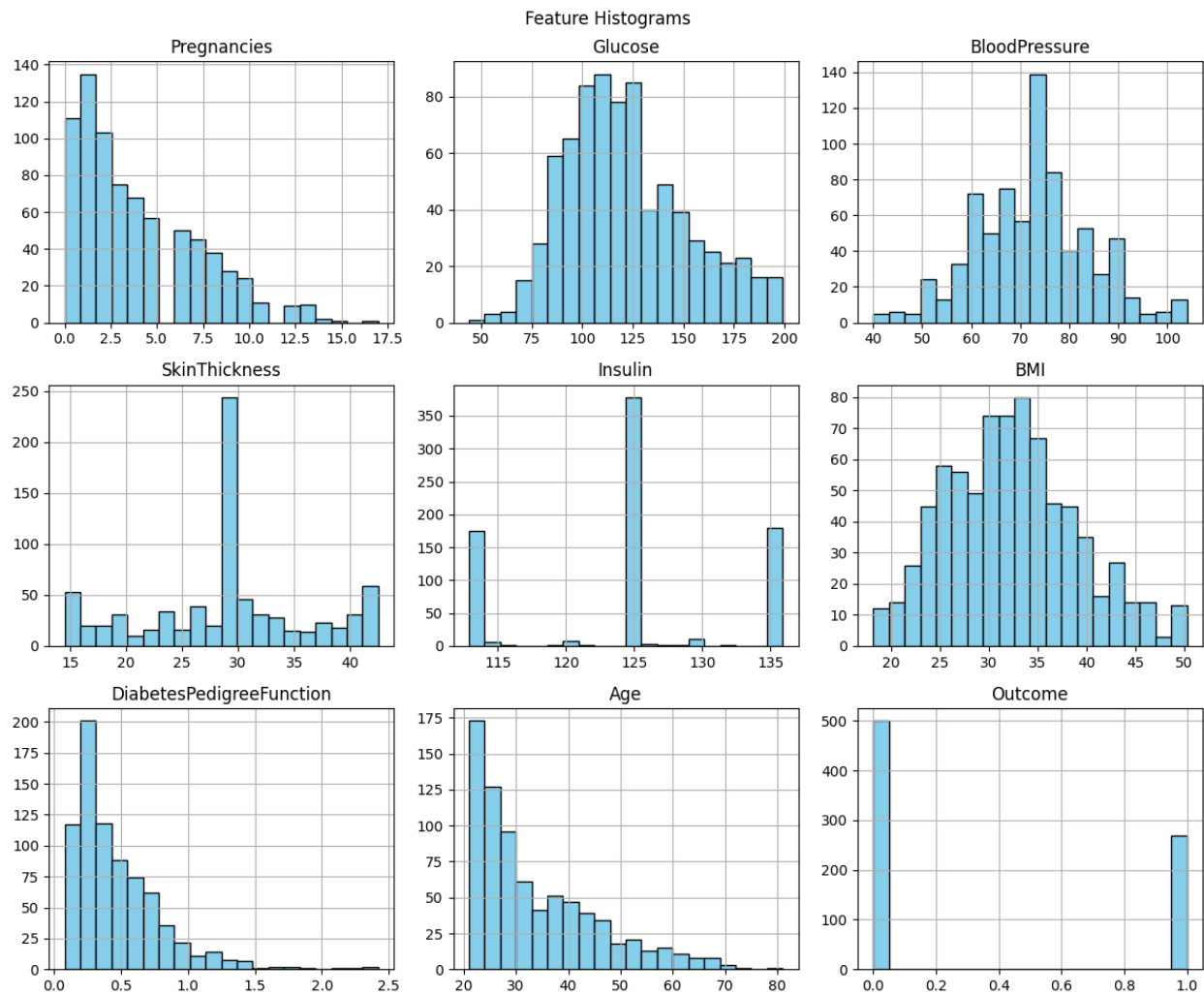
The results that were obtained were analyzed and it has been determined the GA + MCTS had the highest accuracy. However, due to limited time and resources, the model did not fully optimize the weights.

