CHAPTER 5

AN IMPROVED NEURAL NETWORK FOR MAMMOGRAM CLASSIFICATION USING GENETIC OPTIMIZATION

5.1 INTRODUCTION

Since mammography images have higher spatial resolution, it permits to discover a very subtle scale signs like MCC and masses (Torrent et al. 2010). It is hard to understand the mammography images that have very low contrast and very minute micro-calcifications. The computer system helps in radiologists screen mammography images and decreases the huge number of negative biopsies.

An early symptom of breast carcinoma is the calcification clusters. Micro-calcifications includes the deposit of minute bits of calcium inside the soft breast tissue which are represented as a cluster or pattern like a circle or line associated with extra cell activity in the breast region. CAD in neural network applications indicates the main stream of computational intelligence in medical imaging.

In all medical problems their involvement is there due to the capable of adaptive learning from input information and by use of an appropriate learning protocol leads to improve themselves and to change the input content. Neural Network (NN) optimize the relationship between input and output through distributed computing, training, processing and resulting to dependable solutions. A medical diagnosis depends on visual inspections.
where the medical imaging is a tool to facilitate such inspection and visualizations.

Recently, ANNs are being increasingly used in medical image processing. GA, an optimization method is used for features selection for textures classifier on synthetic aperture radar airborne imagery by discovering more efficient features than other methods.

5.2 GENETIC ALGORITHM (GA)

Genetic algorithm is used to solve an optimization problem through simulation of process selection (Jona & Nagaveni 2012). A set of chromosomes are coded and every chromosome relates to a potential solution of the optimization issue. Chromosome consists of genes and GA searches it with better combination. The solution is achieved through an evolution process. Chromosomes are generated from the current population via parent selection, crossovers and mutations.

Chromosome is chosen that are associated with its fitness to resolve the optimization problem. A chromosome with better fitness leads a change to reproduce than those with lesser fitness, exactly like the principle of natural selection. Fitness function calculates the fitness and is formulated based on optimization conditions of the problem. Chromosome is chosen as a parent like a normalized fitness expressed as the fitness of the chromosome in which the sum of fitness are divided for every chromosome.

The parent chromosomes are permitted to arbitrarily crossover, mutate through novel genes, chromosomes into the population. A novel population of chromosomes is created which evolves a better solution. Feature selection issues are employed by GA. Encoding of chromosome are:
all genes are specified as bit 1 and 0s where the gene location relates to certain features. Bit value at a location 1 chooses the related feature for the solution of the problem, else, it is not chosen.

Fisher’s linear classifier or NN is used for classification based on the chosen features set. The fitness function reveals the success of chosen features set for the resolution of the classification problem.

In medical applications, GA are used to characterize features and to find in reports. For data classification, earlier studies focused on the implementation of the protocols to mammography reports and to validate in more broad applications for determining scalability and adequacy over a spectrum of patient’s data. GA built for mammography during hypothesis test is expanded for usage with patients having Abdominal Aortic Aneurysms (AAAs).

Initialize the input such as population set, number of iterations and so on with algorithm for selection, crossover and mutation. Selection process selects any two arbitrary pixels for comparison and crossover is carried out on the pixel to select next pixel followed by mutation to make changes as needed. A valid threshold value is returned with the decision on the pixel selection as the tumour area when the process is complete. Chosen pixel area is shown as the detected tumour in the image.

5.3 METHODOLOGY

Figure 5.1 illustrates the flow chart of the proposed method diagrammatically.
Figure 5.1 Flowchart for proposed methodology

5.3.1 Proposed Feature Selection using Genetic Algorithm (GA)

For classification, feature extractions achievement is important and features selection in data mining is used vastly to reduce the quantity of features, to remove redundant data results to enhance the performance of classification protocol. During feature selection, the subsets are chosen from original features based on some evaluation conditions to obtain the optimum features subset.
S be the set of features, P be the misclassification quality metric, \( F^* \) is the features sub-set determined as in equation (5.1) during feature selection process:

\[
P(F^*) = \min_{F \in S} P(F)
\] (5.1)

Optimum features sub-set discovered becomes NP-hard (Nondeterministic Polynomial time hard) when the quantity of attributes rises. Filters or wrappers based feature selection technique do not leads to an optimum sub-set. Genetic Algorithm (GA), an optimizing tool looks for optimum feature subset in the proposed method.

