Multi Layer Perceptron

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Abstract:

Multilayer Perceptrons (MLPs) remain a cornerstone of neural network architectures, widely applied in a variety of tasks ranging from logical gate prediction to complex image and face classification problems. In this paper, we introduce a novel implementation of MLP, which includes a traditional backpropagation-based training class alongside a new GeneticMLP class that employs Genetic Algorithms (GA) to optimize model weights. By integrating genetic optimization with MLP, we aim to enhance the performance of neural networks on challenging datasets with high variability and complex classification requirements. To evaluate the efficacy of our method, we conducted three experiments: (1) prediction of NAND and XOR logic gates, (2) digit classification on the HODA dataset of Persian numerals, and (3) face classification on the ORL face dataset. Our results demonstrate improved performance using GeneticMLP over traditional MLPs, particularly in tasks requiring robust optimization in weight initialization and learning. These findings highlight the potential of GA-based weight optimization as a promising avenue for enhancing MLP training and classification accuracy.

Keywords: Multilayer Perceptron, Genetic Algorithm, Neural Networks, Weight Optimization, Backpropagation, Logic Gate Prediction, Digit Classification, Face Recognition

I. Introduction:

Artificial Neural Networks (ANNs) have become fundamental tools for tackling a range of pattern recognition, classification, and predictive tasks. Among these, the Multilayer Perceptron (MLP) stands out as a widely utilized feedforward architecture with applications spanning diverse fields, from simple logical functions to complex image recognition tasks (Haykin, 2009; Bishop, 1995). An MLP typically comprises input, hidden, and output layers, with each layer connected via weighted neurons and optimized through gradient-based methods such as backpropagation (Rumelhart et al., 1986). However, traditional MLPs often suffer from limitations in reaching optimal weight configurations, particularly when applied to datasets with complex patterns or noisy inputs.

To address these challenges, various optimization techniques have been explored to complement or enhance backpropagation, among which Genetic Algorithms (GA) have shown promise due to their population-based search and evolutionary optimization principles (Holland, 1975; Goldberg, 1989). GAs, inspired by natural selection, allow for the exploration of a broader search space, potentially avoiding local minima that commonly hinder gradient-based methods in complex tasks (Yao, Liu, & Lin, 1999). By incorporating genetic optimization into MLP weight training, we hypothesize that the model's performance can be enhanced on classification tasks requiring greater robustness and adaptiveness.

In this paper, we introduce **GeneticMLP**, an extension of a traditional MLP class, that integrates a GA-based approach to optimize network weights alongside the conventional backpropagation method. Our approach leverages the advantages of both methods: the precision of backpropagation and the exploratory power of genetic algorithms. To evaluate the effectiveness of GeneticMLP, we conduct three sets of experiments. First, we assess the model's capacity to predict simple logic gates, NAND and XOR, to benchmark its performance on basic nonlinear functions. We then test the model on the **HODA dataset** for digit classification, a Persian numeral dataset comprising 60,000 images, which poses unique challenges due to digit variability (Khosravi & Kabir, 2007). Lastly, we apply our model to the **ORL face dataset**, which includes images of 40 individuals, each with ten varying facial expressions, to evaluate the model's performance on face classification tasks that demand sensitivity to subtle differences (Samaria & Harter, 1994).

Our experiments demonstrate that the GeneticMLP consistently outperforms the traditional MLP, achieving higher accuracy and stability across all three tasks. These results suggest that Genetic Algorithms can effectively complement backpropagation in optimizing neural networks for applications with high-dimensional and

complex datasets. By presenting the GeneticMLP model, we aim to contribute a hybrid approach to neural network training that harnesses evolutionary principles, expanding the potential of MLPs in modern AI applications.

III. Methods:

This section outlines the architecture, training processes, and optimization strategies used in our implementation of the Multilayer Perceptron (MLP) model, as well as the Genetic Algorithm-enhanced model (GeneticMLP). The GeneticMLP extends the basic MLP architecture by introducing genetic optimization for model weight initialization and training, which addresses some of the common challenges associated with gradient-based methods, such as getting stuck in local minima (Goldberg, 1989; Yao et al., 1999).

