IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

# ANALYSIS ON OPTIMIZATION OF NEURAL NETWORK WEIGHT SELECTION USING GENETIC ALGORITHM

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## ABSTRACT

Multilayered feed forward neural networks have a variety of characteristics that make them particularly well-suited to challenges with complicated patterns. There is currently no training algorithm that can quickly and accurately determine an almost globally optimal set of weights, hence their use in real-world issues has been limited so far. As a class of optimization methods, genetic algorithms excel at intelligently exploring huge and complex spaces in search of values that are as close as possible to the global optimal. It is used in this paper to find the best weights for artificial neural networks (ANNs) using a genetic algorithm (GA). 78 questions were asked of 228 patients with first-time low-trauma hip fractures and 215 patients without a hip fracture in this study. We used logistic regression to select five relevant characteristics for building artificial neural networks that can predict the likelihood of a hip fracture (namely, bone mineral density, fracture experience, average hand grip strength, coffee intake, and peak expiratory flow rate).

## 1. INTRODUCTION

There are many reasons why neural networks have become popular in recent years, including the fact that they are based on the human brain. Because they are simple to construct, but nonetheless give very general computational capabilities [HORN89], this is an important consideration. For one thing, they may be built directly in VLSI hardware, which means that huge parallelism can be achieved at a relatively low cost. As a result, they can learn by selecting numerical "weights" and adjusting themselves to different tasks (i.e., adapting). Choosing these weights is an important part of neural network implementation. Weight selection algorithms for each neural network architecture are the most common method.

Over time, the prevalence of osteoporosis increases, which can lead to devastating pathological fractures. It is estimated that there were 9 million new cases of hip, forearm, and vertebral osteoporotic fractures in the year 2000. Most of these fissures occurred in the Western Pacific and Southeast Asia [1]. Europe and North America accounted for 51% of these fissures. One year following a hip fracture there is a reported death rate of 20–24 percent, and this risk persists for at least five years after the fracture [2, 3]. While the majority of patients who sustain a hip

fracture survive the incident, some are left with long-term effects include chronic pain, restricted mobility and impairment as well as a growing level of reliance [5]. A high health care bill is also a financial burden for the patients who bear the brunt of these costs.

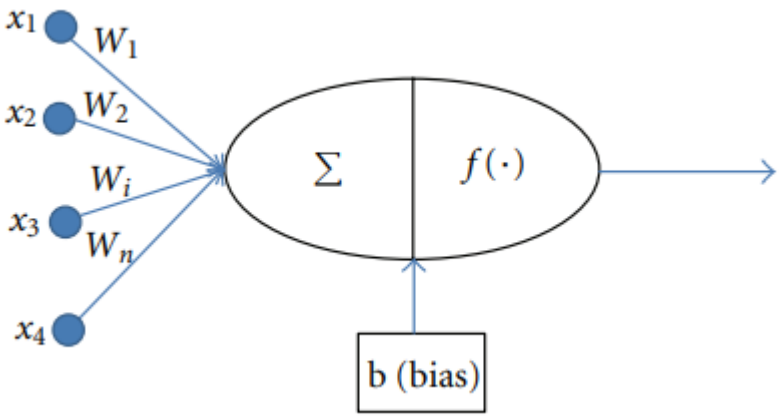


Figure 1: The diagram of one neuron.

The development of a predictive model for hip fracture risk necessitated the identification of risk factors for fracture prevention and health promotion. [7] For risk minimization, SVMs are the most advanced machine learning approaches. There has been an explosion in the study of SVMs since its inception, both in theory and in practical applications. The use of SVMs in the actual world has been proven in a variety of contexts [8, 9].

Optimisation and learning can be accomplished via neural networks or genetic algorithms, both of which have their own advantages and disadvantages. In general, the two have taken divergent paths to development. Recently, though, efforts have been made to merge the two methods. According to Davis, any neural network can be reconstructed as a genetic algorithm known as a classifier system (1988). Genetic algorithms were tried in vain by Whitley (1988) to train feedforward neural networks. To train feedforward networks, we provide a new genetic algorithm. On a difficult example, it not only succeeds, but it also exceeds backpropagation, the industry standard for training algorithm. This achievement can be attributed to the genetic algorithm being specifically tailored to neural network training. This algonthm's progress and eventual success are recorded through a set of studies.

## 2. LITERATURE REVIEW

Nayak & Misra (2019) The weights were optimised using a chemical reaction optimization module and a neurofuzzy network (CNFN). After reading the literature, we discovered that ANNs are excellent at learning input–output patterns. Local minima and network paralysis can occur as a result of the weights assigned by learning algorithms like backpropagation. On the other hand, genetic algorithms are useful for optimization but difficult to use when searching for fitness parameters.

