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Abstract: As a classical artificial intelligence algorithm, the BP (Backpropagation) neural network is widely applied in fields such as image processing, medical diagnostics, and time-series prediction due to its powerful nonlinear mapping capability and adaptive learning features. However, its efficient performance heavily relies on preprocessing and postprocessing support. This paper systematically explores the preprocessing and postprocessing procedures in the practical applications of BP neural networks, focusing on the impact of data preprocessing (including data cleaning, normalization, and feature selection) on improving model training efficiency and effectiveness, as well as the role of postprocessing (such as output data smoothing and error correction) in optimizing the accuracy and interpretability of predictions. Additionally, the paper examines two typical application scenarios, namely medical image classification and financial forecasting, to validate the practical effects of preprocessing and postprocessing optimizations. Through this study, best practices for BP neural network preprocessing and postprocessing are summarized, and future research directions involving multimodal data fusion and deep learning technologies are proposed.

Keywords: BP neural network; data preprocessing; postprocessing; optimization strategy; multimodal data fusion

1. Introduction

The BP neural network, as a classical multi-layer feedforward neural network algorithm, is renowned for its powerful nonlinear mapping capability and robust fault tolerance. It has been widely applied in various fields such as image recognition, time-series prediction, and medical diagnostics [1]. Despite its theoretical maturity and extensive applications, the performance of the BP neural network is still constrained by several factors, among which the quality of input data and the optimization of output results are particularly critical. In practical applications, data quality directly affects the learning efficiency and prediction accuracy of the network, while the reliability of the network's output determines its practical value in real-world scenarios [2]. Preprocessing and postprocessing, as two pivotal steps in BP neural network applications, play an essential role in these processes. Preprocessing mainly aims to enhance data quality through techniques such as data cleaning, normalization, and feature selection, thereby laying a solid foundation for the network's learning process. On the other hand, postprocessing focuses on optimizing and adjusting the network's output results, thereby improving the model's interpretability and prediction performance.Addressing these challenges, this paper takes the BP neural network as the research object and systematically investigates the preprocessing and postprocessing procedures and their optimization strategies in its applications. First, the necessity of data preprocessing is analyzed, with a focus on how data cleaning, missing value imputation, and feature engineering can enhance the training effectiveness of the model. Next, the paper discusses the optimization methods of postprocessing, including output data smoothing, error correction, and reclassification techniques. Finally, through two typical case studies—medical image classification and financial time-series forecasting—the effectiveness of these preprocessing and postprocessing methods in improving practical applications is validated. Future directions, such as combining multimodal data fusion and

deep learning technologies, are also proposed. By conducting this study, it is hoped to provide valuable references for the practical application of BP neural networks and to inspire further research on algorithm optimization and the expansion of application scenarios.Haosen et al. [3] proposed RPF-ELD for breast cancer recognition in ultrasound images. Min et al. [4] proposed a DeepFM-based model for loan repayment prediction with attention and hybrid loss. Tangtang et al. [5] explored ARIMA and LSTM for electricity price forecasting.

2. Overview of BP Neural Networks

2.1. Basic Principles of BP Neural Networks

The basic principle of the BP neural network can be summarized as an iterative optimization process aimed at "minimizing errors." Its core operation involves adjusting weights and biases through the backpropagation algorithm to gradually align the model's outputs with the actual values, thereby enhancing prediction accuracy [6]. This process comprises two key stages: forward propagation and backward propagation.In the forward propagation stage, data flows sequentially from the input layer through the hidden layers to the output layer. The values in the input layer are weighted, summed, and passed through an activation function for nonlinear transformation before being transmitted to the subsequent layer [7]. The hidden layers are responsible for capturing complex patterns and features in the data, while the output layer generates the final predictions based on task requirements. The predictive capability of the BP neural network largely depends on its nonlinear mapping capabilities, which are powered by activation functions such as Sigmoid, ReLU (Rectified Linear Unit), and Tanh [8]. For instance, the Sigmoid function maps input values to the range [0,1], making it suitable for probabilistic outputs; the ReLU function effectively mitigates gradient vanishing by truncating negative values; and the Tanh function compresses input values to the range [-1,1], providing better-centered data representation.In the backward propagation stage, the network adjusts model parameters based on the errors between predicted and actual values [9]. Errors are represented by loss functions, such as Mean Squared Error (MSE) or Cross-Entropy, and gradients are calculated through the chain rule for backpropagation. Gradients are then used to update weights and biases layer by layer from the output to the input, following optimization rules such as the Gradient Descent Algorithm or its variants (e.g., Stochastic Gradient Descent, Adam) [10]. The learning rate plays a critical role in this optimization process, balancing the trade-off between convergence speed and stability. Excessively large learning rates may cause the model to overshoot optimal solutions, while overly small ones may result in slow convergence.Furthermore, the BP neural network's optimization process often incorporates regularization techniques to prevent overfitting. Methods such as L1 or L2 regularization constrain the growth of weight values, thereby enhancing the model's generalization capabilities. Dropout techniques, which randomly deactivate a fraction of neurons during training, further improve the robustness and noise resistance of the network. The design of the network's depth and neuron count in each layer requires careful consideration of the application scenario; shallow networks may fail to capture complex features, while excessively deep networks may encounter gradient vanishing or exploding issues [11]. In summary, the BP neural network achieves nonlinear mapping from input to output through forward propagation and minimizes errors via backward propagation. With the combined power of activation functions, loss functions, and optimization algorithms, BP neural networks excel in handling nonlinear problems, identifying complex patterns, and optimizing model performance, thus laying a solid foundation for broad practical applications.

