

# Effect of the Number of Hidden Layer Neurons on the Accuracy of the Back Propagation Neural Network

Tiancheng Deng

School of Pharmacy, East China University of Science and Technology, Shanghai, China  
21013383@mail.ecust.edu.cn

**Abstract.** Back propagation neural network (BPNN) is one of the most basic and commonly used models in machine learning. Hidden layers play a crucial function in maximizing the performance of neural networks, especially when solving complicated issues that demand strict adherence to accuracy and time complexity requirements. The only reliable ways at the moment are just experience and attempting each situation, as the process of determining the amount of Hidden Layer neurons is still unclear. To investigate this relationship, this article conducted extensive experiments involving designing and training the BPNN model with varying numbers of hidden layer neurons. Leverage benchmark data sets and quantify accuracy with appropriate error metrics. The analysis in this article focuses on understanding the impact of different neuron counts on network performance. Under specific assumptions, the findings show a relationship between the quantity of hidden layer neurons and BPNN accuracy. According to statistics of some recent neural network applications, it can be observed that if the number of neurons in the hidden layer is decreased, it will have an effect on the network's accuracy because complex problems with a small number of hidden layers may cause the network to be incorrectly trained; However, relative to the accuracy gain, the time complexity rises orders of magnitude as the number of hidden layer neurons exceeds the ideal amount.

**Keywords:** BP neural network; neurons; machine learning; hidden layer; deep learning.

## 1. Introduction

### 1.1. Basic Theory

The Back Propagation Neural Network (BPNN) is a widely recognized and extensively implemented machine learning algorithm that has demonstrated impressive accuracy in various fields. By iteratively adjusting the weights between layers and training on large datasets, neural networks can learn complex patterns and make accurate predictions [1, 2]. The hidden layer in a BPNN acts as a bridge between the input and output layers, capturing and encoding the underlying patterns within the data [3].

The number of neurons within the hidden layer is a critical architectural choice that significantly affects the network's performance [4]. Too few hidden layer neurons may result in underfitting, where the network struggles to capture complex patterns and yields low accuracy. In contrast, too many hidden layer neurons may lead to overfitting, when the network becomes overly focused on the training set, resulting in poor generalization and decreased accuracy on brand-new, untried data [2-5].

It is imperative that the ideal number of buried layer neurons in a BPNN be established. It directly impacts the network's ability to accurately learn and generalize from the input data. Therefore, it is essential to comprehend the connection between a BPNN's accuracy and the amount of hidden layer neurons in order to ensure reliable and efficient learning. [3]. This study tries to determine how a BPNN's accuracy is affected by changing the number of hidden layer neurons. We specifically want to investigate the trade-off between the quantity of hidden layer neurons and the network's final accuracy[6]. This research assess and analyze the accuracy of the trained BPNN model while systematically changing the number of neurons and holding other parameters constant.

Furthermore, we will investigate any potential computational implications associated with increasing the number of hidden layer neurons. A larger number of neurons may require additional

computational resources and increase the training time significantly. Therefore, we will assess the computational efficiency and the BPNN models' accuracy to determine the optimal balance between accuracy and computational cost.

The results of this study will provide important light on how the quantity of hidden layer neurons affects the precision of BPNNs. This knowledge will aid researchers and practitioners in effectively designing and optimizing BPNN architectures for specific problem domains, improving their predictive accuracy while optimizing computational resources and training time. Ultimately, this research will contribute to the advancement and broader implementation of BPNNs in real-world applications.

