ICIC Express Letters
Part B: Applications
Volume **11**, Number **6**, June **2020**

ICIC International ©2020 ISSN 2185-2766
pp. 601–606

EXAMINATION OF JUDGMENT ITEMS OF LIVER DISEASE PATIENTS BY FUZZY INPUT USING LRP

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Received December 2019; accepted March 2020

Abstract. *Nowadays, the technological development of neural networks is used in the medical field. With the progress of medicine, the average life span of people is on the rise. In order to investigate the cause of the disease, the patient's data is obtained by blood collection and then the treatment is performed. From the data obtained by blood collection, it is judged whether it is sick or not. By comparing physical characteristics between patients with specific symptoms and healthy people, it is possible to find out the cause of symptoms and to early detect symptoms. In this paper, we use data on liver disease patients. We construct an over-learning model of binary classification, and create two membership functions for each input size. And it determines the important factors that become the basis of classification by LRP method.*

Keywords: Liver patient, Fuzzy, Important factor, Layer-wise Relevance Propagation (LRP)

1. **Introduction.** The three major causes of liver disease are viruses, alcohol and obesity. Life-style causes alcohol and obesity account for a large percentage. When examining whether it is actually liver disease, blood test is the first. This allows examination of various items in liver function. However, blood tests can only estimate some of the changes in the body and cannot lead to disease. In addition, a detailed inspection must be conducted [1,2]. Or, the present condition is that diagnosis is performed by empirical observation based on past data. In medical applications fields, an interpretation of a decision is as important as the decision itself. Interpretation of non-linear models has recently gained much interest. Several works have been dedicated to the understanding of general non-linear estimators. The success of deep neural networks has sparked research into the interpretation of the predictions of deep neural networks. One outcome in this field is layer-wise relevance propagation. As a proposal, it is considered to be one judgment material for diagnosis of a person who is considered to be a liver disease patient by specifying, by LRP, an element that causes a diagnosis of liver disease to be diagnosed.

Physical differences between those diagnosed with liver disease and those not diagnosed can be calculated by LRP. This makes it possible to discover different important factors between liver disease patients and healthy people. Also, it converts input items into two large and small membership functions. By converting the input to be fuzzy, it can be inferred that the item is judged to be important if it is large or small. Thereby, the importance of each item can be clearly shown among the comparison targets [8-15].

2. **Related Works.** When there is a learning model that outputs $f(x)$ to the d-dimensional input vector x, the LRP method finds the degree R_i that each input element x_i ($1 \leq$

DOI: 10.24507/icicelb.11.06.601

$i \le d$) is related to $f(x)$. The degree of association R_i indicates an important part in the input vector x. The operation of the LRP method for the fully coupled neural network model is described in Figure 1. In the prediction in the neural network model, as shown in Figure 1(a), $z_{ij} = x_i w_{ij}$ is calculated from the active value $x_j = \sigma(\Sigma_i z_{ij} + b_j)$ of element i of layer l and the weight w_{ij} to element j of layer $l+1$. b_j is a bias term, and σ is an activation function. On the other hand, in the LRP method, when the input x and the output $f(x)$ are given, the degree of association is back-propagated from the output layer to the input layer as shown in Figure 1(b) [8].

