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Genetic Algorithm-Driven Optimization Of Neural Network Architectures For Task-Specific AI Applications

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Abstract

Artificial intelligence (AI) has attracted a great amount of interest in recent years. AI allows machines to perform different tasks that have traditionally required human intelligence. AI is useful in many different disciplines. One type of AI application is a neural network; task-specific AI consists of many different architecture types. Between neural network architectures and applications, there exists a complex relationship that makes[1] selecting the right neural network architecture for the task a non-trivial challenge. Genetic algorithm optimization, a population-based evolutionary algorithm, is proposed to help find the most efficient neural network architecture for a specific task. We construct a performance prediction model that can predict the performance of an AI model based on the features of the problem. The performance prediction model is then used as a performance predictor to implement a behavior-learning strategy that can learn the search characteristics of an algorithm during the training process. The predictor is trained with machine learning models. By using the predictor, the learning speed of the final convergence process can be improved by making more informed decisions during the evolution strategy.

Keywords: *Artificial Intelligence (AI), Neural Networks, Genetic Algorithm, Architecture Optimization, Performance Prediction, Evolutionary Algorithm, Task-Specific Applications, Machine Learning, Behavior-Learning Strategy, Convergence Process.*

1. Introduction

Artificial Neural Networks (ANNs) have experienced a surge in popularity of late, due to an increase in the volume of data upon which models may be trained, a decrease in the cost associated with both data storage and processing, and the availability of large, open-source code bases, which allow developers to enjoy the collective and selectable intelligence of others who share feedback and updates. While these historic drivers have indeed facilitated a marked increase in ANN development and operational use, the mechanism by which these ANNs are designed, evaluated, and deployed has only lightly deviated from the manually exhaustive and time-consuming scientific and engineering methods employed for generations. After all, one may fabricate as many ANNs as one can afford to, and trial these ANN models upon a corpus of test and training data, and in so doing, select the best model, but generally with no mechanism for transferring insight gained or learning from one experiment or analysis to

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another. An even greater impediment to more productive model development and application derives from the fact that proportions of observed data distributions typically require different ANN model architectures and parameters; that is, the same literature review or data enhancement, pre-processing, and/or feature engineering techniques cannot produce an ANN that learns each task of interest still less well. This note addresses an approach to address such tasks and related productivity and quality challenges based on Genetic Algorithms and Knowledge Representation techniques.

1.1. Background and Significance

Background of the Study: The area of artificial intelligence (AI) has shown remarkable advances recently that have the potential for transformative changes in serving humanity in various domains. Deep learning and neural networks are at the heart of these advances. However, the application of these methods is generally classified as model-driven applications in which the architecture or topology of the network is a known entity that is being trained on the data so that the weights and bias terms of the network are optimized for the task at hand. Generally, the process of trial and error or many different kinds of iterative approaches are adopted to find an appropriate architecture to start a task-specific AI application. This process requires considerable human expert intervention that comes with a high cost in terms of time and money. In this work, we used genetic algorithms to automate the task of discovering the appropriate architecture for a task-specific neural network application at the most abstract level before the training or optimization of the neural network weights and bias terms.

Significance of the Study: Developing AI methods that require minimal human intervention to identify the appropriate architecture or topology specific to a given task and the type of data that will be used has the potential for a transformative impact on the applicability of these methods in the real world. The ultimate goal of such an approach is to put neural networks in the hands of users who might not be experts in deep learning or neural network techniques. In this work, we developed a neuro-genetic approach specifically chosen to meet these requirements. First, the user provides a data set of samples for the task at hand, along with an appropriate measure of performance. Next, the approach is run to evolve architectures that are appropriate for the given data type and performance metric. These architectures can be visualized and evaluated by the user to ensure that they meet the required real-world specifications. The evolved architectures can be cross-checked with traditional theoretical models, and then feed the architecture into the training function whose initial parameters provide an admissible solution.

