Neural network parameters optimization with genetic algorithm to improve liver disease estimation

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Abstract. Liver disease is an important public health problem. Over the past few decades, machine learning has developed rapidly and it has been introduced for application in medical-related fields. In this study we use neural network method to solve regression task of liver disorder dataset. Genetic algorithm applied for optimize NN parameters to improve the estimation performance value. NN-GA performance results show the most superior value compared to another methods.

1. Introduction
Liver Disease is an important public health problem that mostly manifested as abnormal liver function Test [1]. Patient with liver disease have been increasing with continuously because of many causes such as excessive alcohol consumption, drugs, intake of contaminated foods, inhale of harmful gases, pickles, [2], inherited metabolic liver disease [3], epidemic, and endemic outbreaks by geographical settings [4].

Over the past few decades, machine learning has developed rapidly and it has been introduced for application in medical-related fields[1], like cervical cancer classification [5], fertility rate analysis [6], breast cancer diagnosis [7], seminal quality prediction [8], and so on. Therefore, in the regression tasks several machine learning methods are widely applied such as K-NN [9], and Neural Network [10], K-NN is an efficient algorithm and has successfully been developed in real application [11], however locally linear reconstruction(LLR) in k-NN does not provide a confidence interval for the k neighbors-based reconstruction of a query point, and its fixed linear structure makes the local reconstruction model unstable [12]. Neural networks can be used to achieve non-linear statistical modeling and can make accurate estimation with comparatively less statistical training [13]. However traditional NN-based model give the “local minimum” effect [14].

There are many local minima difficulties are closely related to the neuron saturation in the hidden layer. in some cases, the network can no longer learn. Moreover, the convergence behavior also depends on the selection of network topology, initial weights and biases, learning rate, momentum coefficient, activation function, and gain value [15] Genetic algorithm has been widely used to overcome parameter optimization problem [16]. To avoid NN’s backward Genetic
Algorithm (GA) is utilized to optimize learning rate and momentum coefficient of NN to improve the estimation performance value.

2. Proposed Method

The data used in this research is Liver Disorder dataset from UCI Machine Learning Repository from BUPA medical research. The dataset consists of 345 rows and 7 columns. Each row corresponds to one human male subject [17]. The first 5 columns are integer-valued and represent the results of various blood test which may be of use in diagnosing alcohol related liver disorders. The 6th column is a real-valued and represents the number of alcoholic drinks taken per day by the subject, by self-reported. The last column is the “selectors” that split the dataset into training and testing subsets. It was created by the BMRDL researchers.

2.1. Initial data processing

The attributes of the dataset namely MCV (Mean Corpuscular Volume), ALKPHOSE (Alkaline Phosphotase), SGPT (Alanine Aminotransferase), SGOT (Aspartate Aminotransferase), GAMMAGT (Gamma Glutamyl Tranpepsidase), drinks number of half-pint equivalent of alcoholic beverages drunk per day, and the selector to split the dataset into training and testing subsets. The methodology that we use in this study are differ with our previous research [18] for test another powerful machine learning. However, liver disorders datasets has been misinterpreted by many studies for classification tasks for which the classification target is the last attribute of the datasets. Therefore [17] suggested to use the 6th attribute as a target of regression tasks.

2.2. Method

In the first step we delete the last attribute of the dataset since we use 10-fold cross validation method to split the dataset into 90% of training and 10% of testing. Then the data is trained and tested 10 times by the NN with manually optimize parameter. The Second step, the parameters of NN will optimized directly with genetic algorithm 10 times. So the RMSE value can be compared and the means of all iteration between NN and NN-GA can be compared with t-test. After that we compare the lowest value of NN RMSE with another regression method, and for the final step we use a t-test to test wether h1 is accepted or rejected.

![Proposed Method](image)

**Figure 1. Proposed Method**
The proposed method can be seen in Figure 1. In the proposed method, after pre-processing, it will produce a new data set which is then processed using the neural network method. Then the data will be split into training data and testing data using 10 fold cross validation. After that the RMSE value will be obtained. The RMSE value is then compared to the previous work and another machine learning.

3. Result and Discussion

Based on the experiment, the result of optimizing parameter with manual effort can be seen in Table 1. The result of optimizing neural network parameter with genetic algorithm can be seen in Table 1.

| Manually NN Parameter setting | NN parameter optimization by GA |
|------------------------------|---------------------------------|
| Learning Rate | Momentum | RMSE | LR Range | Momentum Range | Optimum LR | Optimum Momentum | RMSE |
| 0.01 | 0.9 | 3.134 | 0.0004-1 | 0.5-1 | 0.01424 | 0.78047 | 2.936 |
| 0.01 | 0.8 | 3.14 | 0.0005-1 | 0.1-1 | 0.06461 | 0.31573 | 2.926 |
| 0.01 | 0.7 | 3.518 | 0.0006-1 | 0.05-1 | 0.06471 | 0.2767 | 2.921 |
| 0.009 | 0.6 | 3.514 | 0.0007-1 | 0.05-1 | 0.06480 | 0.27676 | 2.921 |
| 0.0005 | 0.5 | 3.062 | 0.0006-1 | 0.3-1 | 0.06471 | 0.47163 | 2.957 |
| 0.0003 | 0.9 | 3.127 | 0.0006-1 | 0.03-1 | 0.06471 | 0.26117 | 2.919 |
| 0.0005 | 0.8 | 3.163 | 0.06-1 | 0.1-1 | 0.12 | 0.3157 | 0.316 |
| 0.01 | 0.85 | 3.11 | 0.006-1 | 0.15-1 | 0.06974 | 0.35471 | 2.941 |
| 0.01 | 0.885 | 3.071 | 0.009-1 | 0.01-1 | 0.07253 | 0.24558 | 2.926 |
| 0.01 | 0.9105 | 3.061 | 0.0006-1 | 0.1505-1 | 0.06471 | 0.3551 | 2.933 |

