EvoNet: Evolutionary Network to Adapt AI through Genetic Algorithm

[1]Shashwath Raghunath , [2]Shamanth M ,[3]Rishab S Rao , [4] Abdul Haq Nalband
[1,2,3,4]*School of Electronics and Communication Engineering*
REVA University, Bengaluru, India
[1]shashwathgowda059@gmail.com ,[2]shamanth23sr@gmail.com, [3]rishabrao42@gmail.com, [4]abdulhaq@reva.edu.in

***Abstract*—As the development of AI increases day by day, we find the need to adapt to ever changing dynamics of the digital world. As data becomes more abundant in few cases and redundant in other, we need a method that can efficiently and effectively analysing and build machine learning models that can adapt through this ever-changing environment. At the forefront of AI development is neural networks, which have become an integral part of every aspect of AI & ML. In this computer heavy world, we chose to analyse the root idea of neural networks, i.e. natural principles that govern the development of brains and neurons in the ever-evolving natural world. We implemented nature's laws and Darwin's principle, to understand how it can affect the development of these neural networks. Using various types of neural networks such as ANN, CNN and RNN, in multiple tasks such as disease detection, disease classification and sentiment analysis, we have identified that our models outperform their traditional counterparts, in both accuracy and efficiency.**

***Index Terms*—Artificial intelligence, Machine learning, Neural network and Genetic algorithms, classifiers**

I. Introduction

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative technologies, revolutionizing various fields by enabling systems to learn, adapt, and make decisions independently. At the heart of these advancements lies the inspiration drawn from nature, particularly the development of brains among organism, everything from simple brains consisting of couple of thousands of neurons, to highly complex brains such as human brains, with billions and trillions of neurons.

Over the course of evolution of these organisms, which has lasted millions of years, we have observed repeatedly, the strength and adaptability of evolution. Thus, this feature of nature to evolve becomes a key feature, which helps the development of the future of AI and Neutral networks [1]. This law of nature has been described and documented in the revolutionary theory of Charles Darwin [2]. In his theory of natural selection, Darwin describes his ground-breaking theory of evolution [3], which emphasize the principles of Darwinism, and how they have helped shape the dynamic and ever-changing world of nature.

Charles Darwin's theory of natural selection, presented in his seminal work "On the Origin of Species," [4] postulates that species evolve over time through the differential survival and reproduction of organisms with advantageous traits. Three key principles underpin this theory: variation, heritability, and

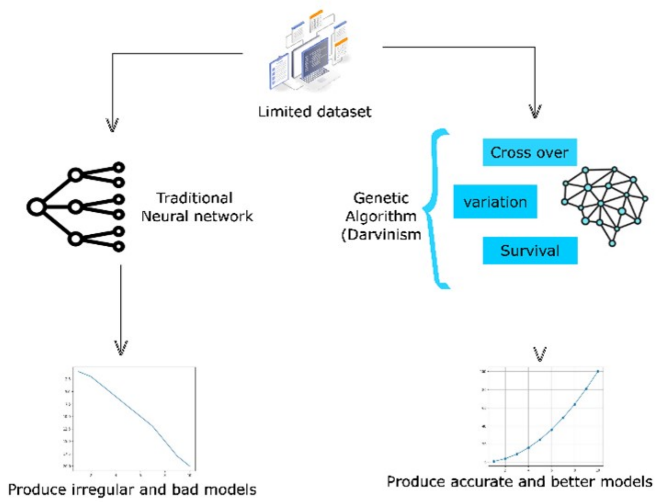

Fig. 1. Implementation of Darwinism into neural networks

differential fitness [5]. The process of natural selection relies these principles to drive evolutionary change. Variation refers to the diversity of traits within a population, which arises from random mutations and affects an organism's ability to survive and reproduce. Heritability ensures that advantageous traits are passed on to offspring through genetic transmission. Differential fitness determines the likelihood of individuals with beneficial traits surviving and reproducing, leading to the gradual accumulation of advantageous traits in the population.

Darwin's theory of natural selection [6] not only explains the diversity of life on Earth but when integrated into artificial intelligence and machine learning, we can leverage these principles to create intelligent and adaptive systems capable of solving complex problems and adapting to dynamic environments. As we have identified in our study, in various applications of these genetically modified neural networks, we have observed enhanced efficiency, decreased training time and lower loss rates, showing superiority over traditional models, in presence of less amount of available data, which we call, "starved data situations" [7].