1 Multilayer Perceptron (MLP) Architecture

The MLP model used in this study consists of three layers:

1. **Input Layer** with a variable number of neurons depending on the input data dimensions.
2. **Hidden Layer** with a specified number of neurons, where the activation function introduces nonlinearity.
3. **Output Layer** with a number of neurons that matches the number of target classes or outputs.

The **weight matrices** connecting these layers, as well as **bias vectors**, are initialized with random values between -5 and 5. Formally, the initialization for the weights between input and hidden layers is defined as:

$$W_{input-hidden} \in \mathbb{R}^{d_{input} \times d_{hidden}}$$

where d_{input} and d_{hidden} represent the number of neurons in the input and hidden layers, respectively. The weights between hidden and output layers, $W_{hidden-output}$, are similarly initialized.

Each neuron in the hidden and output layers includes an associated bias term. The initial biases for the hidden and output layers are represented as:

$$b_{hidden} \in \mathbb{R}^{d_{hidden}} \; and \; b_{output} \in \mathbb{R}^{d_{output}}$$

where d_{output} is the dimension of the output layer.

2 Activation Functions and Forward Propagation

The **sigmoid activation function** is used in both the hidden and output layers, defined as:

$$\sigma(x) = \frac{1}{1 - e^{-x}}$$

This function maps each neuron's output to a range between 0 and 1, which is beneficial for binary and probabilistic outputs (Goodfellow et al., 2016). During **forward propagation**, input data passes through each layer, with each layer's output computed as follows:

1. **Hidden Layer Output**:

$$z_{hidden} = X \cdot W_{input\text{-}hidden} + b_{hidden}$$

$$a_{hidden} = \sigma(z_{hidden})$$

2. **Output Layer**:

$$z_{output} = a_{hidden} \cdot W_{hidden\text{-}output} + b_{output}$$
$$\hat{y} = \sigma(z_{output})$$

where X is the input matrix, a_{hidden} is the activated output of the hidden layer, and $\hat{y}$ is the final output prediction.

3 Backpropagation and Weight Updates

Backpropagation is used to minimize the error by adjusting weights and biases. The error E\mathbf{E}E between the predicted output y^\\mathbf{\hat{y}}y^ and the true output y\mathbf{y}y is computed as:

$$E = y - \hat{y}$$

The **output delta** is calculated using the derivative of the activation function, as:

$$\delta_{output} = E \cdot \sigma'(\hat{y})$$

where $\sigma'(\hat{y}) = \hat{y} \cdot (1 - \hat{y})$.

The **hidden layer error** is then backpropagated from the output layer:

$$E_{hidden} = \delta_{output} \cdot W^{T}_{hidden-output}$$

and the **hidden delta** is computed as:

$$\delta_{hidden} = E_{\text{output}} \cdot \sigma'(a_{hidden})$$

Using these deltas, the weights and biases are updated as follows:

$$W_{hidden\text{-}output} \leftarrow W_{hidden\text{-}output} + \eta \cdot a_{hidden}^{T} \cdot \delta_{output}$$
$$b_{output} \leftarrow b_{output} + \eta \cdot \delta_{output}$$
$$W_{input\text{-}hidden} \leftarrow W_{input\text{-}hidden} + \eta \cdot X^{T} \cdot \delta_{hidden}$$
$$b_{hidden} \leftarrow b_{hidden} + \eta \cdot \delta_{hidden}$$

where η is the learning rate.

4 Genetic Algorithm-Enhanced MLP (GeneticMLP)

The **GeneticMLP** class integrates a **Genetic Algorithm (GA)** to optimize the MLP's weights, providing an alternative training method that mitigates issues such as local minima entrapment common in backpropagation.