Pre Processing :

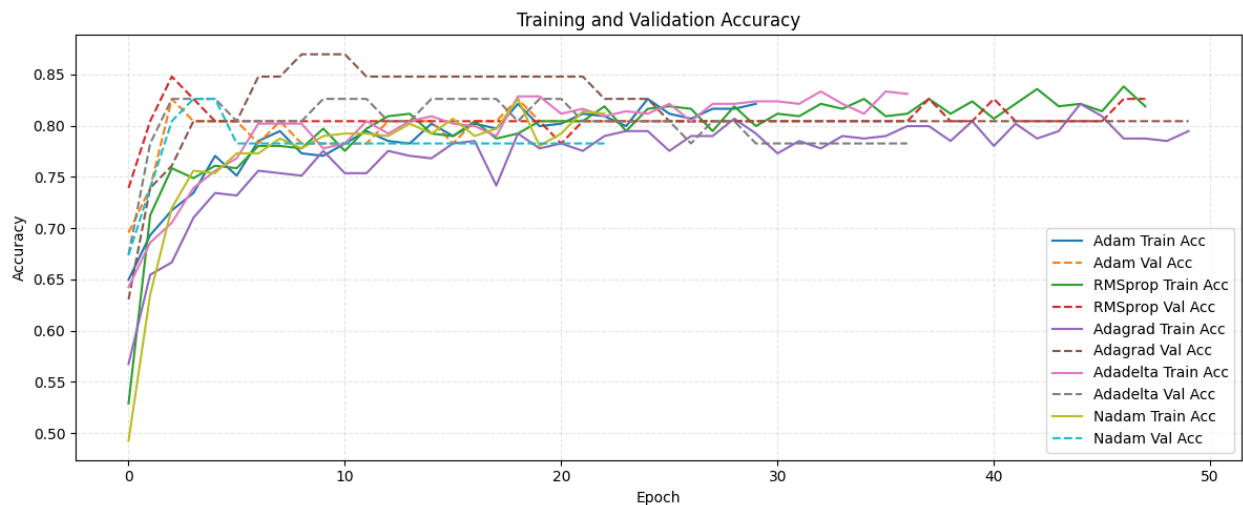
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