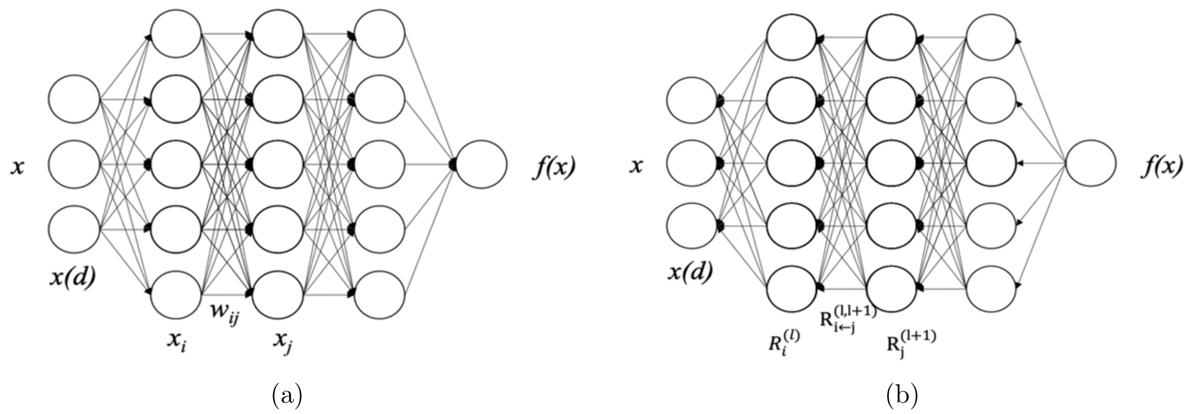

FIGURE 1. (a) Forward propagation model; (b) back propagation by LRP

The degree of association $R_i^{(l)}$ of the layer l is calculated based on the degree of association $R_j^{(l+1)}$ between the elements j of the layer $l+1$. Here, $z_j = \Sigma_i z_{ij}$, and the degree of association R_i of the input element x_i is defined as $R_i^{(l)}$.

$$R_i^{(l)} = \sum_j R_{i \leftarrow j}^{(l,l+1)}, \quad R_{i \leftarrow j}^{(l,l+1)} = \frac{z_{ij}}{z_j} R_j^{(l+1)} \tag{1}$$

By using LRP, the degree of relevance of the input to the output can be specified. And, the degree of association of each input item can be compared.

In other studies, it designed and evaluated a model that combined a fuzzy system and a convolutional neural network. In a convolutional neural network, features are extracted from an input image (MNIST, etc.), and data is clustered in a feature space derived by a clustering algorithm [16].

In this study, we design a model that combines fuzzy system and deep learning, and examine feature extraction in numerical data. Then by making input items fuzzy, it is clarified not only the input items but also whether it is important to be large or small.

3. **Method.** We use LRP to examine diagnostic important factors from over-learning models of liver disease patients and non-patients binary classification. At this time, by converting the input into a large and a small fuzzy, it is judged up to the magnitude of the important factor. The procedure is shown below.

- Assign all input items to two membership functions for each designed size.
- Build binary classification over-learning model for patients with liver disease and non-liver disease.
- Calculate important factors by LRP, and examine importance regarding the size of factors.

4. **Experiments.**

4.1. **Data preparation.** A part of the original data set is shown in Table 1. This is part of a data set of 416 liver disease patients (label = 1) and 167 non-liver disease patients (label = 2). It consists of 441 males and 142 females. In this data set, continuous value data is created with two membership functions for each item, large and small [3-7]. Categorical data is converted to one-hot. Label 1 is a liver disease patient and label 2 is a non-liver disease patient. After the neural network learns the manipulated data, calculate the contribution of the input by LRP.

TABLE 1. Part of the original Indian liver patient dataset

Age	Gender	Total Bilirubin	Direct Bilirubin	Alkaline_ Phosphotase	Alamine Aminotr-ansferase	Aspartate Aminotr-ansferase	Total Protiens	Albumin	Albumin and Globulin Ratio	Labelt
29	1	0.9	0.3	202	14	11	6.7	3.6	1.1	1
17	0	0.9	0.3	202	22	19	7.4	4.1	1.2	2
55	0	0.7	0.2	290	53	58	6.8	3.4	1	1

For continuous value data, we create two membership functions for each item. Categorical data is converted to one-hot. Simply, the number of input dimensions is twice that of the original data set.

As an example, the age membership functions are shown in Figure 2. The creation of membership functions is based on the criteria of the Health Insurance Organization [1,2].

