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Comparison of Multi Layered Percepton and Radial Basis Function Classification Performance of Lung Cancer Data

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Abstract. Lung cancer was the most commonly diagnosed cancer as well as the leading cause of cancer death in males in 2008 globally. The way used to detect lung cancer are through examination chest X-ray, Computed Tomography (CT) scan, and Magnetic Resonance Imaging results. The accurate and efisien analysis of the imaging results are important to ensure the minimal time processing. A computed assisted diagnosis system is the crusial research which can conduct the analysis efficiently and efectively. This paper aimed to compare the classification performances of Multi Layered Perceptron (MLP) and Radial Basis Function (RBF) techniques. The public lung cancer datasets was used as training and testing data in the classfication techniques. Ten fold cross validation was used for dividing data before classifying techniques. The accuracy performances are compared to check a better technique for classification step.

1. Introduction

Lung cancer is the cancer which more often causes men to die than other cancers, which are often the cause of cancer the lungs are smoking. Lung cancer was the most commonly diagnosed cancer as well as the leading cause of cancer death in males in 2008 globally [1]. The high risk of death of the patient lung disease showed that this type of disease needs to be taken seriously. This is related to a lack of awareness the public will be the health of the lungs. Moreover, currently, air pollution is increasing that due to smoke from active smokers, smoke industrial plants, motor vehicle fumes, and various other pollutants. The polluted air when inhalation can cause health conditions the lungs are disturbed. Lung cancer is basically a tumor malignant of the bronchial epithelium. The process of malignancy on this bronchial epithelium will be preceded by what is called pre-cancerous times. The first change occurring in pre-cancerous times is referred to as squamous metaplasia characterized by changes in the

shape of the epithelium and the disappearance of cilia. This squamous metaplasia can result in various influences from outside the body, such as sucking gases and smoke like that contained in cigarette smoke and some chemicals industrial results.
Overview of machine learning (ML) (called deep learning emerged in the computer vision field) in medical imaging are presented in Suzuki (2017), Lundervold & Lundervold (2019) [2], [3]. The use of the deep learning has been increasing rapidly in the medical imaging field, including computer-aided diagnosis (CAD), radiomics, and medical image analysis. In recent years, the deep learning has emerged as a powerful alternative to designing solution for pattern recognition applications by using neural networks, which can learn a representation of data from the raw data itself. The most used incarnation of deep neural networks are convolutional networks [4], a supervised learning algorithm particularly suited to solve problems of classification of natural images [5], which has recently been applied to some applications in chest CT analysis [6]. The deep learning has used for biomedical application in automatic pulmonary nodule management in lung cancer screening [6]–[8]. An assisted diagnosis system has been built for detection of early pulmonary nodule in computed tomography images [9].
Different artificial neural network (ANN) architectures such as Recurrent Neural Networks (RNNs), Radial Basis Function (RBF) [10] and Multilayered Perceptron (MLP) [11] have all been proposed in the literature for pattern classification problems. Currently, ANN is often used for pattern recognition for lung cancer data [12], [13], [22]–[24], [14]–[21].
MLP and RBF well suited for function approximation and pattern recognition due to their simple topological structure [10]. There are several studies have used the RBF neural network in their biomedical application research [25]–[28]. Meanwhile, MLP is used by several studies [11], [29], [30]. Based on the literature review about the use of the ANN in deep learning, this research aims to compare the performance of both neural network structures to differentiate lung cancer data. The result of this research is used for the next research planning.

2. Methodology
In this research, datasets from database of medical data freely access were used for input to neural network. The data consisted of 32 samples which have 56 features for three classes of output nodes. The 56 features as input for the input nodes, several hidden and epoach node sets, and three output nodes were determined for the structure of the neural networks. The multi layered percepton-Levern Marquat (MLP-LM) neural networks and radial basis function (RBF) were used for classification steps. The MLP-LM and RBF performances were compared the results of accuracies. The detail structure of MLP-LM and RBF are presented in figure 1. The MLP neural network also consists of three layers (figure 1a). The detailed of the MLP can be shown in our published paper [29]. RBF Neural Network (RBFNN) consists of three layers (figure 1b). Usually, the nonlinear transfer function in hidden node is chosen as Gaussian transfer function. Values of hidden nodes are derived from (4) and the output of the RBFNN is calculated using (5) in published paper [10].