Alhnaity & Abbod (2020) Intelligent modelling techniques and an algorithm for extracting features are combined in a novel three-step hybrid predictive model in this paper. To help with model fitting, the original data are first decomposed using ensemble empirical mode decomposition. Models for the features are then proposed using neural networks and support vector regression. With this in mind, an ensemble average that incorporates a genetic algorithm-based approach is offered for a more accurate prediction.

Prado et al. (2020) Forecasting aggregated long-term energy demand was done using ARIMA, ANN, fuzzy inference system model, adaptive neuro-fuzzy inference system (SVR), extreme ML, and GA.

Recently, Peng et al. (2021) the selection of features for DNN models based on technical analysis indicators to forecast stock price direction was explored

Ballı (2020) Machine learning techniques such as learning regression, support vector machine (SVM), multilayer perceptron, and random forecast were also developed to analyse the pandemic's data.

Momeni et al. The axial bearing capacity of concrete piles can be predicted using the Pile Driving Analyzer (PDA).

## 3. NEURAL NETWORKS

Algorithms for optimization and learning are based on neural network concepts, which are derived from brain-related research.

Generally speaking, they have five main components:

1. The network topology is a directed graph whose arcs are referred to as links.
2. Each node has its own state variable.
3. Each link has a real-valued weight attached to it.
4. Nodes have real-world biases in their values.
5. For each node, a transfer function that determines the node's state as a) function of its bias b) the weights, wt, and the states, x of its incoming links.

In a feedforward network, there are no closed routes in the network's structure. No arcs lead to its input nodes, and no arcs lead out of its output nodes. Those other nodes are invisible. As values propagate across the network, all nodes can set their own states once all input nodes have set their own states. If you use a feedforward network, the outputs are computed based on the input data. In a layer feedforward network, every path from an input node to an output node crosses the same number of arcs. The nth layer of such a network includes all nodes that are n arcs away from an input node. Layers with hidden nodes are known as "hidden layers."

For a variety of reasons, layered feedforward networks have grown in popularity. According to a recent study, they have been discovered to be able to generalise well in practise, which means that they can often offer the correct output for an input that wasn't included in the training set. Backpropagation, a training procedure, can typically identify a reasonable set of weights (and biases) in a reasonable amount of time. Gradient search is what it's called here. Most often, an optimization criterion known as least-squares is used. Backpropagation can be used to determine the gradient of an error with respect to the weights of a given input.

Backpropagation has various disadvantages. In addition, the "scaling problem" must be addressed. Backpropagation is a good tool for training simple issues. Due to increasing problem complexity, the performance of backpropagation decreases quickly.... Section 4 describes one such real-world problem that this approach can be applied to. Complex spaces have near-global minima that are sparse among the local minima, and this appears to be the cause of the performance degradation. It's common for gradient search algorithms to get stuck in local minima. Backpropagation can break out of these local minima if the gain (or momentum) is great enough. The problem is that they don't know what to expect from the next one they locate. As a result, backpropagation can get bogged down in local minima rather than bouncing back and forth between them, resulting in a very slow training process.

## 4. RESEARCH METHODOLOGY

### 4.1 Genetic Algorithms

Genetic algorithms (GAs) are optimization and learning algorithms based on the principles of biological evolution. They require five components:

1. On the chromosomes, there is a way to encode solutions to the problem.
2. It returns a rating for each chromosome that it evaluates.
3. A method of establishing a new chromosome population.
4. Operators that can be used to alter the genetic composition of parents when they reproduce. Genetic mutations, crossover recombination, and domain-specific operators are among the possibilities.
5. Setting parameters for the algorithm, operators, and so on.

The following are the steps that a genetic algorithm takes when given these five components:

1. As shown in C3, the population is established. There are chromosomes determined in C2 as a result of initialising C1.
2. The function in CI is used to assess each individual in the population.
3. Evaluations can be normalised, but the most important thing is to maintain the relative rankings of evaluations.

It's up to the population to decide when it's time to stop reproduction. The following three steps are involved in reproduction:

(a) To reproduce, one or more parents are chosen. The parents with the highest evaluations are given preference in the selection process can be influenced by C5 parameter

(b) The C4 operators are applied to the parents in order to produce offspring. In order to use the right operators, C5's parameters can be used.

(c) The children are screened and incorporated into the general population after their evaluation. A population's entire genetic make-up can be replaced in a single reproduction cycle in some versions of the genetic algorithm. Subsets are replaced in other instances.