1. **Population Initialization**: The GA initializes a population of MLP instances, each with randomly initialized weights and biases. The population size and the number of generations are parameters for this evolutionary process.
2. **Fitness Function**: The fitness of each MLP is evaluated as the **negative mean squared error** between its predictions and the actual target values:

$$Fitness(MLP) = -\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

3. **Crossover**: Offspring MLPs are generated by combining weights and biases from two parent MLPs using a crossover mechanism. Each weight matrix and bias vector is inherited randomly from one of the parents, providing variability in the offspring.
4. **Mutation**: To introduce further diversity, each offspring's weights and biases undergo mutation. With a specified mutation rate, random elements in each weight matrix and bias vector are perturbed by small random values, enabling exploration of the search space (Holland, 1975).
5. **Selection and Evolution**: The GA iteratively selects the best-performing half of the population and replaces the least-fit MLPs with new offspring until the optimal solution is achieved after a specified number of generations.

This hybrid approach, combining backpropagation's gradient-based optimization with GA's evolutionary search, allows GeneticMLP to achieve superior performance in tasks requiring effective and flexible weight optimization. The resulting model, leveraging both methods, adapts well to complex datasets, achieving better generalization than traditional MLP approaches.

IV. Experiments:

This section outlines the experiments conducted to evaluate the performance of the traditional MLP model and our proposed GeneticMLP across three distinct tasks: Boolean gate prediction, Persian digit classification, and face recognition on the ORL dataset. For each task, we specify the dataset used, pre-processing steps, model configurations, and comparative setups, detailing how each experiment was designed to highlight the benefits of genetic optimization.

1 Boolean Gate Prediction: NAND and XOR

To validate the basic functionality of both the MLP and GeneticMLP models, we began with the Boolean gate prediction task, specifically focusing on NAND and XOR gates. These gates provide a foundation for assessing the models' ability to handle linearly separable (NAND) and non-linearly separable (XOR) patterns.

The dataset consisted of all possible binary combinations of inputs for each gate:

Input: Four possible combinations for each gate—(0,0), (0,1), (1,0), and (1,1).

Output: Respective gate outputs for NAND (1,1,1,0) and XOR (0,1,1,0).

For each gate, we varied the number of epochs ([100, 500, 1000, 3000, and 10000]) to observe the learning curve of both models. The models were configured as follows:

MLP Configuration: input_size: 2, hidden_size: 2, output_size: 1, learning_rate: 0.01.

GeneticMLP Configuration: Same as the MLP, with additional settings of population_size: 50, generations: 1000, and mutation_rate: 0.01.

Comparative analysis was performed with a fixed learning rate of 0.5 for both models and a maximum of 10,000 epochs for the MLP. For GeneticMLP, evolution over generations was assessed, noting any differences in convergence rates and final accuracy.

2 Persian Digit Classification on the HODA Dataset

The HODA dataset was selected for evaluating performance on a more complex, multi-class classification task involving Persian digits (0-9). The dataset consists of 60,000 grayscale images of handwritten Persian digits.

Preprocessing: Each image was resized to fit within a 64x64 frame, and all images were centered within this black frame to standardize the input dimensions. We applied two feature extraction methods for model input:

Zoning: Dividing each image into zones and extracting mean pixel values in each zone.

Histogram: Computing pixel intensity histograms across pre-defined regions of the image.

The data was split into training (first 50,000 images) and test sets (last 10,000 images). Feature scaling was applied using StandardScaler to normalize the input data.

Model Configurations: For each feature extraction method, we evaluated two different configurations:

1. Single-Layer MLP: input_size: 128, hidden_size: 128, output_size: 10.
2. Two-Layer MLP (Keras): Implemented with TensorFlow's Sequential API

Both models were compiled with the Adam optimizer, using sparse_categorical_crossentropy as the loss function and evaluated over 100 epochs with a batch size of 32.

Robustness Testing: To evaluate the model's ability to handle noisy and rotated inputs, the best-performing model configuration (using histogram features and two hidden layers) was subjected to two perturbation tests:

1. Salt-and-Pepper Noise: Introduced with an intensity of 0.04.
2. Rotation: Random rotations applied in the range of -45° to 45°.