In situations such as a rare diseases or novel situations in

TABLE I
CRITICAL SURVEY OF SIMILAR PAPERS

Year	Algorithm Adopted	Applications	Results	Remarks
2021	CNN and GA.	Alzheimer's Detection.	Observed enhanced results by 11%	Shows the idea that GA with Neural network has enhanced performance, but lacks in details about GA [8].
2021	Genetic Algorithm (GA) integrated with Stacked Autoencoder (SAE) and Convolutional Neural Network (CNN).	Nutritional Anemia disease classification.	Observes optimized results in the GA-CNN model.	The authors analysed huge dataset compiled from over 5 years. Needs analysis of its performance in a data starved environment [9].
2013	Bayesian network.	Erythemato-squamous diseases detection.	Observed enhanced results, by 3-4% across various test groups.	The paper shows the advantages of GA integrated prediction models [10].
2015	CNN and GA	Semi-automated system based on an integration of the technology of genetic algorithm	Demonstrates how GA and CNN can be integrated into modern healthcare technology.	Shows that the integration of GA-CNN into modern tech can lead to more efficient workflow and results [11].
2013	K-Nearest neighbour and GA	Heart disease classification.	Improved classification accuracy of heart disease ranging from 5% to 15%	The paper outlines the steps of the proposed algorithm, starting from loading the dataset to applying genetic search [12].

which we have a lack of data, most recent example being the sudden occurrence of Covid-19 pandemic, we were stuck in a disadvantageous situation due to lack on data and information about the virus, which lead to millions of deaths worldwide, all these deaths could have been avoided. By the development of such AI algorithms, which can thrive on starved data. By presenting our study, we aim to inspire a new method on integrating nature's principles into AI, thus helping the rapid development of AI and ML, allowing us an efficient way to tackle such dynamic problems thrown to us by the world.

II. Problem Formulation

With the highly unpredictable and dynamic nature of our current global situations, we are faced with the challenge of always having to be prepared for events that happen without notice. The field of Artificial Intelligence and machine learning has come a long way in its technological advancements and offers a major helping hand in the current era.

These AI & ML models are driven highly by data [13] this drive is so extreme that their models can be extremely biased and lack accuracy, just with a shift in the dataset provided to them. Modern methods of data analysis have come a long way in trying to negate these disadvantages, but the key problem arises when we are faced with a drastic situation while lacking even the minimal amount of required data. Such situations leave us vulnerable until we can gather information and analyse the situation. While we cannot completely move away from reliance on existing data, we can still develop models that can learn and evolve in data-starved situations, where they are trained and optimized to provide accurate results despite a lack of training data [14].

III. Genetic Algorithm

Genetic Algorithms (GAs) [15] represent a paradigm inspired by Darwinian evolution and natural selection, providing a powerful framework for optimization and learning in machine intelligence. These algorithms operate on populations of potential solutions to a given problem, using mechanisms such as crossover, mutation, and selection to iteratively evolve and refine solutions over generations.

A. Crossover

In the context of genetic algorithms for machine learning, crossover simulates genetic recombination [16]. It involves combining the genetic material of two parent individuals to create new offspring. In the realm of neural networks or other machine learning algorithms, crossover might represent the exchange of parameters or weights between two parent solutions, producing offspring with a combination of their features. This process mimics the biological concept of recombination, where genetic material is exchanged during sexual reproduction, leading to offspring with a unique combination of traits inherited from both parents.

B. Mutation

Genetic algorithms introduce randomness through mutation, mirroring the concept of genetic mutations in biology [16]. In the context of machine learning, mutation can involve altering specific parameters or introducing new elements to the solution. This randomness adds diversity to the population, preventing convergence to local optima and promoting exploration of the solution space. Through mutation, genetic algorithms ensure that the search for optimal solutions is not confined to a narrow region of the solution space, allowing for the discovery of novel and potentially superior solutions.