## 1.2. Related Works

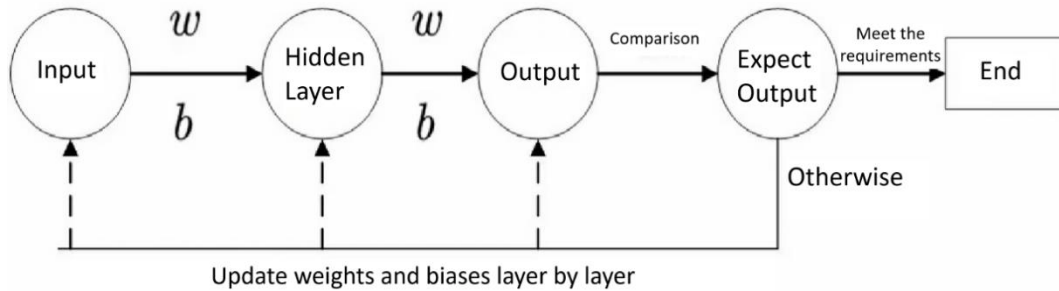
Researchers observed that the number of neurons in the hidden layer of the propagation neural network model had an impact on the network's performance when used to forecast how effectively ammonia nitrogen would be removed from wastewater. According to their belief, as the number of neurons in a neural network is less than the number of input variables, the error increases progressively. This is because the dimension of the variables reduces after the combination of neuronal nodes in the hidden layer. Typically, increasing the number of neurons enhances the network's accuracy, peaking at 10 neurons. However, further increasing the number of neurons may lead to an increase in error, possibly indicating overfitting during training. Therefore, it is best to avoid excessively large numbers of neurons, with 10 neurons being the optimal choice.[7, 8]. Dr. Rajawat and S. Jain used a  $2N + 1$  configuration that runs continuously, and its output is used as input for the output layer. The weights between the hidden layer and input layer, as well as the weights assigned to the hidden layers and output layers, are important parameters in the algorithm [2]. A try-and-error approach was used by F. and M. Panchal to reduce the quantity of neurons and hidden layers in a BNN. They defined a term and noted that when the number of epochs increased, temporal complexity would rise. [9]. S. Xua and L. Chen investigate the FNN algorithm for modeling and forecasting Australia's overall tax income. They initially utilized a network with three hidden layers and later experimented with five hidden layers. The resulting error rates were found to be 11.8 and 5.53 respectively [10]. G. Huang proposed an FNN algorithm consisting of two hidden layers and hidden neurons, capable of effectively learning various sample types with minimal errors. The author configured the first hidden layer to have a maximum size and the second hidden layer to have a narrower size. Additionally, the connections between these layers were analytically determined, with the first hidden layer connected to the input layer [11]. M. Uzair and N. Jamil found that determining the optimal network topology based on input and output numbers alone is challenging. However, the efficiency and accuracy of training may be increased by using the proper number of hidden layers. There are various approaches for determining the required number of hidden layers, with effectiveness depending on the specific database. While a large number of hidden layers can slow down training, it is suitable for achieving higher accuracy. However, in time-sensitive applications, many hidden layers may not be ideal and can lead to overfitting. Analyzing the training database before designing the network helps estimate the appropriate number of layers and neurons [3].

## 2. Methodology

### 2.1. Data Collection

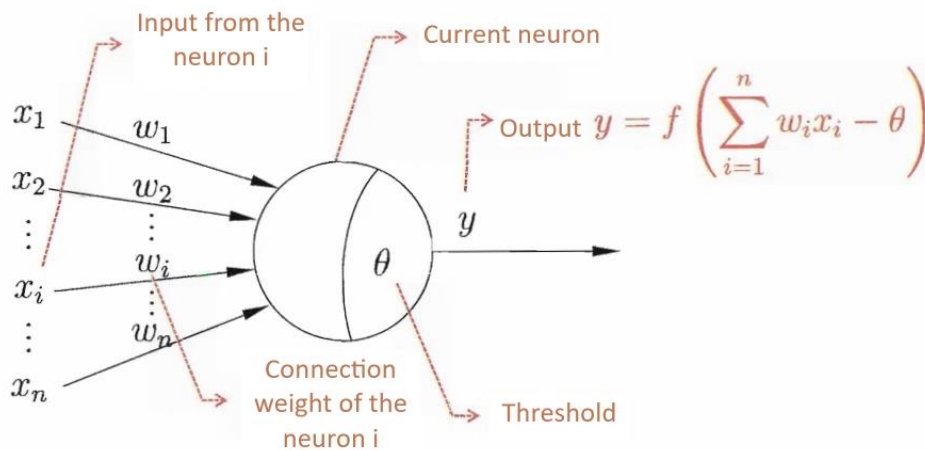
In this study, the performance of multiple models will be compared and evaluated using a comprehensive methodology. The selected BP models are mainly generated and trained based on the problems in industrial and practical application issues. They will be implemented and trained using a carefully curated dataset. Considering that large-scale and high-sample neural network model training will cause a great burden on computing resources, this study will focus on selecting one type of model for in-depth and comprehensive analysis, while other models will be relatively streamlined analysis, hoping to achieve more efficient work.