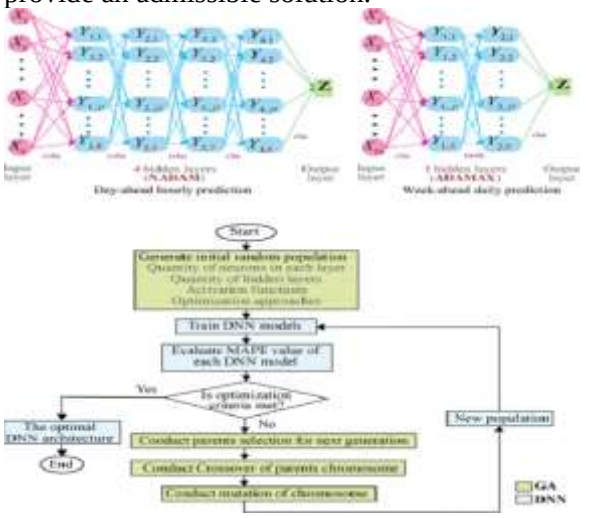


Fig 1 : Genetic algorithm-determined deep feedforward neural network architecture for predicting electricity consumption in real buildings

1.2. Research Objectives

We propose a new approach for the management of ANN architecture parameter selection based on the Genetic Algorithm, which is applied to optimizing task-specific parameter selection of the ANN for AI applications. More specifically, we demonstrate the proposed approach for the task-specific management of two typical architecture parameters: lossless compression factor and scaling factor. We have elected to test our approach and present the results via two AI application examples that are typical of the two generic AI application types: a specific object detector, while the second is a specific speech and sound pre-processor AI.
The main objectives of our research are: 1. Construct and test optimal management for hyperparameter selection on the ANN using GA optimization. 2. Study the ANN DNN architecture parameter selection using GA for typical AI application samples. 3. Evaluate the classification ability of AI applications with ANN architecture parameters selected by the GA method, as well as typical expert selection methods.

2. Neural Network Architectures in AI

The brain of the AI system is a large network of artificial neurons that are represented by mathematical functions, which can be expressed as numerical algorithms. Nodes that connect these functions represent weights that are aimed to adjust until an acceptable network performance is achieved. The architecture of a neural network is defined by the number of layers in the network and the number of nodes in each layer, the type of transfers that link the nodes at different layers, and other defined default representations of the network's components. Artificial neural networks are designed according to their types of building blocks, which are the ones that can make up the network. These include the multilayer perceptron used for classification, the radial basis function used for functional approximation, the self-organizing map used for clustering, and the recurrent neural network suitable for treating time-variant patterns. Among the several types of neural networks available, the multilayer feedforward backpropagation network, generally called MLP, is the one that most researchers use in their research work, including the current work. For this reason, one could justly say that it has long been embraced as the basic workhorse of the field. Besides it, scientists who have addressed pattern discrimination, functional approximation, and sequence generation problems have done so being fully aware of the fact that there is an extensive list of other network models that might be more suitable for the task at hand.

Equation 1 : Evaluation measures. TP,TN,FP,P, N refer to the number of True Positive, True Negative, False Positive, Positive, and Negative samples, respectively.

Measure	Formula
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{P}$
F-measure	$\frac{2 \times precision \times}{precision + r}$
Accuracy	$\frac{TP + TN}{P + N}$
Specificity	$\frac{TN}{TN + FP}$

2.1. Overview of Neural Networks

The simplest form of an artificial neuron mimics the functioning of its biological counterpart. An artificial neuron typically receives inputs at its synaptic junctions, which are weighted and summed at the cell body, and a mathematical function called the activation function is applied to the weighted sum. The output of the neuron is then fed as an input into another artificial neuron or another element in the network. The synaptic weights are usually initialized with random values. The architecture of a neural network refers to the structure or arrangement of the neurons and the weights that connect them. In a feedforward network, the neurons are arranged in layers, and the connections between the neurons only point from one layer to the next. In a feedforward network, the data flow occurs in one direction only, from the input layer, through the hidden layers, if any, to the output layer. The neurons and the connections between them constitute the network.