Features sub-set selections utilized a fewer attributes to achieve accuracy and features count. A validation dataset was used for predicting performance classifier for guiding GAs. If both features sub-set achieves an equal performance with varying features count choosing a sub-set with lesser features. Accuracy is important than size of the feature sub-set. Proposed method studies on novel fitness function for features selection expressed as in equation (5.2):

\[
\text{fitness} = \alpha \frac{F_{\text{tot}} - F_{\text{lo}}}{F_{\text{tot}}} + \beta \left( \frac{mc}{T} \right)
\]

where

- \( F_{\text{tot}} \) is the total available features
- \( F_{\text{lo}} \) is the left out features
- \( mc \) is the wrongly classified instances
- \( T \) is the total number of instances
- \( \alpha \) and \( \beta \) beta are constants between 0 & 1 such that \( \alpha + \beta = 1 \) (5.2)

For a generation, fitness is checked and fulfilled with iterations until reaching the terminating condition.
Figure 5.2 illustrates an evolutionary process cycle of GA.

![Evolutionary cycle diagram]

**Figure 5.2 Evolutionary cycle**

Features space is coded by binary representations stating 0 as feature not being chosen and 1 as feature being chosen. Sample chromosomes are mentioned in table 5.1:

<table>
<thead>
<tr>
<th>Table 5.1 Sample Chromosomes</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
</tr>
<tr>
<td>-----</td>
</tr>
<tr>
<td>0</td>
</tr>
<tr>
<td>1</td>
</tr>
</tbody>
</table>

First and second chromosomes use attributes like F2, F3, F4 & F7, and F1, F5, F8 & F9 for sub-set evaluation respectively. Figure 5.3 shows the quantity of features chosen as GA iterates. The quantities of attributes are chosen and it converges after 130th cycle of GA. Due to space constraint, the sample crossover and mutation is shown for 10 features. Since the features are
selected randomly, the output of the sample shown can be extrapolated to full set of features.

![Figure 5.3 Features Selected for Proposed Method](image)

**Figure 5.3 Features Selected for Proposed Method**

### 5.3.2 Proposed Neural Network Weight Optimization

With the basis of MLPNN in error-correction learning rules, the novel weight optimized neural network is proposed with decrease of network connections by assigning its weight as 0 and by preventing the connections between neurons. Genetic Algorithm (GA) generates a neural network structure in which 1 indicates the link between input and hidden layer neurons where 0 denotes no link. Sigmoid activation functions with every neuron in the 2nd hidden layer interconnects with output are applied in proposed method. Momentum factor contribute to a rapid convergence. An optimum values for Momentum and Learning Rate was found by applying Genetic Algorithm in the investigation.
5.4 RESULTS AND DISCUSSION

Two classifications such as micro-calcified and nonmicro-calcified was done using mammogram. For evaluation, subset of Mini Mammographic Image Analysis Society (MIAS) is used with dataset containing 244 images (128 images without tumor and 116 images with tumor). The images considered are in bilateral medio-lateral oblique view. Joyce-Loebl scanning microdensitometer is used to carry out the digitalization.

Figure 5.4 shows the sample image 3 used in this investigation.

![Figure 5.4 Sample Image 3](image)

Figure 5.5 shows the DCT coefficients for sample image 3.
Figure 5.5 DCT Coefficients for Sample Image 3

Figure 5.6 shows the Gabor filter (0°) for sample image 3.

Figure 5.6 Gabor Filter (0°) for Sample Image 3

Figure 5.7 shows the Gabor filter (45°) for sample image 3.

Figure 5.7 Gabor Filter (45°) for Sample Image 3
Figure 5.7 Gabor Filter (45°) for Sample Image 3

Figure 5.8 shows the Gabor filter (90°) for sample image 3.