## 5. THE PROPOSED GENETIC ALGORITHM MODEL

### 5.1 Modeling Strategy.

Initial weight optimization strategies for artificial neural networks were tested in two ways. As an initial step, a genetic algorithm would select 15 of the best chromosomes for each artificial neural network rather than 15 random initial weights (see Figure 2(a)), and then it would evolve the population using different training data. Using type 1, this was accomplished here. On the other hand, a small change in training data can cause the neural network to become unstable. When training data for each artificial neural network (ANN) had been defined, the genetic algorithm (Figure 2b) was used to find its optimal initial weights.

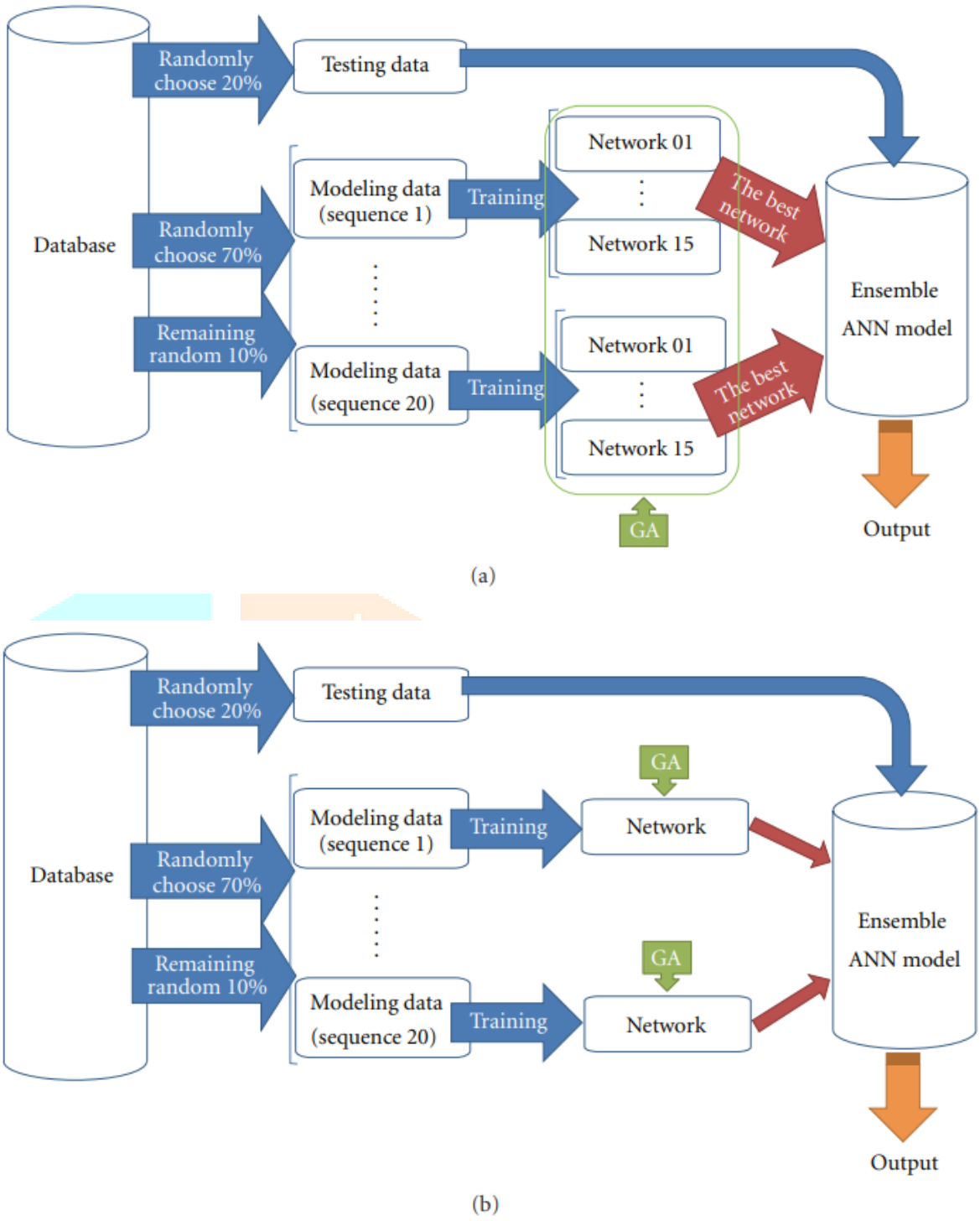


Figure 2: The skeleton with GA-based initial weights: (a) type 1 and (b) type 2.