C. Survival of the Fittest

The guiding principle of natural selection, survival of the fittest [17], is mirrored in GAs for machine learning. Individuals within a population are assigned a fitness score based on their performance in solving the given problem. Those with higher fitness scores are more likely to be selected for reproduction, simulating the biological concept of reproductive

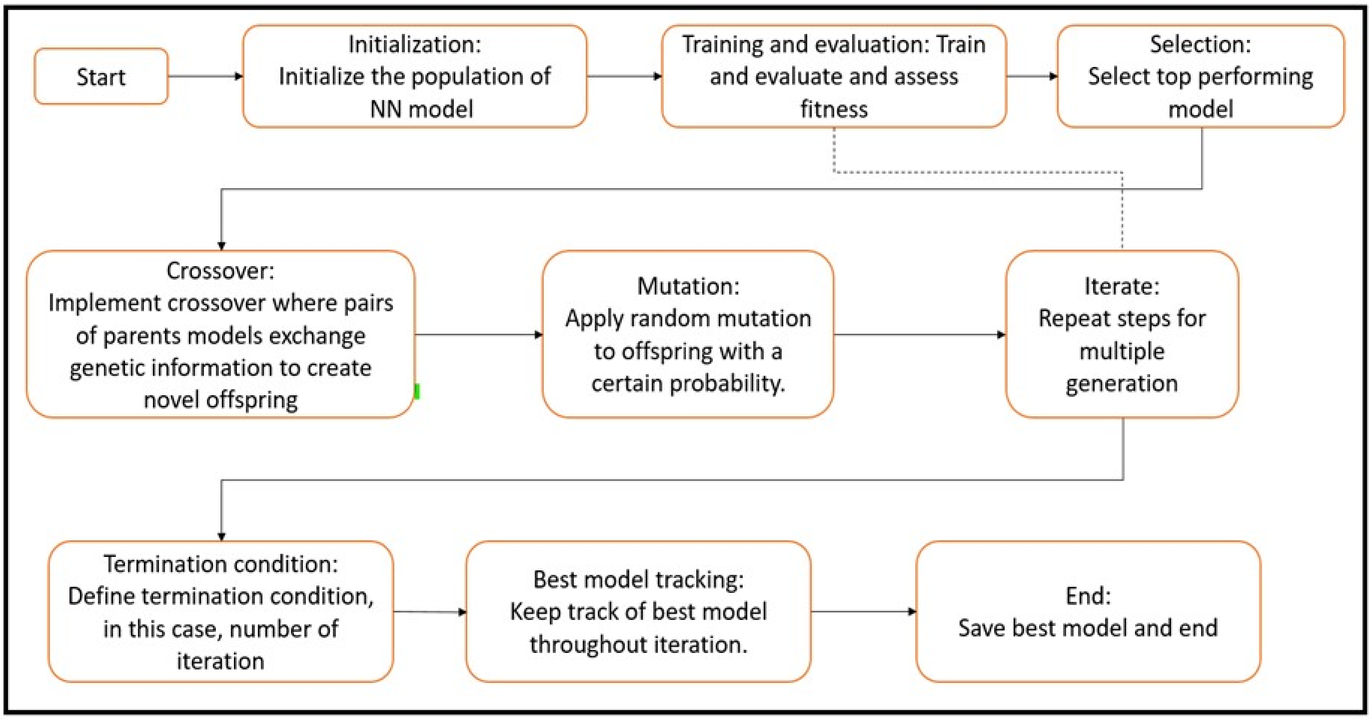

Fig. 2. Flow chart of the methodology employed

success. This selective process ensures that traits contributing to better problem-solving capabilities are propagated through successive generations, gradually improving the overall population's ability to tackle the specified task. The application of genetic algorithms in machine learning extends beyond traditional optimization methods, offering a dynamic and adaptive approach to problem-solving. Unlike static algorithms with fixed parameters, genetic algorithms allow systems to evolve and adapt to changing conditions, making them particularly well suited for complex and dynamic environments. This adaptability is crucial in scenarios where the optimal solution may change over time, and the algorithm needs to continuously adjust its parameters to meet evolving requirements.

The iterative nature of genetic algorithms, with repeated cycles of reproduction, crossover, and mutation, enables them to explore a vast solution space efficiently. This exploration is especially beneficial in situations where the optimal solution is not immediately apparent or is located in a complex and high-dimensional space. Genetic algorithms, inspired by the relentless optimization observed in natural evolution, excel in navigating such spaces and converging towards solutions that might be challenging for traditional algorithms to discover.