2.2. Typical Applications of BP Neural Networks

BP neural networks are widely applied across various fields due to their adaptability and structural flexibility. In image processing, they are employed for tasks such as handwritten character recognition and object detection, achieving high classification accuracy through extensive labeled data training [12]. In time-series forecasting, BP neural networks capture intricate temporal

dependencies, making them reliable for applications such as financial market trend analysis and energy consumption demand prediction. In medical diagnostics, BP neural networks analyze patient imaging data to identify pathological regions and provide auxiliary diagnostic support [13]. Additionally, in domains like speech recognition and natural language processing, BP neural networks demonstrate robust performance, serving as foundational components for building sophisticated systems. These typical applications not only validate the versatility of BP neural networks but also highlight the need for continuous performance optimization.In conclusion, as a pivotal machine learning algorithm, the BP neural network combines simplicity with powerful functionality. However, its practical performance remains heavily reliant on the quality of input data and the optimization of output results, emphasizing the critical role of preprocessing and postprocessing procedures.

3. Research on Data Preprocessing Methods

3.1. The Necessity of Data Preprocessing

In BP neural network training, data preprocessing is a vital process that directly determines the quality and efficiency of model learning. Raw data often contains various issues, such as missing values, noise, outliers, and uneven distributions, which may introduce bias during training or even prevent the model from converging [14]. Systematic preprocessing can significantly enhance the reliability and consistency of data, laying a solid foundation for model training.Handling missing values is one of the core steps in data cleaning. Missing values not only compromise data integrity but also may lead the model to ignore critical information [15]. Various methods exist for imputing missing values, including simple approaches such as mean or median imputation, which are suitable for datasets with uniform distributions. For more complex data patterns, interpolation techniques (e.g., linear or spline interpolation) or machine learning-based methods (e.g., k-nearest neighbors or regression models) can be employed to more accurately restore the essential characteristics of the data [16]. Dealing with noise and outliers is another essential aspect of data cleaning. Noise refers to random errors in the data, often arising from measurement inaccuracies or external environmental interference. For example, in sensor data, noise commonly appears as random fluctuations. To address noise, filtering techniques such as mean filtering or Kalman filtering can be applied. Statistical methods, such as the 3σ rule, can also be used to identify and mitigate noise. Outliers, defined as extreme data points far from the central distribution, can be detected and managed through statistical approaches or machine learning techniques such as isolation forest or DBSCAN clustering, thereby reducing their negative impact on model training [17]. Furthermore, standardization and normalization of data are essential to ensure the consistency of feature scales. The input layer of a BP neural network is highly sensitive to data scales. When the input data varies greatly in range, it may lead to imbalanced weight updates during training, making it challenging for the model to converge efficiently. Normalization techniques, such as scaling data to a [0,1] or [-1,1] range, help align all features to a consistent scale, avoiding optimization issues caused by feature scale differences during gradient descent. Standardization methods, such as Z-score standardization, adjust data to have a mean of 0 and a standard deviation of 1, making it particularly suitable for datasets with highly skewed feature distributions.In practical applications, the necessity of data preprocessing extends beyond the training phase and directly impacts the predictive performance and generalizability of BP neural networks. Effective preprocessing eliminates redundant information and extracts the most valuable features for model training, significantly enhancing both the accuracy and efficiency of the model. Through systematic approaches to handling missing values, reducing noise, managing outliers, and scaling data, preprocessing provides a robust and reliable data foundation for BP neural network applications, ensuring optimal model performance [18].