The investigation of model performance typically involves the evaluation of common parameters, including time complexity and accuracy. These parameters play a pivotal role in neural network models, as they directly affect the learning time and the generation of results, particularly under conditions of underfitting or overfitting. Assessing these constraints is crucial for understanding the effectiveness of neural networks and their suitability for practical applications. Figure 1 showed the Algorithmic flow of BP neural network.



**Fig. 1** Algorithmic flow of BP neural network

This research investigation tries to find out how the Backpropagation (BP) model performs when the number of hidden layers is changed. By systematically altering the architectural configuration of the BP model, we have a curiosity in understanding how the model's capacity for learning and overall accuracy in prediction is impacted by the number of hidden layers. The experiment will involve training multiple BP models with different numbers of hidden layers using a carefully curated dataset. The effectiveness of hidden layer modification on the model's predictive capabilities will be evaluated using performance assessment measures including recall, accuracy, and precision. The findings of this model will provide valuable insights and recommendations for optimizing the architecture of BP models in the context of the selected problem domain [12]. Figure 2 showed the classical neuron model.



**Fig. 2** Neuron model

**2.2. Variable Settings**

This scientific investigation intends to find out how the performance of the Backpropagation (BP) model is affected by changing the number of hidden layers. By systematically altering the architectural configuration of the BP model, we are interested in understanding how the model's capacity for learning and overall prediction accuracy is impacted by the number of hidden layers. The experiment will involve training the BP model with different numbers of hidden layers using a carefully curated dataset. To gauge how hidden layer modifications affect the model's predictive power, performance assessment measures including recall, accuracy, and precision will be employed. [3].

### 2.3. Result hypothesis

The ideal scenario is that the backpropagation neural network's accuracy is strongly influenced by the amount of hidden layer neurons. Accuracy is anticipated to improve when the number of buried layer neurons expands past a certain threshold., but there will likely be an optimal number where maximum accuracy is achieved. Adding more neurons beyond this point could lead to diminishing returns or overfitting. It is also predicted that the quantity and complexity of the dataset utilized would have an impact on the accuracy when changing the number of hidden layer neurons [2, 6, 10].

## 3. Results

### 3.1. Comparison Study Based on Existing Models

The general-model research involving multiple types of neural networks is mainly based on changes in accuracy and time complexity. Learning time and result production are significant constraints in neural networks, particularly when dealing with underfitting or overfitting conditions. The efficacy and efficiency of the network are greatly influenced by these limits. Table 1 compared the accuracy and temporal complexity of several neural networks with varying numbers of neurons in the hidden layer.

**Table 1.** Comparison of several neural networks with varying numbers of hidden layer neurons in terms of accuracy and time complexity [3]

Num.	Model	Number of hidden layers and neuron	Accuracy	Time Complexity
1	Novel waiting in a single hidden layer feed-forward Neural networks for data classification[13]	A single layer with a large number of neurons	Accuracy indicates satisfaction in simple problems, but not in complex ones.	Increasing the number of neurons leads to improved time complexity.
2	Backpropagation neuron nets with one and two hidden layers[14]	Three hidden layers with several neurons	This approach achieves peak accuracy until the third hidden layer, after which it may lead to other problems instead of significant gains.	The optimal time complexity is achieved with three hidden layers, as adding more layers beyond this point significantly worsens the time complexity.
3	Impact of Varying Neurons and hidden layers in Neural network Architecture for a time Frequency Application[15]	One or a maximum of two hidden layers with a larger number of neurons within the hidden layer	Excellent accuracy was achieved by training the network with a high number of neurons and multiple hidden layers.	By increasing the number of neurons within a hidden layer, one can expect to achieve more accurate time complexity compared to simply adding more hidden layers.
4	Review on methods of selecting Number of Hidden Nodes in Artificial Neural Network[9]	One or two for the small problems and three to five for the complex problems	In some cases, achieving exceptional accuracy can result in a perfect 100 percent accuracy, as the model adapts specifically to the problem at hand.	Excellent time complexity with minimal hidden layers allows for quick training of the network.
5	Approximating Number of Hidden Layer Neurons in Multiple Hidden Layer BPNN Architecture[4]	Three or less than three hidden layers	An accuracy of over 90% will be approximately achieved.	Achieving the best time complexity while maintaining accuracy for a given problem.