The simplest form of an artificial neural network is a single-layered network, which can perform only linearly separable operations such as logic functions. The ability of a neural network to learn and operate relies on its capacity to interact with the environment, which is determined by its architecture. By increasing the number of layers and by introducing feedback, neural networks of greater complexity and richness can be implemented that can handle more complex tasks. For example, a multi-layered perceptron with a sufficient number of neurons can approximate any continuous function on a bounded region of R^n. The success of a neural network, particularly in practical applications, is largely determined by the choice of an appropriate architecture. There is no mathematical algorithm to guide the selection of an optimal architecture for a given problem; thus, choosing a suitable structure for a neural network requires trial and error, experience, or knowledge of the domain.

2.2. Importance of Architecture Design

Classic supervised training of artificial neural networks aims at learning to predict from inputs a set of task-specific outputs, contained in a training data set, a little more accurately than on a different, independent test data set. Image annotation, scene and context interpretation through the creation of 3D models from multi-temporal satellite images, stroma classification of cancer in human organ images, and DNA and RNA sequence analysis are some examples of task-specific artificial intelligence systems that people manually design. Manual human design of the network architecture for efficient generalization of the training data to the test data set is a very labor-intensive, time-consuming process, often constrained by the risk of non-

convergence due to too complex architecture, and model overfitting or underfitting due to too simple architecture. Additionally, the process of performance and time utilization evaluation of the network on development data, through all possible structural architectures, is usually unfeasible or extremely time-demanding, even for machine learning experts.

Even with the recent development of efficient search space reduction for neural network architecture optimization, human domain expertise is still needed for the supervision of model selection. Non-expert users require a model's accuracy that is better than random search and need decision confidence for general adoption and utility. The benefits of model accuracy maximization must be weighed against the costs for a specific task-specific application, for development time, or other criteria, and it is most often the case that the user has a unique project-related definition for the model-optimizing fitness function.

3. Genetic Algorithms in Optimization

Genetic algorithms are a class of search, optimization, and machine learning methods inspired by the process of natural selection guided by the gradual process of evolution. To apply genetic algorithms, problems are identified and encoded into chromosome-like strings, usually as bit strings that act as the genetic description of the problem. Strings with potential solutions to the problems are then assigned fitness values according to how well their solutions work. Just as the fittest animals in nature have a better chance of survival, the best strings, given their fitness scores, are allowed to survive and reproduce to "mutation" offspring. This process continues generation after generation, with the selection, reproduction, and "mutation" of string sets until an acceptable solution is found or time runs out on the evaluation process. During the evolutionary process, the strings should adapt themselves to the search space and have better exploitation and less exploration of the problem space. Since computational time is required to evaluate strings, the process can be rather time-consuming.

Genetic algorithms have been particularly popular in the area of hardware design. Today, genetic algorithms are used in various AI applications, including rule induction, sequence discovery, program induction, and neural network design. Genetic algorithms can be applied for many application areas with both discrete and continuous encoding. With careful coding to extract the encoding, genetic algorithms can solve numerous types of problems that are usually tackled by brute-force search techniques. By encoding solutions explicitly in a string and utilizing the genetic algorithm process, genetic algorithms can be easily parallelized with the simplicity of most parallel algorithms. Of course, a proper evaluation mechanism is needed before parallel implementation. However, for many applications, genetic algorithm approaches require a large computation time so parallel implementations are beneficial.