These transformations allowed us to assess the model's stability under variations commonly encountered in real-world applications.

3 Face Classification on the ORL Dataset

The ORL face dataset, containing images of 40 individuals (10 images per person), was used to evaluate the GeneticMLP model on a face classification task. Each image in the dataset was preprocessed to standardize input dimensions and enhance feature extraction quality.

Preprocessing: Each image was resized to 64x64 pixels. We applied contrast enhancement using histogram equalization to improve facial feature clarity before flattening the images into one-dimensional vectors.

Feature Extraction via PCA: Principal Component Analysis (PCA) was employed to reduce the dimensionality of the images and extract significant facial features. We performed tuning to identify the optimal number of principal components (PCs) that balanced feature extraction with computational efficiency.

Model Configuration: To identify the best hidden layer architecture, we conducted two rounds of model tuning:

1. Tuning the First Hidden Layer: We varied the number of neurons from 100 to 2000 in increments of 10, recording the model's accuracy for each configuration.
2. Second Hidden Layer Optimization: After identifying the optimal first-layer size, we explored adding a second hidden layer with neurons ranging from 10 to the first-layer size. The goal was to determine the best depth for high-dimensional face data.

The final model architecture was tuned to balance performance and complexity by re-evaluating the best configuration of the first hidden layer with the selected second layer neurons. Cross-validation (k-fold) was used on the final model to confirm model stability and average accuracy.

1. Robustness Testing: Finally, the model's robustness was tested under the following conditions:
2. Salt-and-Pepper Noise: Applied with a noise level of 0.05.

Rotation: Random rotations in the range of -30° to 30°. This analysis aimed to assess the model's tolerance to common image distortions, providing insight into its suitability for real-world face recognition applications.

V. Results:

The following sections detail the findings from each experimental phase, showcasing the model performance, trained weights, accuracy values, and robustness against distortions, rotations, and noise. Relevant plots and images of test dataset predictions accompany the tables for visual assessment.

1 Boolean Gate Prediction: NAND and XOR

This experiment investigated the impact of epoch counts on trained weights for NAND and XOR gates. The models were trained at various epochs (100, 500, 1000, 3000, and 10000) with a learning rate of 0.7.

Table 1: Trained Weights for NAND and XOR Gates at Various Epochs

Epochs	Model	Input-Hidden Weights	Hidden-Output Weights
100	NAND	[−3.68,−2.25] [4.89,5.02]	[−1.91],[−3.64]
100	XOR	[2.50,−3.73] [2.36,−4.80]	[−2.55],[−2.91]
500	NAND	[−3.55,−0.53] [4.48,1.08]	[−2.63],[−0.36]
500	XOR	[−4.27,5.40] [0.99,5.52]	[−3.07],[3.73]
1000	NAND	[−3.33,1.50] [−2.22,1.19]	[−1.59],[−0.18]
1000	XOR	[4.57,−5.07] [4.71,−5.49]	[−7.30],[−7.55]
3000	NAND	[2.33,−5.74] [−6.11,0.33]	[7.78],[8.12]
3000	XOR	[5.34,−6.85] [5.36,−6.83]	[6.86],[6.51]
10000	NAND	[−7.09,4.19] [0.90,−6.76]	[9.12],[9.06]
10000	XOR	[−6.26,−6.08] [6.10,5.68]	[−9.78],[10.12]