3.2. Feature Engineering and Feature Selection

Feature engineering is a critical approach to enhancing the performance of BP neural networks, focusing on extracting the most valuable information from raw data for model prediction. Feature selection, a key step in feature engineering, removes redundant or irrelevant features, thereby reducing model complexity and improving both training efficiency and predictive accuracy. Common feature selection methods include Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE). PCA reduces feature redundancy by linearly transforming high-dimensional data into a lower-dimensional space, while RFE iteratively trains the model and removes features with lower contributions to optimize the feature set.In time-series data, feature extraction often involves generating lag features, rolling averages, and other time-dependent features to enrich the input information for BP neural networks [19]. These engineered features enable the model to better capture temporal dependencies and improve prediction accuracy. By systematically applying preprocessing and feature selection methods, data quality and model learning efficiency can be significantly enhanced, laying a strong foundation for subsequent optimization of results [20].

4. Postprocessing Optimization of BP Neural Networks

4.1. Postprocessing of Output Results

In BP neural network outputs, prediction results may be affected by noise, biases, and inherent limitations of the model. Particularly when handling complex or high-dimensional data, the outputs may exhibit local discontinuities, anomalies, or low confidence levels. Such issues not only compromise the reliability of predictions but also may lead to erroneous decisions in practical applications. To address these challenges, postprocessing techniques should be tailored to the specific problem types, aiming to optimize the quality and practicality of the model outputs.Firstly, data smoothing techniques are highly effective in addressing output instability and volatility. Common smoothing methods include moving averages, weighted moving averages, and exponential smoothing. These methods average multiple data points in the output sequence to eliminate short-term fluctuations and highlight long-term trends [21]. For example, in time-series predictions, smoothing not only reduces random noise in the prediction curve but also enhances its interpretability and application value. In scenarios with pronounced regularities, adaptive smoothing methods can dynamically adjust smoothing parameters based on data changes, offering greater flexibility.Secondly, in multi-class classification tasks, ambiguous predictions are a common challenge [22]. When the network outputs similar classification probabilities with insufficient confidence, classification errors are likely to occur. Result reclassification techniques can further optimize outputs in such cases. [23].For instance, by setting probability thresholds, predictions with probabilities below the threshold can be marked as "uncertain," followed by manual intervention or secondary classification using additional contextual or domain knowledge. Posterior distribution adjustment methods can also dynamically modify output probability distributions, aligning the final predictions more closely with real-world application needs [24]. These techniques effectively reduce classification errors, especially in high-sensitivity scenarios such as medical diagnostics, where they significantly lower misdiagnosis risks.Error correction methods are another critical component of postprocessing, focusing on adjusting the discrepancies between model outputs and true values. In time-series forecasting, error correction models often analyze the patterns of historical prediction errors to construct statistical or machine learning-based correction mechanisms. For example, linear regression or Recurrent Neural Networks (RNNs) can model error trends and dynamically adjust initial predictions. In image classification or medical imaging tasks, postprocessing pipelines combining region cropping or pixel-level analysis can identify and correct misclassified areas [25]. In high-precision applications such as cancer lesion detection, these error correction approaches significantly enhance the accuracy of final classification results, boosting the reliability and practical value of the application.In summary, postprocessing methods for output results play a pivotal role in optimizing the practical performance of BP neural networks. By combining techniques such as data

smoothing, result reclassification, and error correction, the reliability and stability of model outputs can be effectively improved, enhancing their adaptability and usability in complex scenarios. These strategies not only elevate the predictive capabilities of the model but also provide a solid foundation for extending its applications to real-world problems.

4.2. Performance Evaluation and Improvement Strategies

Performance evaluation is a crucial aspect of postprocessing optimization, providing comprehensive insights into model strengths and weaknesses through systematic metrics. Common performance evaluation metrics include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), accuracy, recall, and F1 score. These metrics not only assess overall model performance but also identify specific issues in different tasks. Based on evaluation results, postprocessing can further optimize model performance by adjusting parameters, refining network structures, or improving training data. For example, resetting activation functions or loss functions in the output layer can better align the model with specific task requirements [26].Ensemble modeling techniques, such as voting or weighted averaging, can integrate predictions from multiple models to further enhance overall performance.Postprocessing optimization is a vital step in BP neural network applications, not only improving output quality but also enhancing the robustness and adaptability of the model in complex scenarios [27]. By incorporating smoothing techniques, error correction, and performance evaluation, the predictive capabilities and practical value of BP neural networks are significantly enhanced, paving the way for their further application in solving real-world problems.