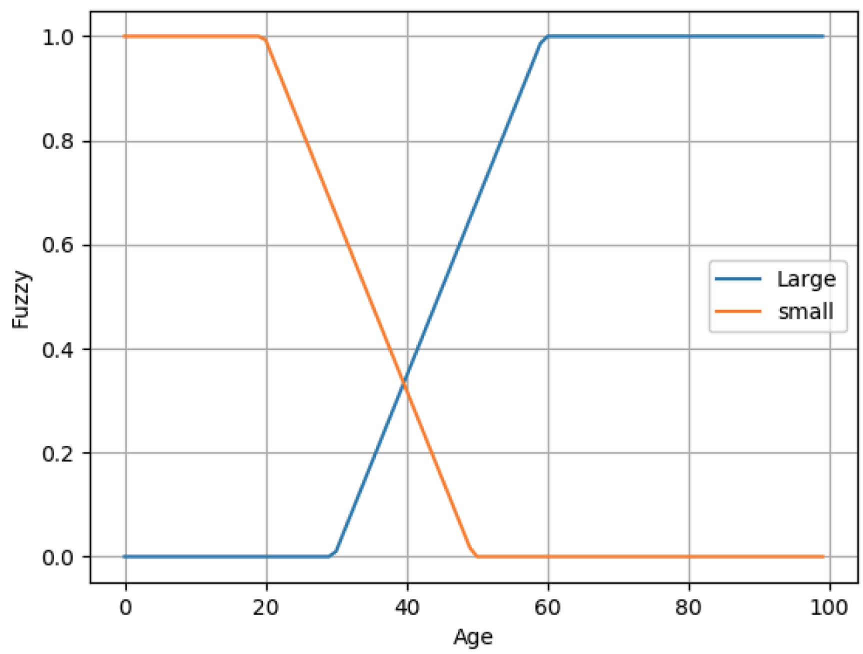

FIGURE 2. Two membership functions: large and small images

4.2. **Architectures.** Input layer has 20 units. There are 3 hidden layers, each consisting of 40, 20 and 10 units. Output layer has 2 units due to 2 classification problem. The relu function was used for the activation function of each layer.

First, we learn all the preprocessed data. At this time, all data are used for learning. This causes over-learning on the learning data. The model learns the features of the data largely by over-learning. By using LRP for over-learned models, measure the degree of association between input and output in classification.

5. **Results and Discussion.** We show the result of using LRP with a model that has been learned. Figure 3 shows the results of using LRP for data on liver disease patients (label = 1). Figure 4 shows the results of using LRP for data on non-liver disease patients (label = 2).

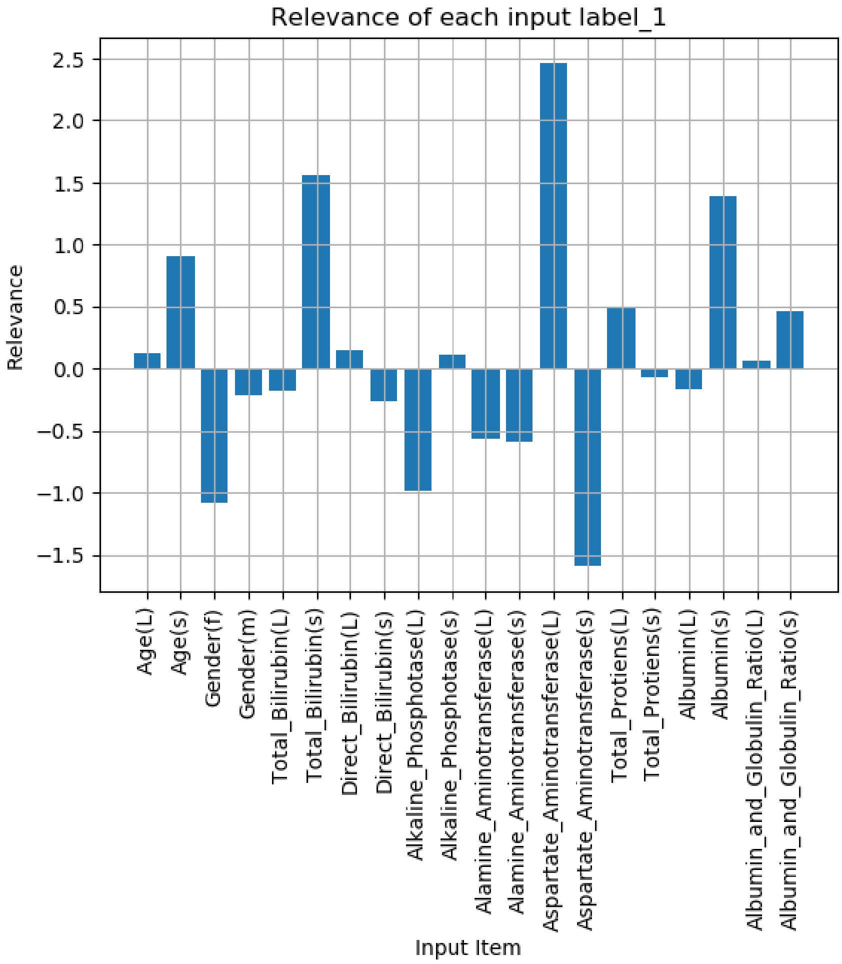

FIGURE 3. Relevance of input to output of liver disease patients (label = 1)