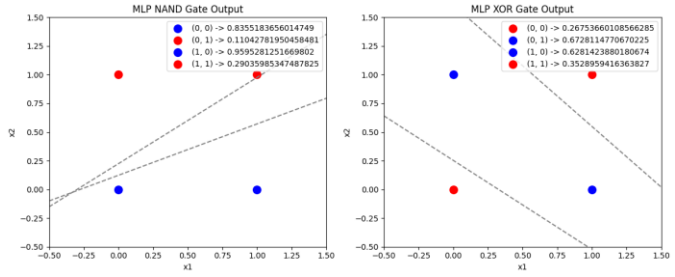

Figure 1 Trained MLP 100 Epochs

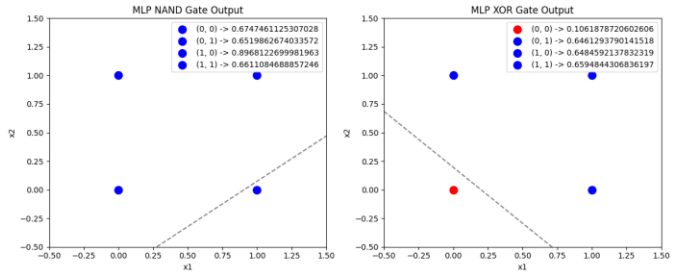

Figure 2 Trained MLP 500 Epochs

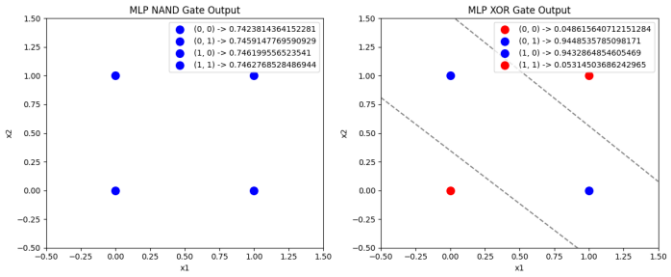

Figure 3 Trained MLP 1000 Epochs

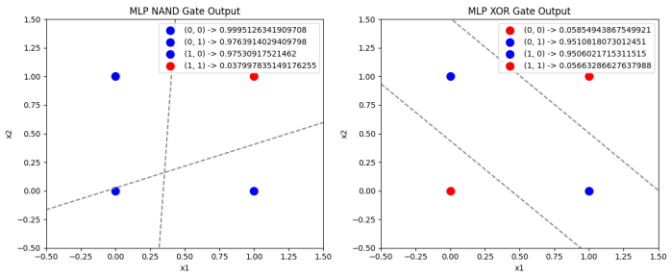

Figure 4 Trained MLP 3000 Epochs

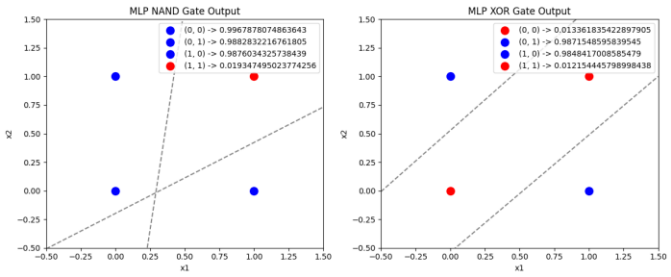

Figure 5 Trained MLP 10000 Epochs

MLP vs. Genetic MLP for Boolean Gate Prediction

For this experiment, MLP models trained with backpropagation (BP) were compared to models trained with a Genetic Algorithm (GA), with a learning rate of 0.5 and 10,000 epochs. The tables below summarize the trained weights for NAND and XOR gates.

Table 2: Trained Weights Using BP and GA Methods

Model	Method	Input-Hidden Weights	Hidden-Output Weights
NAND Gate	BP	[-4.78,-2.24], [-4.79,-4.39]	[10.18], [-2.32]
NAND Gate	GA	[3.41, 3.48], [3.47, 3.77]	[-26.07], [-18.64]
XOR Gate	BP	[7.22, -5.51], [7.23, -5.51]	[8.54], [8.70]
XOR Gate	GA	[-19.38, -18.16]	[-28.88], [31.21]