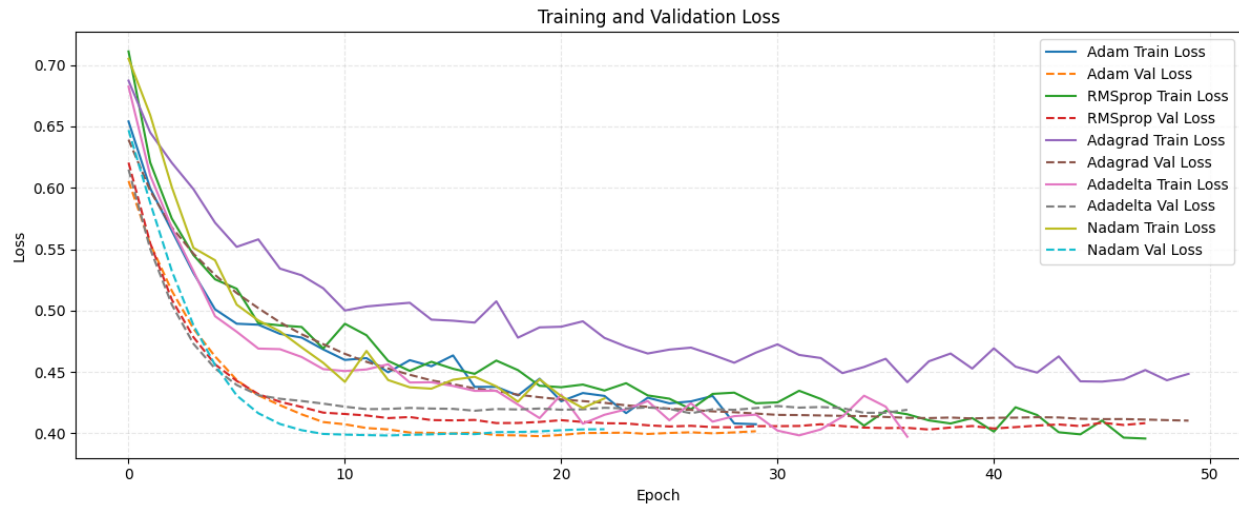
768 rows × 9 columns



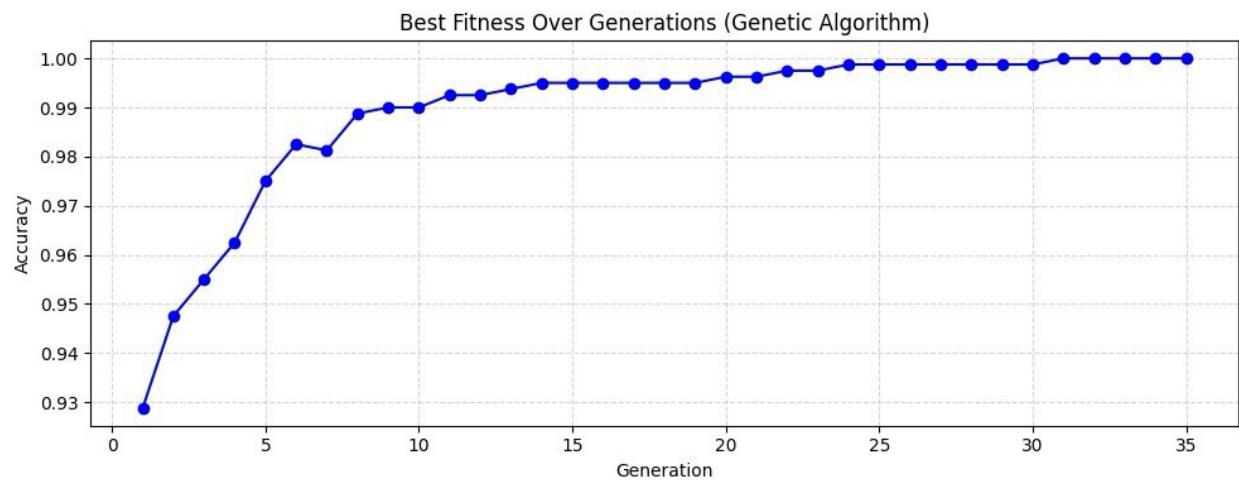
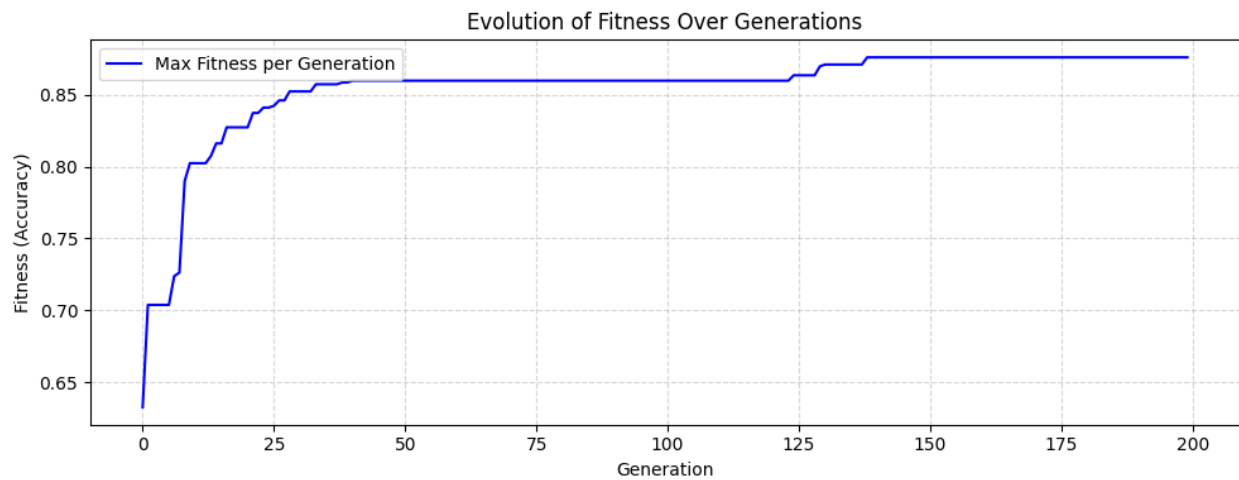


Neural Network





Genetic Algorithm



Future work:

While the results were achieved were satisfactory, there is still some space for improving the optimization of the neural network. For instance, the MCTS can be implemented with other heuristic algorithms to display a better performance. Additionally, adaptive strategies can be applied to properly hupertune the parameters of the GA and MCTS to enhance the performance. Moreover, parallelization technique can also be applied to reduce the time needed to implement the optimization.

Conclusion

By the end of our research, we were able to integrate Genetic Algorithm with Monte Carlo Tree Search to optimize the weights of the neural networks. However, there might be a need for improvement since it was quite a challenge to perform it due to resources and time limitation.

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