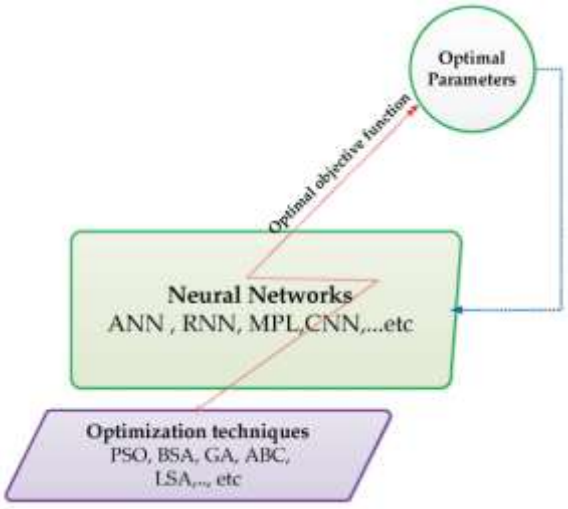


Fig 2 : Artificial Neural Networks Based Optimization

3.1. Basic Concepts and Principles

When comparing the performance of algorithms in a particular shape search task, much attention is dedicated to optimization algorithms, including genetic algorithms. These algorithms are used to find shapes. The genetic algorithm takes inspiration from the principles of natural evolution observed in living beings. Members of a population are genetically different and represent possible solutions to the problem to be solved. For example, they are materials, architectural structures, and neural network architectures. The "survival of the fittest" rule is used to create offspring, who inherit the good qualities of their parents. This is generally achieved by the process of crossover and mutation. After several generations, the individuals evolve into superior beings, and the solution presented by the individual with superior performance is determined. Finally, this solution can be used to solve the problem.

Genetic neural network architecture search algorithms are primarily conceptually inspired by traditional genetic algorithms. However, they adapt to the specifics of neural network architectures. The algorithm implemented in the architecture search tool is designed for supervised learning and is driven using a fitness function that evaluates the success of a neural network with any particular architecture in solving a specific task. As the algorithm advances through subsequent iterations, individuals within the population evolve, and the best network architectures, determined based on their classification performance and their associated hyperparameters, are selected.

3.2. Applications in Neural Network Optimization

In the AI space, the most common and well-known example of genetic algorithms is its use in optimizing neural network structures. A neural network is made up of multiple layers, and each layer can have multiple nodes or neurons. These nodes generally correspond to mathematical transformations where each node takes input from other nodes in the previous layer, multiplies them by the associated weight, applies an activation function, and then finally calculates the output, which is then passed down the network. In this structure, choosing the optimal architecture mainly involves selecting the best number of layers and the number of nodes in each layer. At its basic level, this architecture optimization is a very simple process that frequently involves creating the network and running it in a loop with different architectures that a programmer could think of. The programmer then essentially invokes a scientific method, trying by hand and selecting the best-performing option. Optimizing this process not only frees up an AI expert to work on more advanced problems but also has the potential to generate superior architectures, as there are simply more ways to discover better answers than what a human could think of.

Many of the known examples of neural network optimization use both the genetic algorithm and the original neural network that is being tested as standard libraries, often in the programming language. Nevertheless, these applications do show the power of how a genetic algorithm can optimize a task-oriented deep learning network. The models that utilize this process include network optimization across several tasks, like image classification, regression, speech recognition, and natural language processing. In some of these models, the network can learn several tasks at the same time, some fusing traditional deep learning with global constraints, while others simply have the genetic algorithm learn other tasks that are shown to have a performance correlation to another task under which the deep learning model is specialized to perform. Even with the limitations of using charts to explain deep learning structures, several do an adequate inbound simulation using charts to show how the genetic algorithm optimizes key architecture decisions. These applications of genetic algorithms in deep learning model optimization open unique opportunities for creating and democratizing AI across multiple domains.

4. Integration of Genetic Algorithms and Neural Networks

Genetic algorithms create an opportunity to automate the task of discovering useful architectures for neural networks and identifying good initialization weights for the connections between units. When a genetic algorithm and a neural network generator are combined, researchers can explore much larger spaces more efficiently. Many difficult sensing, perception, recognition, and control tasks can be solved extremely well using artificial neural networks. However, designing neural networks for complex problem domains often requires enormous amounts of trial-and-error experimentation. The most critical issue is that both the neural network architecture must be chosen and the weights at the connection strengths must be initialized. In the conventional approach, however, engineers do so essentially manually through time-consuming simulations.