IV. Methodology

Our proposed methodology, taking for example one of our proposed image classifier models, revolves around the application of a genetic algorithm to the evolution of Neural Network architectures [18], tailored for solving a classification problem with various dataset. The process initiates by creating a diverse population of NN models with random architectural parameters, including filters, kernel sizes, and dense units. These models undergo training and evaluation on a designated training set, with their fitness determined by accuracy on a separate validation set. The top-performing models, as determined by their fitness scores, are selected for reproduction. The reproductive process involves the implementation of a crossover operation, akin to genetic recombination, where pairs of parent models exchange genetic information, represented by their architectural parameters, to generate novel offspring models. This step introduces diversity to the population, allowing it to explore a broader solution space. To further augment diversity, random mutations are applied to the offspring models with a certain probability. These mutations involve alterations to architectural parameters, such as the number of filters or dense units, ensuring a level of unpredictability in the evolution process.

As the algorithm progresses through multiple generations, each comprising the evaluation, selection, crossover, and mutation phases, the population of Neural Network models iteratively evolves. The overarching goal is to mimic the principles of natural selection, whereby models with higher fitness, or accuracy in this context, are favoured for reproduction, leading to the gradual refinement and adaptation of the population. The algorithm's ability to discover optimal architectures is highlighted by the continuous exploration of diverse solutions, preventing premature convergence to suboptimal solutions. The convergence toward improved architectures is facilitated by the consistent evaluation of fitness, the selective propagation of superior models, and the injection of novel genetic material through crossover and mutation operations. The iterative