Figure 5.8 Gabor Filter (90°) for Sample Image 3
Figure 5.9 shows the Gabor filter (135°) for sample image 3.

Figure 5.9 Gabor Filter (135°) for Sample Image 3

Figure 5.10 shows the sample image 3 for surface plot of DCT coefficients.
Figure 5.10 Surface Plot of DCT Coefficients for Sample Image 3

For the developments of following method some experiments were carried out. MLP Neural Network is used for classifying:

i. Proposed MLP NN (GA based momentum and learning rate optimization)

ii. MLP NN with GA based Feature Selection

iii. Proposed MLP NN with GA based Feature Selection

iv. Proposed MLP NN with GA based weight optimization

v. Proposed MLP NN with GA based Feature Selection and Weight Optimization
A table 5.2 shows the experimental setup used and table 5.3 shows the classification accuracy. Figure 5.11 to Figure 5.14 shows the results obtained for classification accuracy, precision and recall respectively.

**Table 5.2 Experimental Setup**

<table>
<thead>
<tr>
<th>Dataset Used</th>
<th>MIAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Images Taken</td>
<td>128 without tumor, 116 with</td>
</tr>
<tr>
<td>Features selected for classification</td>
<td>Top 25 images</td>
</tr>
<tr>
<td>Filter type</td>
<td>Gabor filter with DCT</td>
</tr>
</tbody>
</table>

**Table 5.3 Classification Accuracy for Proposed MLPNN Weight Optimization**

<table>
<thead>
<tr>
<th>Techniques</th>
<th>Classification accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLP NN</td>
<td>88.52</td>
</tr>
<tr>
<td>Proposed MLP NN</td>
<td>95.9</td>
</tr>
<tr>
<td>MLP NN GA FS</td>
<td>90.16</td>
</tr>
<tr>
<td>Proposed MLP NN GA FS</td>
<td>97.13</td>
</tr>
<tr>
<td>MLP NN GA FS and GA Weight selection</td>
<td>92.21</td>
</tr>
<tr>
<td>Proposed MLP NN GA FS and GA weight selection</td>
<td>98.36</td>
</tr>
</tbody>
</table>
Figure 5.11 Classification Accuracy for Proposed MLPNN Weight Optimization

It is observed from Table 5.2 and Figure 5.11 that the classification accuracy of Proposed MLP NN GA FS and GA weight selection increases with 10.53% than MLP NN, with 2.53% than Proposed MLP NN, with 8.69% than MLP NN GA FS, with 1.26% than Proposed MLP NN GA FS and with 6.45% than MLP NN GA FS and GA weight selection.

Figure 5.12 Average Precision for Proposed MLPNN Weight Optimization
It is observed from Figure 5.12 that the Average Precision of Proposed MLP NN GA FS and GA weight selection increases with 10.37% than MLP NN, with 2.5% than Proposed MLP NN, with 8.63% than MLP NN GA FS, with 1.21% than Proposed MLP NN GA FS and with 6.5% than MLP NN GA FS and GA weight selection.

![Figure 5.13 Average Recall for Proposed MLPNN Weight Optimization](image)

It is observed from Figure 5.13 that the Average Recall of Proposed MLP NN GA FS and GA weight selection increases with 10.46% than MLP NN, with 2.56% than Proposed MLP NN, with 8.73% than MLP NN GA FS, with 1.29% than Proposed MLP NN GA FS and with 6.4% than MLP NN GA FS and GA weight selection.

Figure 5.14 shows that the fitness of proposed method in which the convergence occurred at iteration number 210.
5.5 SUMMARY

A genetic algorithm based feature selection was proposed and to improve the classification for mammogram images, a parallel MLP neural network was proposed. Results show that the classification accuracy of Proposed MLP NN GA FS and GA weight selection increases with 10.53% than MLP NN, with 2.53% than Proposed MLP NN, with 8.69% than MLP NN GA FS, with 1.26% than Proposed MLP NN GA FS and with 6.45% than MLP NN GA FS and GA weight selection.

Figure 5.14 Best Fitness