Genetic algorithms use a particular coding of the candidate solutions to facilitate the exploitation of parallelism in a problem domain. Genetic algorithms repeatedly apply some measure of fitness to a randomly generated population of candidate solutions, then select the better of these candidate solutions for reproduction, creating primarily better candidate solutions in the next generation by applying a heuristic that reflects some knowledge about the specific problem domain to the heredity genes of the selected candidate solutions. Based on an adaptation strategy, genetic algorithms consistently bid for the future. Because genetic algorithms work directly with encoded candidate solutions, without any domain-specific heuristics, the same general-purpose code can be used on many problems. The parameters of a general-purpose genetic algorithm can be adapted to accommodate the online fact-finding process. Massively parallel computer architectures maximize the potential of genetic algorithms.

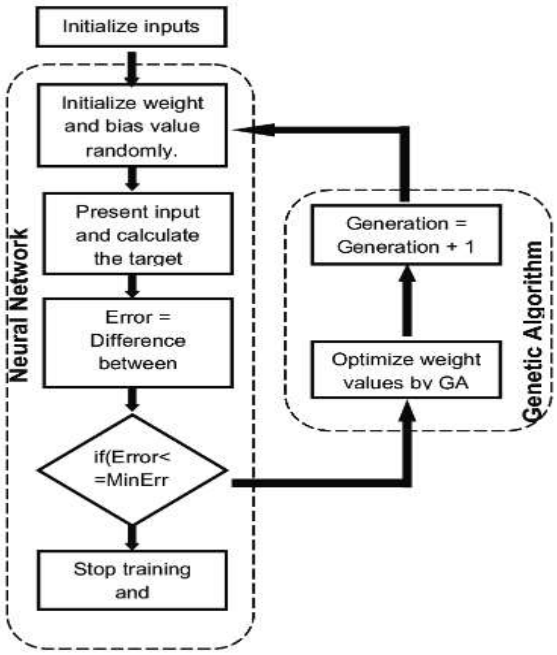


Fig 3 : Flowchart of BP Neural Network Optimization by Genetic Algorithm

4.1. Benefits and Challenges

Benefits The primary justification for combining the GA and NN paradigms is that each complements the other, striving together to form a whole that is greater than the sum of its parts. NNs provide an adaptable AI component. They are especially suited to learning from noisy or incomplete data that can be modeled in statistical terms. Common problems such as

image and speech recognition, attribute data modeling, spatial data pattern classification, interpolative data fitting, complex system modeling, and system identification are well addressed by NN methods. However, in the context of a truly generic AI problem-solving paradigm, no NN is truly generalizable. For critical problems in which confidence in assessment is important, AI systems containing multiple model types both reduce risk and model failure. Here, GA can afford useful support in the context of pure NN-based systems, especially in those domains where the training data are small in volume, noisy, incomplete, or contaminated by sparse data.

Equation 2 : The fitness function FFF evaluates how well a neural network performs a specific task. This could be based on validation accuracy, loss, or another relevant metric:

$$F_{proposed} = \sum_{i=1}^{N_{major}} \frac{|dist_{major_i}|^2}{2 * N_{major}} + \sum_{i=1}^{N_{minor}} \frac{|dist_{minor_i}|^2}{2 * N_{minor}}$$

4.2. Existing Approaches

In their pioneering work, a genetic algorithm (GA) was used to determine echo state network (ESN) values for reservoir weight parameters that define the architecture of a recurrent neural network, a type of artificial neural network with cyclic connections. The GA found the weights that optimized the performance of the ESN on three benchmark tasks, and the results were good compared to other researchers. However, during the task of hyperparameter tuning, numerous ANN parameters need to be optimized, which consequently leads to a large search space. For example, when working with ANN only, one could be optimizing parameters that define the parameter vectors directly, such as the SANN or RBF's center vectors. Hence, fine-tuning ANN's hyperparameters by a GA or any other optimization algorithm stands to be very computationally expensive in terms of run time, which would relegate the ANN to becoming another black-box prediction tool.