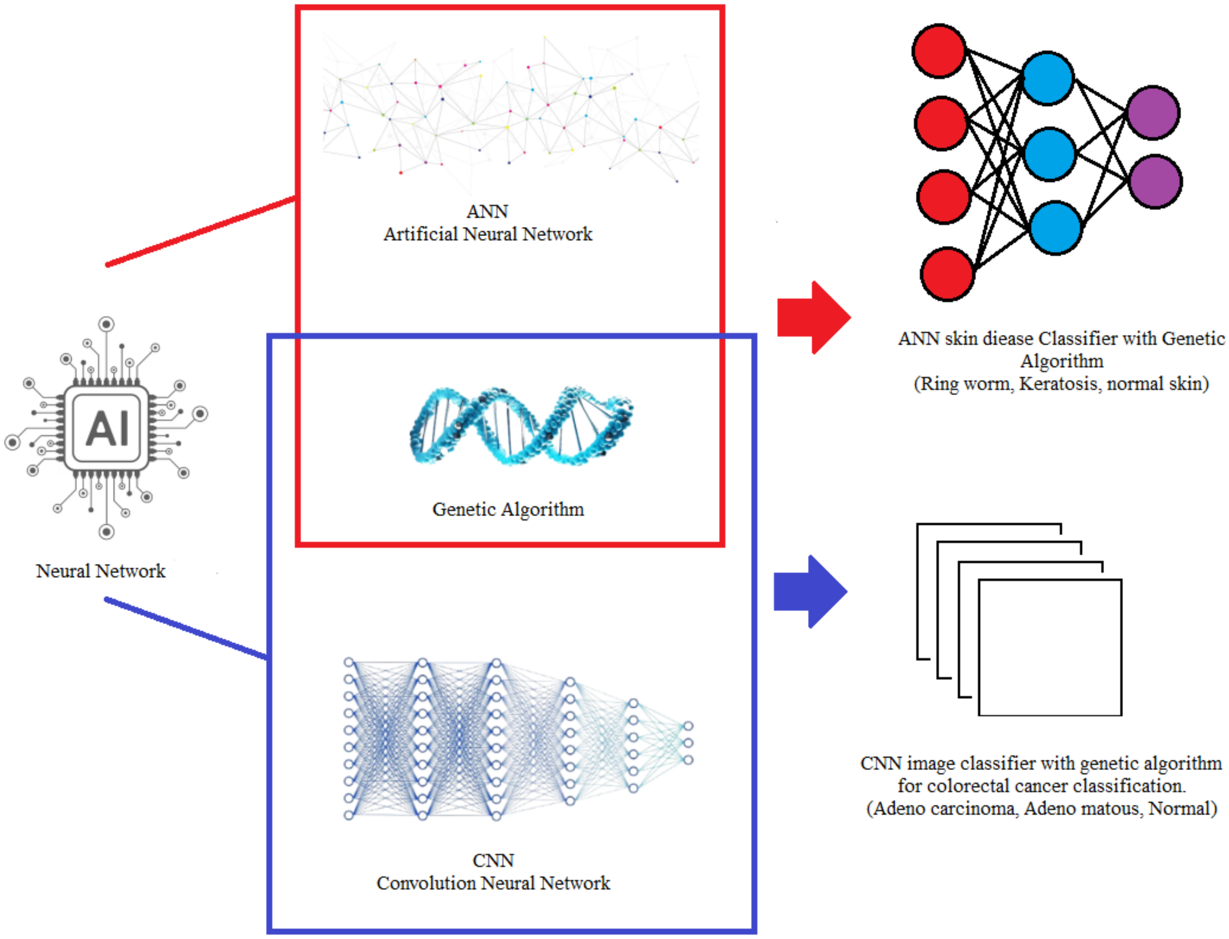

Fig. 3. Implementation of Neural Network with Genetic Algorithm

nature of the genetic algorithm mirrors the evolutionary process observed in nature, where successive generations exhibit incremental improvements, adapting to the demands of the environment. Notably, the methodology incorporates a level of randomness through mutation, preventing the algorithm from becoming overly deterministic and allowing it to navigate the high-dimensional solution space effectively. Throughout the generations, the algorithm keeps track of the best-performing model based on validation accuracy, providing a measure of the overall progress. The identified best model, representing the pinnacle of the evolutionary process, is then saved for potential deployment or further analysis. The methodology concludes by summarizing the architecture and training history of the best model, highlighting its adaptability and effectiveness in addressing the given classification task.

A. Implementation using CNN

We utilized the Genetic algorithm (GA) to optimize the hyperparameters of a Convolutional Neural Network (CNN) [19] for classification. In GA, a population of candidate solutions (CNN models) is iteratively evolved over generations to find the best-performing individuals. Each individual represents a unique combination of hyperparameters, such as the number of filters, kernel size, and dense units in the CNN architecture. During each generation, the models undergo evaluation and selection based on their performance on a validation dataset. This process mimics natural selection, where individuals with higher fitness (better validation accuracy) are more likely to be selected for reproduction. Through crossover (breeding) and mutation operations, new individuals are generated, leading to an evolutionary improvement in the population's overall performance. By leveraging GA, the code systematically explores the hyperparameter space and discovers optimal configurations for the CNN, enhancing its effectiveness in skin disease classification.

B. Implementation using ANN

In the implementation of Artificial Neural Network (ANN) [20] architecture for skin disease classification we used the genetic algorithm to optimize hyperparameters. The ANN consists of convolutional layers followed by max-pooling and dropout layers to extract features and prevent overfitting, topped with densely connected layers for classification. The genetic algorithm iteratively evolves a population of models

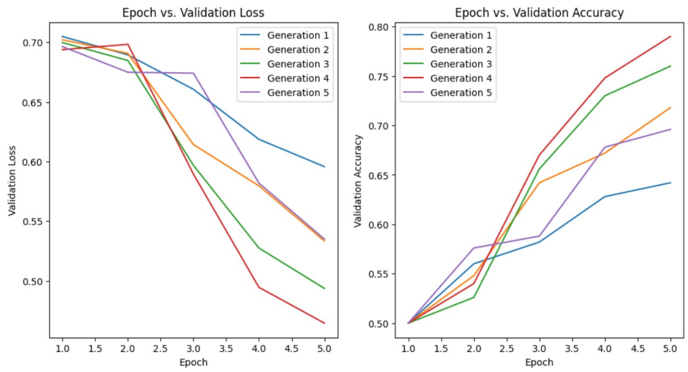

Fig. 4. Results loss and accuracy graph of models trained using starved data CNN classifier using GA

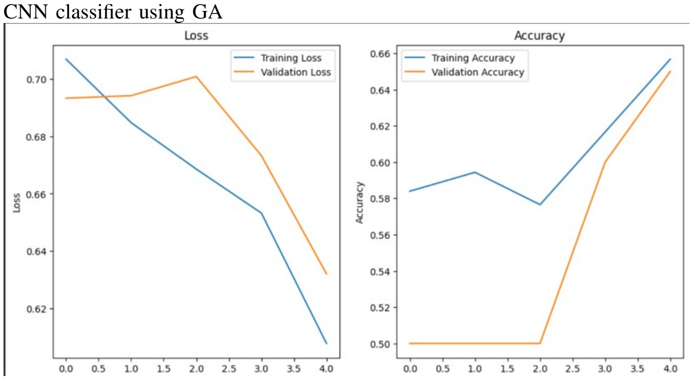

Fig. 5. Results loss and accuracy graph of models trained using starved data traditional CNN classifier