### 3.2. Graphical representation of the Effect of Numbers of Neurons on Accuracy

Figure 3 demonstrates the fact that the accuracy value, given as variance, tends to decrease as the number of hidden layer neurons grows. According to Figure 4, within a reasonable range of values used in this study, the fitting accuracy of the model reaches a relative maximum when the number of neurons is 9.

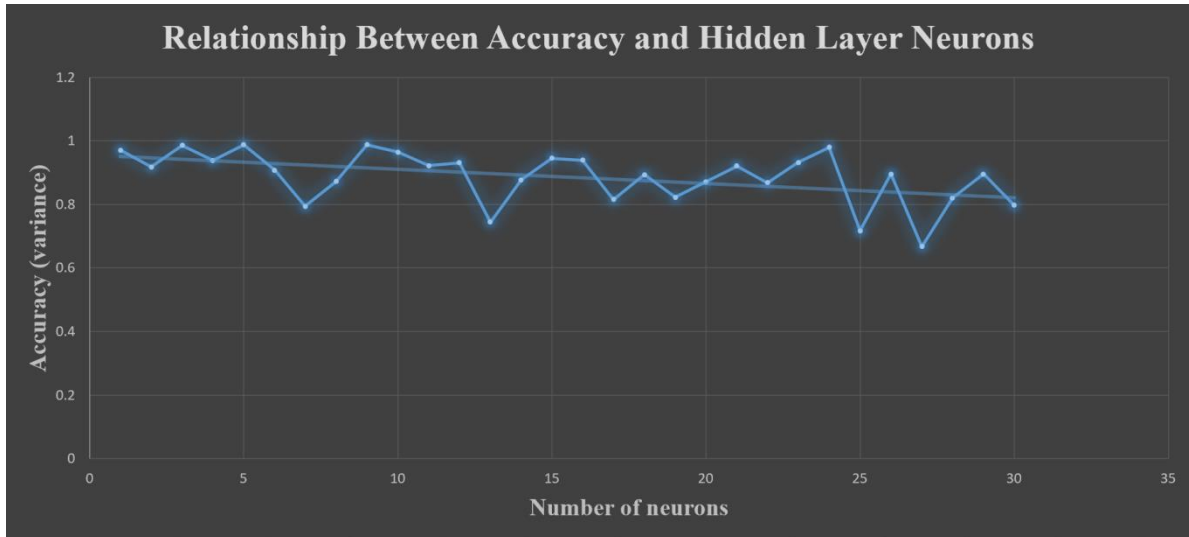


Fig. 3 Trend analysis for accuracy

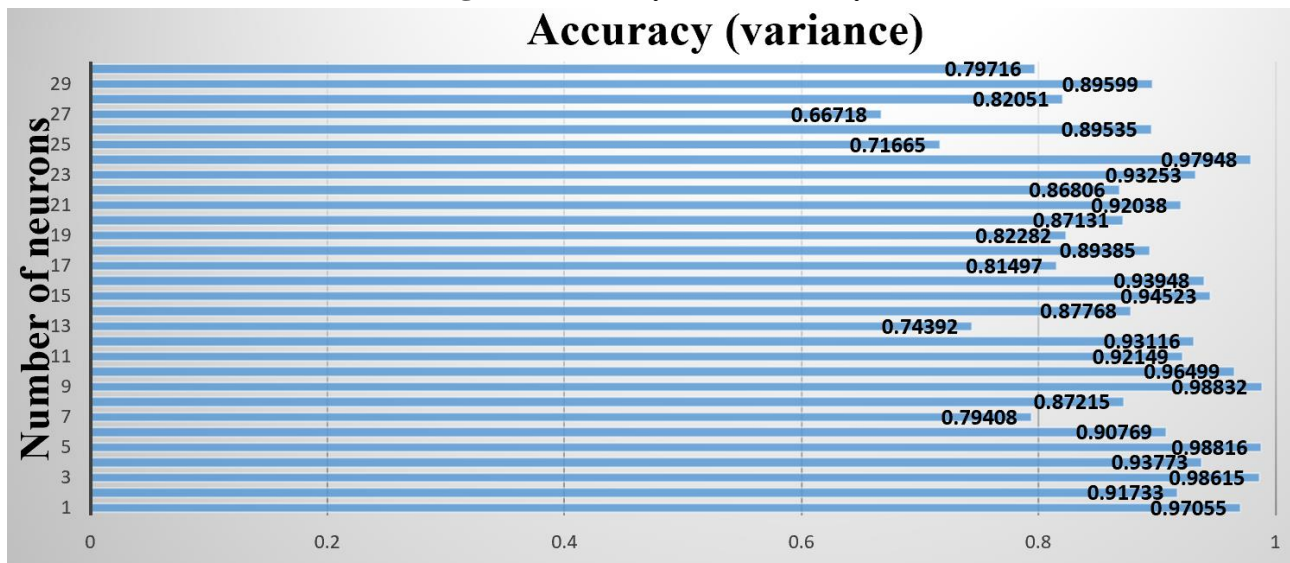


Fig. 4 Relationship of hidden layer neurons and accuracy

### 3.3. Contrast with Hypothetics

The findings demonstrate a strong and constant positive link between the number of hidden layer neurons and the backpropagation neural network's accuracy. The accuracy of the network significantly improves up to a certain point as the hidden layer's number of neurons grows. But if the number of the neurons keep rising higher than the point, the accuracy will decrease in a certain trend.

### 4. Further Research

Determining the optimal number of hidden layers in neural networks remains challenging, and ongoing research seeks to address this issue. It would be beneficial to extend studies to larger applications with training sets exceeding 5,000 input-output pairs. Here are some possible techniques to explore in expanding research on hidden layers:

#### **4.1. Abnormal behavior of additional hidden layers**

Typically, as hidden layers increase, network accuracy improves, albeit with increased time complexity. However, based on observations, it's possible that the third, fourth, fifth on the list, and subsequent concealed layers won't show the same improvement. Understanding this unusual behavior within the time constraints can provide valuable insights.

#### **4.2. Making the first hidden layer's number of neurons as optimal as possible**

It is feasible to solve complicated issues with a maximum of three hidden layers by figuring out the ideal number of neurons for the first hidden levels. Researchers are now looking at this aspect since it has the potential to make network design simpler while yet having strong problem-solving skills.