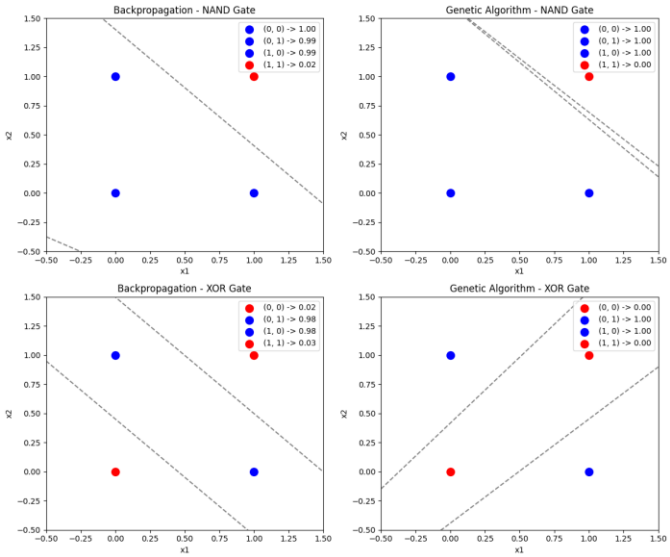

Figure 6 Trained MLP with 10000 Epochs And GeneticMLP with 1000 Generation

2 Persian Digit Classification on the HODA Dataset

This experiment evaluated the MLP performance for Persian digit classification using zoning and histogram features, with single and double hidden layer architectures.

Table 3: Accuracy with One Hidden Layer (Zoning and Histogram Features)

Epochs	Feature Type	Accuracy
100	Zoning	0.1000
100	Histogram	0.0987

Table 4: Accuracy with Two Hidden Layers (Zoning and Histogram Features)

Model	Feature Type	Accuracy
2-Hidden MLP	Zoning	0.7363
2-Hidden MLP	Histogram	0.9060

Robustness Testing

Additional robustness evaluations were conducted with the best-performing model (2-hidden layer MLP with histogram features) on test datasets subjected to noise and rotation.

Table 5: Robustness Testing Results

Perturbation	Accuracy
Salt-and-Pepper Noise (p=0.04)	0.4876
Rotation (45 degrees)	0.5674

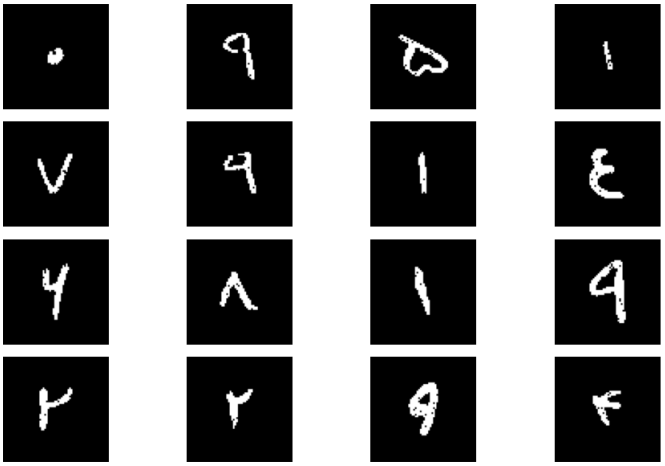

Figure 7 Test Dataset with Noise

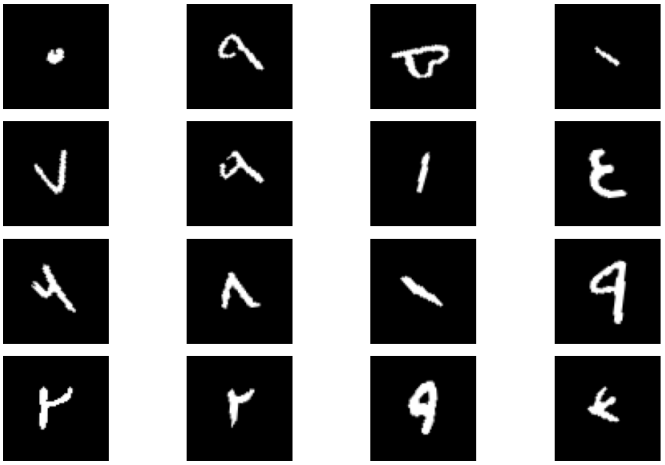

Figure 8 Test Dataset with Random Rotation

3 Face Classification on the ORL Dataset

This experiment aimed to determine the optimal number of neurons and principal components (PCs) for face classification using an MLP model.