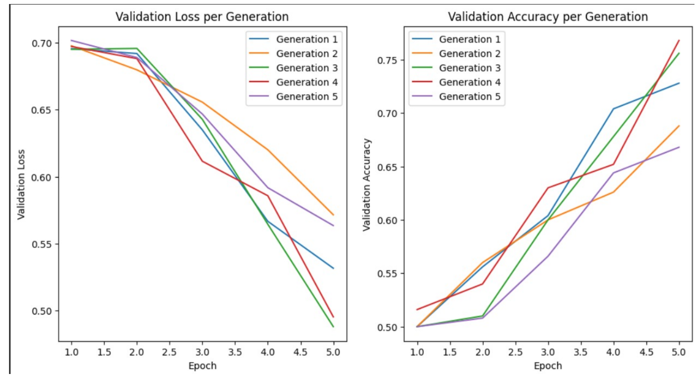

Fig. 6. Results loss and accuracy graph of models trained using starved data ANN classifier using GA algorithm

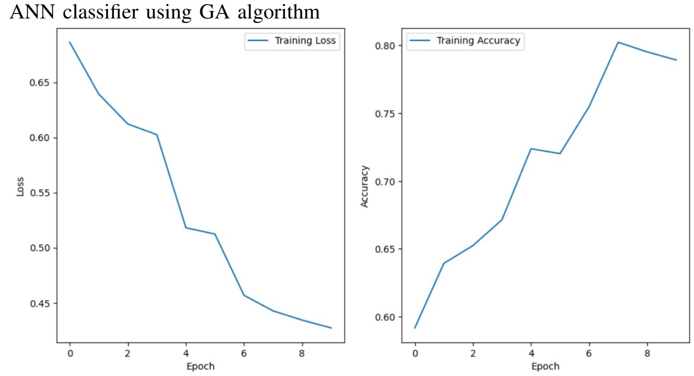

Fig. 7. Results loss and accuracy graph of models trained using starved data and traditional ANN traditional

with randomly selected hyperparameters, training them on the provided dataset. Through multiple generations, it refines the population based on performance, aiming to maximize validation accuracy. The provided visualization depicts how the validation loss and accuracy evolve across generations, demonstrating the genetic algorithm's efficacy in optimizing the ANN architecture for skin disease classification tasks, which could be a valuable contribution to conference papers in the field of medical image analysis.

In essence, our methodology intertwines the principles of genetic evolution with the computational domain of machine learning, creating a dynamic and adaptive framework for the evolution of NN architectures. By leveraging genetic algorithms, the approach offers a systematic and automated means of discovering architectures that excel in solving complex classification problems. The iterative interplay of evaluation, selection, crossover, and mutation encapsulates the essence of natural selection, providing a powerful mechanism for optimizing neural network structures and fostering adaptability in the face of evolving challenges.

V. Results

A skin disease classifier developed using the neural network algorithm in machine learning, adhering to the conventional learning approach. The modified version incorporates both the genetic principle and the principle of natural selection, involving processes such as crossover and mutation.

The classifier is designed to undergo training with a specified generation value, and an additional feature allows the training to halt if five consecutive epochs exhibit the same accuracy or negligible changes. The accuracy versus epoch graphs for the GA and traditional models trained using starved data are given in Fig 04,05,06,07. We have observed enhanced results in the entire neural network algorithm, when they are faced against starved data.

The ANN GA model shows similar results compared to the traditional mode, showing around 82% accuracy using starved data, compared to its traditional counterpart showing around 80%, but at reduced training time, taking 40% less time in reaching the same level of accuracy. The CNN GA classifier model shows higher results compared to its traditional counterpart, getting 20% higher accuracy compared to the traditional model.

VI. Conclusion

Our project aimed to explore the advantages of usage of genetically modified algorithm, in situation where data is sparse or not very well documented or collected. We have achieved superior results compared to the traditional models of CNN and ANN. While this project was just a scratch, we hope to inspire more people to explore the domain of integrating biology into artificial intelligence and machine learning, and help develop more adaptive AI algorithms for the future.

We have observed a few drawbacks such as high demand on the processing capability requirements for the devices to train the algorithms, and as such hope further researchers to aid in optimizing this demand of GA algorithms.

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