**Initial Population.**

To describe a chromosome in genetic algorithms, binary code and real code are the primary schemes. Real coded chromosomes were used in the study because binary-coded chromosomes are neither necessary nor beneficial. The advantages of real code are intuitiveness, resolution, and ease of use (i.e., decoding is not required). As each generation produced 30 chromosomes with 60 weights and 11 biases on each of them, the total number of weights and biases was 60. The experiment was conducted at three different population levels in order to examine the effect of population range on search efficiency. In the beginning, this range was used because after training with a back-propagation neural network, all of the weights fell within this range (BPN).

### 5.2 Genetically tuned artificial neural network (GANN)

ANN has some drawbacks, such as network paralysis and local minima. Because the network is unable to adjust the weights towards local minima, it becomes paralysed, which has a negative impact on the system's accuracy The genetic algorithm does not always yield the best results, however. In order to address these issues, a hybridization of ANN and GA is needed to develop a new forecasting model. An overview of GANN's overall scheme and flow chart for stock data forecasting is shown in Figure 3.

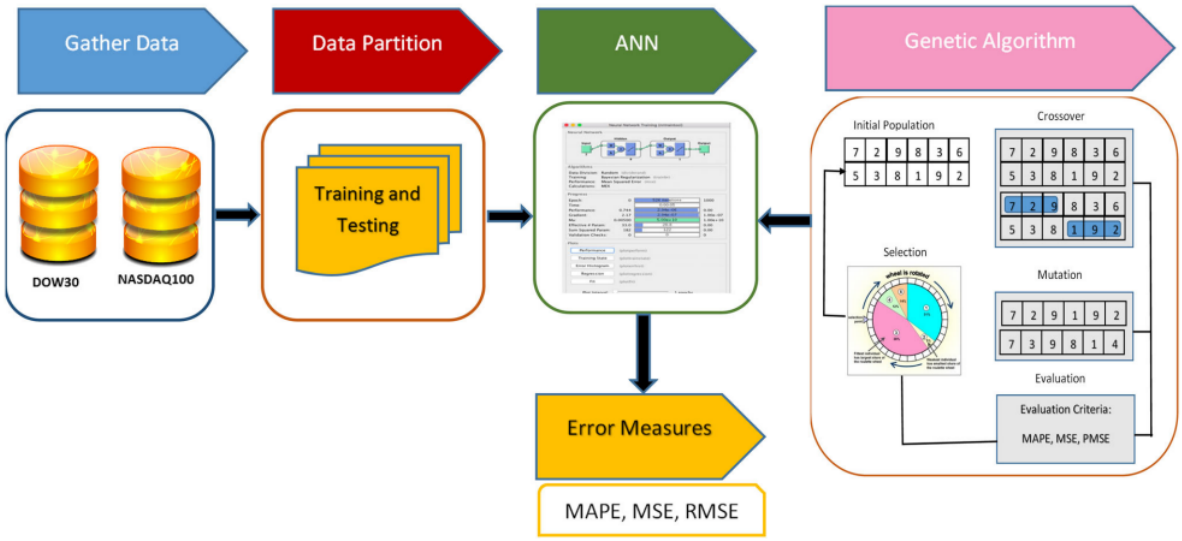


Fig. 3 Scheme of GA tuned ANN (GANN).

It is possible to achieve global optimums with the right selection of genetic algorithm components, but this is only possible if the population is continually improved. To find nearly global optima, genetic algorithms can efficiently search large and complex (i.e., containing many local optimums) spaces. Schemata, or building blocks, are a fundamental concept in genetic algorithms.. A schema is a subset of the chromosome's fields that have been set to specific values, while the rest of the chromosome's fields are free to change. According to [HOLL75], the power of genetic algorithms is derived from the fact that they can simultaneously evaluate and combine large and small sets of schemata.

## CONCLUSION

Neuronal network weight selection and training using genetic algorithms is a rapidly expanding research field with a few distinct trends. More rigorous testing of "standard" datasets is the first trend. In the early stages of research, researchers often used their own datasets on which gradient-based techniques did not work (and hence which required a different type of training algorithm). There are a number of datasets on which gradient-based techniques have had success, and it is now time to compare genetic algorithms against these methods. Genetic algorithms can be used to train neural networks, but this work only scratches the surface. There are a slew of different operators to try out in feedforward networks. Those that use backpropagation in some or all of their processes have the best chance of success. In addition, the genetic algorithm must be adapted to deal with a stream of constantly changing training data rather than fixed training data. This necessitates modifying the genetic algorithm so that it can handle a stochastic evaluation. It should be noted that genetic algorithms can be used to optimise any neural network (and not just feedforward networks whose nodes have smooth transfer functions) that can be evaluated.

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