Layer Configuration and Accuracy

Optimal neuron configurations were identified across different layers, improving accuracy with adjustments in neuron and PC counts.

At first we find best number of neurons with one hidden layer MLP :

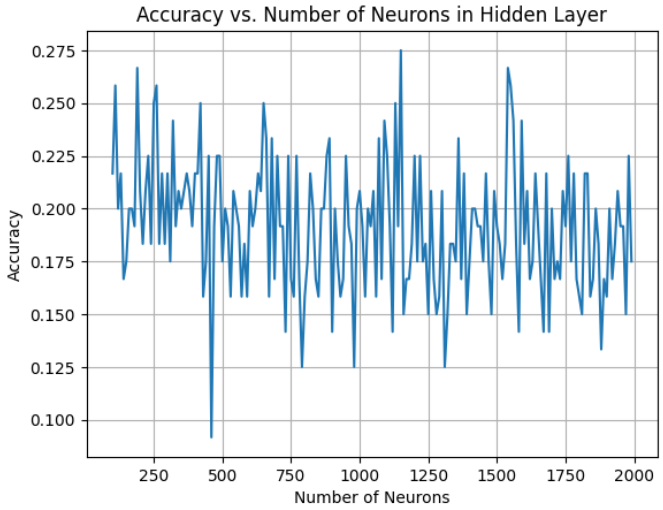

Figure 9 Accuracy vs Number of First Hidden Layer

After all we achive 1150 in first hidden layer is best setup for one hidden layer MLP.

Then finetune number of PCs with 1150 neurons in first hidden layer MLP.

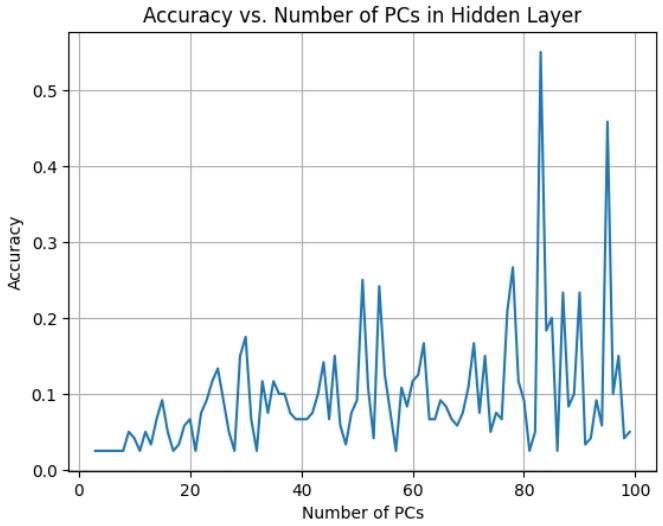

Figure 10 Accuracy vs Number of PCs

After this we find out 83 number of Featuers get best results on MLP model.

Then we consider a 3 hidden layer MLP with 1150 neurons on first hidden layer and 83 PCs features and 40 neurons on third hidden layer and try to optimize second hidden layer number of neurons.