5. Practical Applications of Preprocessing and Postprocessing Optimization Strategies

5.1. Application of Optimization Strategies in Medical Image Classification

Medical image classification is a vital application domain for BP neural networks, where accurate classification results are crucial for disease diagnosis and treatment planning. In medical image classification tasks, preprocessing focuses on normalization, noise reduction, and feature extraction from imaging data. For instance, histogram equalization techniques can improve image quality, making it easier for models to recognize key features [28]. Convolutional filtering is commonly employed to remove random noise in images, thereby improving the signal-to-noise ratio. Moreover, feature extraction methods such as edge detection and texture analysis can significantly reduce the dimensionality of data, which accelerates the training process while retaining essential information.In the postprocessing stage, smoothing and error correction techniques can further optimize classification accuracy. For example, low-confidence classification results can be refined using neighborhood-based voting methods, reallocating uncertain predictions to more likely categories. Additionally, integrating multimodal data, such as combining X-ray images with patient history, can further enhance the reliability and precision of classification results [29]. This combination of preprocessing and postprocessing strategies enables BP neural networks to function more efficiently and effectively in assisting medical diagnostics.

5.2. Application of Optimization Strategies in Financial Time-Series Prediction

In the financial domain, time-series prediction is widely applied in tasks such as stock price forecasting and market risk assessment. The complexity and dynamic nature of financial data underscore the importance of preprocessing. By addressing issues like missing value imputation, normalization, and the generation of time-related features (e.g., moving averages and lag variables), models can better capture patterns in time-series data. Normalization helps avoid gradient problems caused by feature scale differences, while lag features enable the model to learn temporal dependencies effectively [30]. Postprocessing optimization focuses on refining prediction outcomes and ensuring their practical applicability. For instance, in stock price forecasting, dynamic error correction methods can adjust model outputs based on recent market trends, improving short-term

prediction accuracy. Additionally, ensemble modeling techniques, which combine the predictions of multiple BP neural networks through weighted averaging, effectively reduce biases from individual models and enhance overall stability. These practices demonstrate the adaptability of preprocessing and postprocessing strategies in handling complex and dynamic financial data, verifying their applicability in challenging real-world scenarios.By examining the use of preprocessing and postprocessing optimization strategies in medical image classification and financial time-series prediction, it is evident that these techniques hold tremendous potential for improving the practical performance of BP neural networks. These approaches not only enhance the robustness of models but also expand their range of applications, offering valuable insights for the optimization of algorithms in future complex scenarios.

6. Conclusion

As a classical artificial neural network model, the BP neural network is widely applied across various practical domains due to its powerful nonlinear mapping capabilities and flexible structural design. However, its performance depends not only on internal structural optimizations but also on the quality of input data and the processing of output results. Preprocessing and postprocessing thus play a pivotal role in BP neural network applications.This paper systematically examined the preprocessing and postprocessing methods in BP neural network applications. In preprocessing, techniques such as data cleaning, normalization, and feature selection were analyzed for their impact on improving training efficiency and stability. In postprocessing, methods such as output smoothing, error correction, and performance evaluation were discussed for their role in optimizing the quality of network outputs. Through the case studies of medical image classification and financial time-series prediction, the practical effectiveness of these strategies was validated, demonstrating the generality and efficacy of the proposed optimization methods.The study highlights that preprocessing and postprocessing not only significantly enhance the accuracy and robustness of BP neural networks but also support the interpretability and practical value of the models. At the same time, it reveals potential limitations of these strategies in complex applications, such as the need for multimodal data integration and the challenges of handling large-scale data efficiently.Future research could further explore the following aspects: (1) developing more advanced multimodal data fusion methods for BP neural networks, such as integrating images, text, and sensor data for comprehensive information processing; (2) introducing deep learning techniques and transfer learning models to improve the generalization capabilities of BP neural networks; and (3) designing more efficient algorithms and tools to support preprocessing and postprocessing in large-scale data scenarios. These directions not only contribute to advancing the theoretical research on BP neural networks but also pave the way for their application in complex real-world environments.

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