Table 1 shows that the comparison between parameter settings manually with optimization by GA produces different value in RMSE, where the smallest RMSE value is obtained from GA-NN experiment where learning rate value 0.06471 and momentum value 0.26117. Experiments using some machine learning such K-NN and Linear regression were also carried out on this dataset which can be seen in Table 2.

| Experiment liver disorder dataset with another machine learning |
|-----------------------|-----------------|-----------------|-----------------|
| K-Nearest Neighbor | Linear Regression |
| K | RMSE | Forward Alpha | Backward Alpha | RMSE |
| 1 | 4.644 | 0.05 | 0.05 | 3.05 |
| 2 | 3.747 | 0.05 | 0.1 | 3.045 |
| 3 | 3.488 | 0.1 | 0.1 | 3.045 |
| 4 | 3.344 | 0.1 | 0.05 | 3.05 |
| 5 | 3.275 | 0.1 | 0.5 | 3.049 |
| 6 | 3.236 | 0.5 | 0.1 | 3.029 |
| 7 | 3.176 | 0.5 | 0.5 | 3.049 |
| 8 | 3.135 | 0.5 | 0.01 | 3.047 |
| 9 | 3.119 | 0.5 | 0.15 | 3.032 |
| 10 | 3.118 | 0.5 | 0.09 | 3.021 |
Table 2 shows that the smallest RMSE value is obtained from Linear regression experiment where the value of forward alpha 0.5, and Backward alpha 0.09, while in K-NN experiment smallest RMSE value obtained from K value 10. The next step, we compare the averages RMSE values from 10 experiments in each machine learning, including those in the previous work[18].

| Method                  | RMSE  |
|-------------------------|-------|
| K-NN                    | 3.392 |
| Linear Reggression      | 3.428 |
| SVM(DOT)[18]            | 3.229 |
| SVM(Polynomial)[18]     | 3.275 |
| SVM(RBF)[18]            | 3.057 |
| GA-SVM(DOT)[18]         | 3.2042|
| GA-SVM(Polynomial)[18]  | 3.0506|
| GA-SVM(RBF)[18]         | 2.9667|
| NN                      | 3.118 |
| NN-GA                   | 2.939 |

Table 3 shows that the optimization of machine learning parameters by GA has a positive effect on the RMSE value even on previous work[18]. The smallest average RMSE value is obtained from the NN-GA experiment result is 2.939. the RMSE average comparison also shown in Figure 2.

![Figure 2. RMSE average comparison](image)
Table 4. T-Test result between neural network and neural network-genetic algorithm.

| Variabell 1 Variable 2. |       |       |
|-------------------------|-------|-------|
| Mean                    | 3.118 | 2.6696|
| Variance                | 0.00168 | 0.684013822 |
| Observations            | 10    | 10    |
| Pearson Correlation     | -0.403 |       |
| Hypnotized Mean Difference | 0    |       |
| df                      | 9     |       |
| t Stat                  | 1.680122 |       |
| P(T<=t)one tail          | 0.063618 |       |
| t Critical one-tail     | 1.833113 |       |
| P(T<=t)two tail          | 0.127236 |       |
| t Critical two-tail     | 2.262157 |       |

Based on paired two sample t-tests that have been done, the results can be seen in Table 4. In Table 4, the RMSE values are compared to the neural network method with the GA-neural network method. From the results of these comparisons obtained the value of t count of 6.063618, and t table of 2.262157 which means it can be concluded that H0 is rejected and H1 is accepted.

4. Conclusion

In this research, the proposed method is the optimization of NN parameters with Genetic Algorithm. This method is inspired by the previous research of BUPA dataset study. Evaluation of the results of experiments was using Root Mean Square Error (RMSE).

The best RMSE value obtained for experiments with NN methods is 3.061 and the average RMSE is 3.051. While the experiments on the neural network method with GA obtained the best RMSE value of an 2.919 an average RMSE of 2.6696. After evaluating, validation is then performed by comparing the RMSE results of the models with t-test.

The t-tests conducted, all showed that H1 was accepted, which means that the results of the t-tests showed a significant difference between the two models compared. And the proposed method gets the smallest value and a more significant difference compared to the two previous models and also to another machine learning method. For the future work, it is necessary to test the correlation between attributes, make feature selection work, or optimized another NN parameters such as weights, gain, and biases to get a better result.

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