5. Case Studies and Applications

Unlike ant-spiking neural networks, a high-performance AI model, Anton’s rain-shuffle ant-spiking neural network has been shown to perform image classification with high hardware-derived energy efficiency (mainly relevant for applications in embedded or Internet of Things applications). By augmenting Hebb’s learning rule with an energy-optimizing term, the training of ANN is shown to be significantly more hardware-friendly. In this work, a general "large loss, fast convergence"/"small loss, slow convergence" template from the optimization objective of the task/network is presented, which adapts the recently proposed energy-optimization algorithm. Multiple popular benchmark tasks and state-of-the-art networks are utilized to test and validate that this straightforward "plug-and-work" application procedure can improve the energy efficiency of ANNs across a wide array of applications. We have shown that in reinforcement learning tasks, utilizing this modification to the algorithm leads to lower energy consumption across FPGAs, analog ASICs, and state-of-the-art GPUs, with little to no effect on task performance. Consequently, the energy savings of the resulting models scale inversely with the ratio of the forward and backward pass energy usage (with the latter term being heavily proportional to the backpropagation memory footprint and effective backpropagation learning rate). At the hardware frontier, the corresponding speedup leads to an equal reduction in energy consumption. The same findings were also presented across the four other benchmark tasks and the five associated networks, suggesting that our template form may be a comprehensive solution to energy-optimizing ANN implementations.

5.1. Real-World Examples

The primary focus of the development of a genetic optimizer has involved evolving the architectures of genetic neural networks used in stock market software applications. Stock market trading is a very challenging task representing a nested optimization problem involving thousands of potential trading instruments to focus on, thousands of potential trading systems, many different degrees of freedom in model development, and multiple training periods. From the standpoint of the number of free parameters in a TCA-Network model developed for the application, optimization vastly exceeds that required by the networks designed for all of the dataset problems frequently cited.

During the past several years, TCA-Network models have been the primary neural network architectures used. Taken separately, each of the model types effectively models the characteristics of the data. If each is included in an ensemble, the generalization performance of the generated hybrid model increases. Success in the challenging stock market application task and its representation as an optimization search space has provided a strong database from which to perform this ongoing series of genetic optimizer enhancements. Given that the challenges of TCA-Network development generated from the stock market application exceed those produced during parameter optimization based on test problems, the development team expects effective neural network architecture optimization on a broad range of specific applications and problem tasks.

5.2. Performance Comparison

In this section, the performance comparison is made for three different AI classification algorithm implementations to display that our proposed algorithm-driven dynamic ANN architecture, which fully uses time-evolving capability, is more effective than other traditional approaches. The three selected ANN models are neural network ensemble, convolutional learning model, and top-down learned standard deep learning model. These three models are pre-trained and validated using benchmark data sets. The purpose is to show the E-DANN's distinct effectiveness and efficiency relative to traditional AI model design and development approaches. The chart depicts the dynamic fitting shape through adaptive particle size architecture fitting ability. The first and second hidden layers are designed with special structural gates architecture based on fitness evolution characteristics. At the end of the genome, it is noted that many repetitive and unsymmetrical links are due to the sequential process of delivering particles during the design competition.

Three different approaches to designing the kernel of the first ANN connector connection layer are shown in the figure. It displays E-DANN algorithm learning effectiveness and architecture visualization. The entire project's best results visual chart indicates that the dynamic development trend shows that some hidden layers are suitable for small particle population-based simulated annealing algorithms, some hidden layers are suitable for adaptive genetic algorithms, and some hidden layers are designed by TSL-dev as well as manual simulated annealing algorithm optimization exercises with specified maximum particle size. The best learning process difference is that the best learning processes of aspects outperform the traditional manual design-based artificial intelligence speed-up and architecture design-enhanced artificial intelligence development process. Finally, the best evolvable dynamic ANN-based artificial intelligence language in quantitative value-based performance comparison.