It is shown by Figure 3 that "Aspartate Aminotransferase" is large in the input item to be emphasized in liver disease patients. It is shown by Figure 4 that "Albumin and Globulin Ratio" is large in the input item to be emphasized in non-liver disease patients. Next, "Alkaline Phosphotase" in small and "Alamine Aminotransferase" in small are shown at close values. Each input item is an important factor in the diagnosis of liver disease. Among them, factors that should be noted carefully were extracted. However, since this result is an LRP result using an over-learning model, there is a problem that the result is not common every time under the same conditions.

6. **Conclusion.** In this paper, we evaluated the input relevance by LRP. As a suggestion, we converted the input items into fuzzy or one-hot. By the proposed method, it was possible to clearly indicate the size of the input in the degree of association. The items assessed as important in LRP are considered to have a significant impact on liver disease.

In this work, random elements are included in learning. In addition, it is not a general model because we are constructing a model by over-learning. By solving this problem, we show the overwhelmingly accurate degree of association.

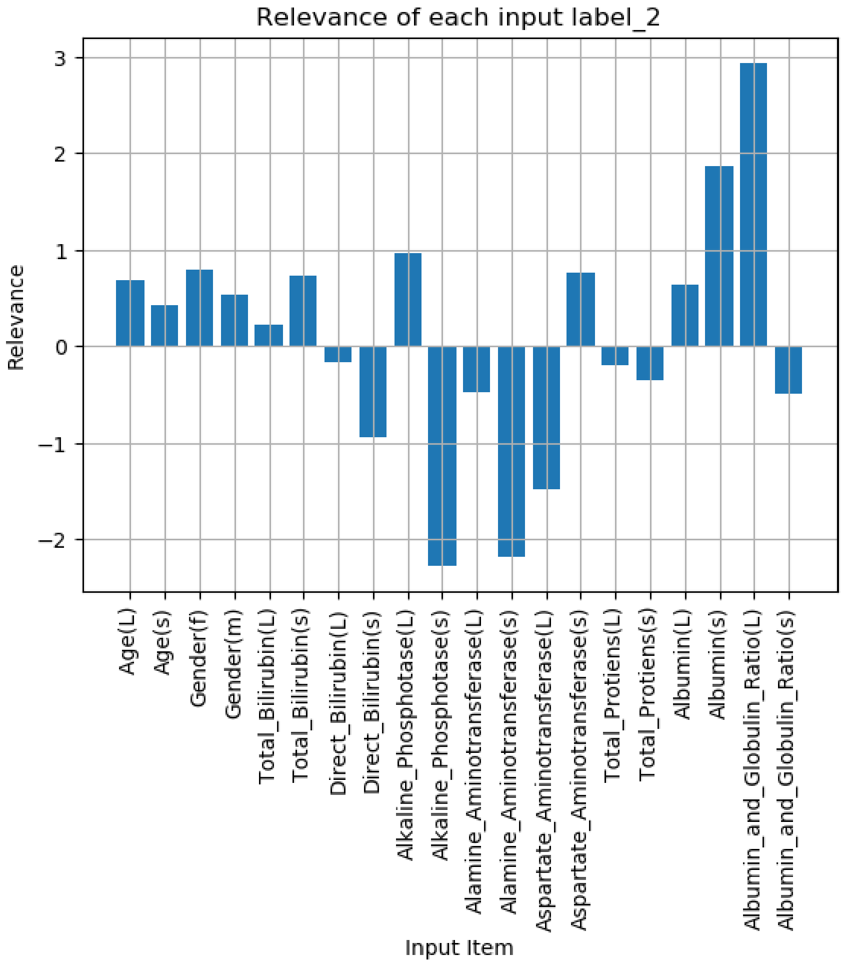

FIGURE 4. Relevance of input to output of non-liver disease patients (label = 2)

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