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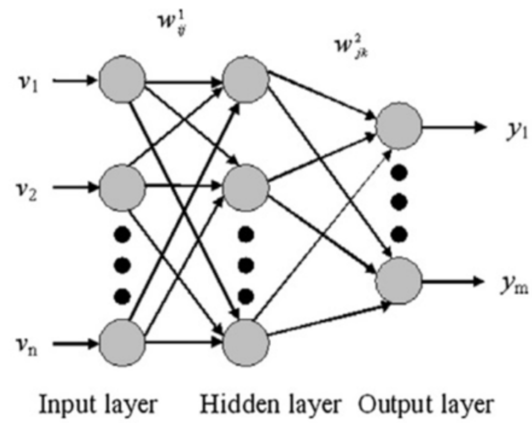
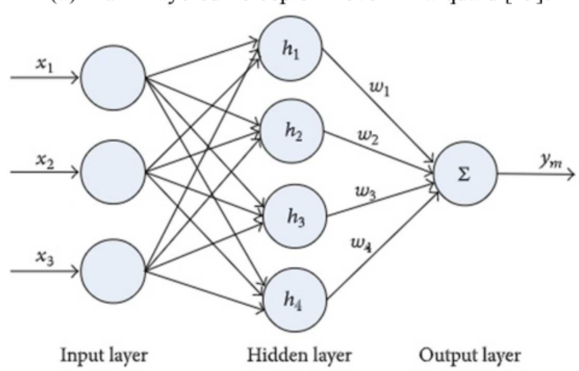


(a) Multi Layered Percepton-Levern Marquard [29].



(b) Radial Basis Function Structure [10].

Figure 1. The detail structure of MLP and RBF neural network.

3. Results and Discussions

Results of both neural networks are tabulated in table 1. The lung cancer data are arranged in to three datasets to test the performance of the neural networks. Epoch nodes are applied in the four modes (I.e. 1, 5, 10, 20) then the hidden nodes are applied in four modes (5, 10, 20, 30). As shown in table 1, performance of MLP network achieved accuracy of 80% to 93% in dataset 1. The accuracy values are 80% for the epoch set 1 and hidden node set 5. The accuracy values are 93% for the epoch set 5 and hidden node set 10. The accuracy values are 80% for the epoch set 10 and hidden node set 20. The accuracy values are 80% for the epoch set 20 and hidden node set 30. The performance of MLP network achieved accuracy of 60% to 80% in both dataset 2 and dataset 3. For dataset 2, the accuracy values are 60% for the epoch set 1 and hidden node set 5. The accuracy values are 80% for the epoch set 5 and hidden node set 10. The accuracy values are 60% for the epoch set 10 and hidden node set 20. The accuracy values are 70% for the epoch set 20 and hidden node set 30. Meanwhile in dataset 3, the accuracy values are 80% for the epoch set 1 and hidden node set 5. The accuracy values are 60% for the epoch set 5 and hidden node set 10. The accuracy values are 60% for the epoch set 10 and hidden node set 20. The accuracy values are 80% for the epoch set 20 and hidden node set 30. The averages of the MLP performance is 74% of accuracy.

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For the RBF network performances, the accuracy values are achieved in range 70% to 80% of accuracy. As shown in table 1, the accuracy values are 80% for the used epoch set 1 to 20 and the used hidden node set 5 to 30 in dataset 1. Meanwhile, in both dataset 2 and dataset 3, the accuracy values are 70% for all the used epochs and hidden nodes. The averages of the RBF performance is 73% of accuracy.

Table 1. Comparison Performances of Radial Basis Function and Multi Layered Perceptron

Datasets	Epoch	HN	RBF	MLP
	1	5	80	80
	5	10	80	93
	10	20	80	80
Dataset1	20	30	80	80
	1	5	70	60
	5	10	70	80
	10	20	70	60
Dataset2	20	30	70	70
	1	5	70	80
	5	10	70	60
	10	20	70	60
Dataset3	20	30	70	80
	Averages		73	74

Based on the overall results, the MLP network is better than the RBF network for the lung cancer data. Based on other research, the MLP was better than Extreme Learning Machine [31]. Meanwhile, in other research, MLP-LM is better than other MLP used in the results [29]. Al-batah et al (2010) states that among all neural network structures, the most commonly and widely used is the MLP structure. The popularity of the MLP is due in part to their computational simplicity, finite parameterization, stability and smaller structure size for a particular problem as compared to other structures. The MLP is generally straightforward to use and provides good approximation of any input–output mapping [30]. Thus, the results of our research are the same as the published paper.

4. Conclusion

This study is to prove the performances of the neural network with Radial Basis Function (RBF) and Multilayered Perceptron (MLP) structures for the lung cancer data. Three datasets are used to test the performance of the neural network structures. The MLP structure is better classification results than RBF structure of neural networks.

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