#### **4.3. Exploring networks without hidden layers**

For smaller problems, networks without hidden layers have been found to produce near-optimal results. Further research in this area may lead to the discovery of networks suitable for simple and small datasets that do not rely on hidden layers. In certain circumstances, the neurons in the input layer as well as the output layer may be sufficient to process the data adequately on their own.

### **5. Conclusion**

In conclusion, this study offers important new understandings into how the quantity of hidden layer neurons affects the backpropagation neural network's accuracy. The research supports a key proposition: there is an ideal number of hidden layer neurons that produces the maximum accuracy. The results show that the neural network's accuracy grows as the number of hidden layer neurons rises. However, after reaching a certain threshold, further increasing the number of neurons does not lead to a significant enhancement in accuracy. To put it another way, there comes a point where adding more neurons has little effect on how well the network functions. For professionals using backpropagation neural networks, this discovery is essential. It highlights how crucial it is to balance the amount of hidden layer neurons in order to get the best level of accuracy. By selecting an appropriate number of neurons, researchers can maximize the network's learning capacity and predictive capability. It is important to acknowledge the potential limitations of this research. Factors like network architecture, activation functions, and learning rate may also influence the network's accuracy. Future research should investigate the interplay of these factors along with the number of hidden layer neurons to gain a more comprehensive understanding of optimizing neural network design.

Overall, this research contributes to the broader understanding of neural network optimization. It guides practitioners to fine-tune their models and achieve the highest accuracy. Researchers may efficiently use neural networks to create more accurate predictions and resolve challenging real-world issues by taking into account the basic principle of determining the ideal number of hidden layer neurons.

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