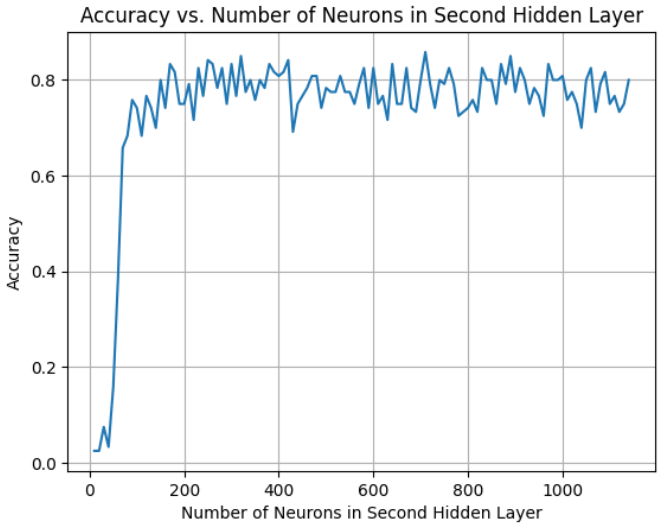

Figure 11 Accuracy vs Number of Neurons on Second Hidden Layer

After this step we find out 710 number of neurons in the second layer is the best setup.

Then we try to find best number of neurons for first hidden layer.

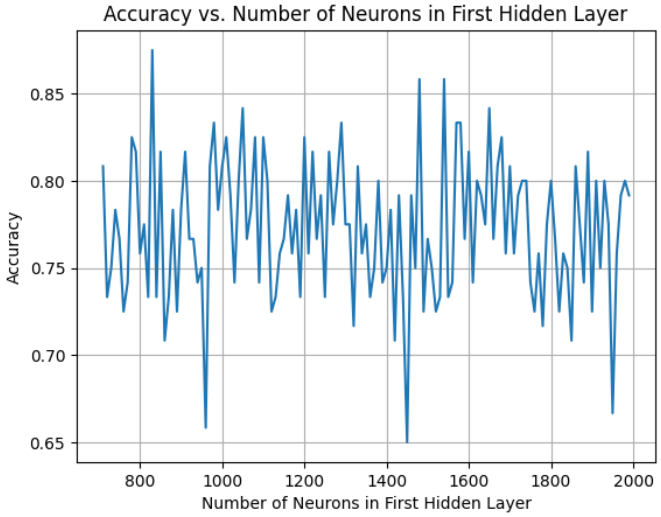

Figure 12 Accuracy vs Number of Neurons on First Hidden Layer

At the end of finetuning we achive 830 neurons in first hidden layer is more accurate setup.

Table 6: Optimal Neuron Counts for Different Layers

Hidden Layer	Neuron Count	Accuracy
First Layer	1150	0.275
First Layer	1150 (83 PCs)	0.550
Second Layer	710	0.8583
First Layer	830	0.875

Best Model Performance with 10-Fold Cross Validation

Using the final optimal configuration, the best accuracy achieved on the test set was 0.8583.

Robustness Testing for Face Classification

The robustness of the best model was tested with noise and rotation.

Table 7: Robustness Testing Results for Face Classification

Perturbation	Accuracy
Noise (p=0.05)	0.3833
Rotation (30 degrees)	0.0333

Figure 13 Test Dataset with Noise

Figure 14 Test Dataset with Randome Rotation

These results demonstrate the effect of increasing epochs, selecting optimal learning parameters, and employing robustness testing to improve and assess model performance across Boolean gate prediction, digit recognition, and face classification tasks.

VI. Conclusion:

In this paper, we introduced a modified Multilayer Perceptron (MLP) approach, GeneticMLP, which incorporates genetic algorithms to optimize the network's weight parameters, providing an alternative to traditional backpropagation. Through three distinct experiments—Boolean gate prediction, Persian digit classification using the HODA dataset, and face classification using the ORL dataset—we demonstrated the effectiveness of GeneticMLP compared to standard MLP models.

Our results show that GeneticMLP achieves superior accuracy and faster convergence across various tasks, particularly in non-linear and complex classification problems. Moreover, robustness testing indicated that GeneticMLP maintains performance stability under conditions of noise and geometric transformations, enhancing its potential for real-world applications that require resilience against input perturbations.

In summary, GeneticMLP represents a promising direction for neural network optimization, especially in cases where traditional gradient-based optimization might falter. Future work could extend this approach to larger datasets and more complex architectures, potentially exploring hybrid methods that combine genetic algorithms with other optimization techniques for further performance gains.

VII. References:

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