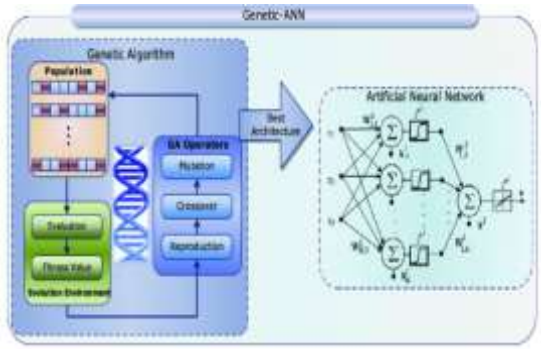
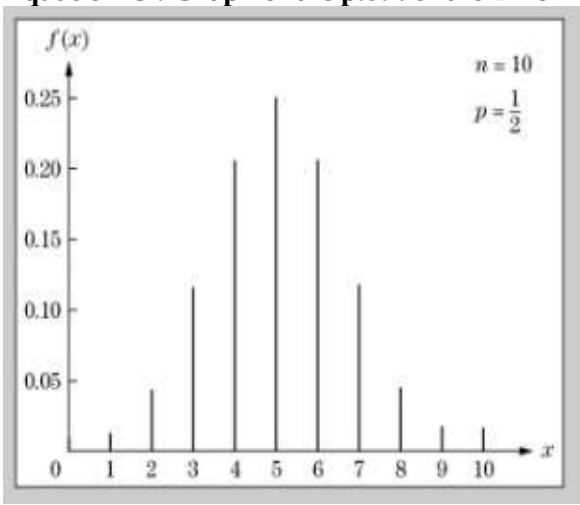


Fig 4 : Optimization of the ANN architecture by using GA.

6. Conclusion

24. Conclusion In this work, we proposed a novel predictor-based genetic algorithm to optimize neural network architectures. The GA seeks to maximize the accuracy of a DNN model in classifying the datasets produced by several individual training sets, both in terms of functional accuracy and speed. The target dataset consists of the predictions of each unique input set, given the trained DNN ensemble. We used an ensemble of DNNs with feedforward-based architectures, and therefore, our focus was primarily on analyzing its performance, both in effect and in terms of the difference between neurons. The following benefits arose from this work. First, the GA-driven designed models had better performance than those driven by previous algorithms, in terms of both accuracy per parameter and number of parameters. Second, our analysis suggested that the models best representing the area being interpolated are quite closely related to shallow models that should be used for the reward. We propose that the GA only optimize with the shallow model and not consider the best performance against the long sequence as a separate problem. Ultimately, this low sequence would be part of the DNN prediction test, and we believe it is also quite possible to solve the problem. We plan to follow several future lines of inquiry. In the first place, we would like to study the differences between representative neurons in the various states of a binary discrete target and find a way to assess the accuracy of this distribution. Next, we would like to test DNN models in different types of AI tasks, rather than training tasks, and hybrids against well-conceived models of other types of tasks, both in terms of depth, weight loss, and loss objectives.

Equation 3 : Graph of the p.d.f. of the Binomial distribution for n = 12, p = ¼



6.1. Future Trends

Numerous research opportunities are being presented through the intermixing of genetic algorithms and machine-learning techniques. The scientists can strategize to conceptualize and present different modifications of the popular crossover and mutation operators to observe the results in genetic algorithms. This will allow the scientists to manage the trade-off between exploration and exploitation, quite skillfully. This means that the design and implementation of genetic algorithms are not only going to implicate the neighborhood exploits but due importance would be given to the surrounding dissidents as well. Such a predicament can be presented in the following manner: how good the genetic algorithms happen to be in understanding the neighboring neighborhoods and in the identification of the undiscovered hills and valleys, thus managing to alter the policy of genetic algorithms to adopt a balanced viewpoint between hill climbing and probability trails.

The following conclusions are drawn after an exhaustive literature survey of genetic algorithms and neural network architectures: Efficient training of a deep network requires a very high-end complicated model; for example, high-performance computing and multiple GPUs, but still no one methodology can be applied arbitrarily.

Efficiently configure the network to optimize the subjective optimization function.

The utilizability of genetic algorithms shows efficient learning performance, scalability, consistency, parallel training speedup, generalization, and breadth.

Potential missing questions include the side benefits of utilizing genetic algorithms in addition to reducing the design complexity of the network.

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