The Comprehensive Investigation of Lung Disease Classification Based on SGD

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Abstract: Lung disease classification is an important research topic in the field of medical imaging. This paper explores the use of the stochastic gradient descent (SGD) algorithm for classifying lung diseases. Initially, it details the principles of the SGD algorithm and its application in lung disease classification. Following this, the paper summarizes existing research on childhood pneumonia and introduces a novel approach named Stochastic Gradient Descent with Warm Restarts Ensemble (SGDRE). This method combines an integration technique, random gradient descent, and a hot restart mechanism to address prevalent issues in deep learning and enhance the precision of early diagnosis. In the automatic detection of pneumonia, researchers use a new deep learning method to simplify the detection process of pneumonia and improve the accuracy by using deep transfer learning, and classify the bacteria and viruses of pneumonia. Finally, this study discussed the future research directions and challenges, including how to use interpretability algorithm, Transfer learning and Federated learning to further improve the interpretability of the model, the application of the system in different data sets, and the protection of patient privacy. This paper aims to provide researchers with a comprehensive understanding of lung disease classification using SGD algorithm.

1 INTRODUCTION

Lung disease has been a major problem in the world's health field for a long time, resulting in severe effects on people's health. Chronic Obstructive Pulmonary Disease (COPD), asthma, pulmonary fibrosis, and so on. All of these conditions have a serious impact on patients' health and quality of life, resulting in difficulty in breathing, coughing, chest pain, and shortness of breath. Not only do they add pain to patients, but they also bring a great burden to the health care system and society. Accurate identification and classification of pulmonary diseases is essential to prevent, diagnose and treat.

The traditional diagnosis method usually depends on the physician's subjective judgement and experience, which results in a high misdiagnosis rate, and restricts the diagnostic accuracy and effectiveness (Qiu, 2022). Therefore, it is a hot spot to use machine learning algorithms to classify lung diseases. Robust Gradient Descent (SGD) is suitable for large data sets. This efficiency makes it possible for the model to learn patterns and features more rapidly, thus increasing the precision of classification. Moreover, the combination of machine learning and SGD algorithms can help us to learn the key features from the lung image and the clinical data. Through training, the model can get the most representative characteristics from the data, which can enhance the validity and generalization capability of the model.

The combination of machine learning models and SGD algorithms for lung disease classification has many advantages. With the continuous development and application of deep learning technology, many research teams and medical institutions have begun to explore how to use optimization algorithms such as SGD to train efficient lung disease classification models. Grega Vrbani is proposing an alternative ensemble method, SGDRE (which uses CNN and SGD with warm restarts), as part of his work. SGDRE is a collection of CNN models that are built in a manner that does not increase training time (Vrbančič, 2022). The identification of pneumonia from chest X-ray images could be done efficiently and effectively using this method. More valuable information about a lung cancer diagnosis can be

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obtained through a CT scan. To enhance diagnosis and treatment procedures, CT scan input pictures are utilized in the formulation of various Machine Learning (ML) and Deep Learning (DL) algorithms (Gopinath, 2023). A method for detecting pneumonia patients using detected X-ray images is proposed using a combination of different optimizers and transfer learning. A benchmark open dataset of chest X-ray images is used to train the proposed deep transfer learning method (Manickam, 2021).

This article aims to systematically review and summarize the research progress of using SGD for lung disease classification in recent years and explore the challenges and future development directions faced in this field. This article will introduce the impact of lung diseases on patient health and the limitations of traditional diagnostic methods, emphasizing the importance of machine learning in lung disease classification. Review and analyze the research achievements of SGD algorithm in the field of lung disease classification, explore the advantages and disadvantages of different algorithm models, and summarize the application effects of existing methods in practice. Finally, the challenges and issues in current research will be discussed, and future research trends and directions will be proposed to provide reference for further promoting the development and application of lung disease classification technology.

2 INTRODUCTION TO THE APPLICATION OF SGD IN PULMONARY DISEASES

Stochastic Gradient Descent, abbreviated as SGD, is a commonly used optimization algorithm in machine learning and deep learning. The gradient descent algorithm has a variant that is perfectly suitable for large datasets.

The main idea behind SGD is to update the model parameters by using only a subset (mini-batch) of training data for each iteration (Ruder, 2016). In each iteration, the algorithm computes a random mini-batch of gradients and updates the parameters in the reverse direction to minimize the loss. This process is repeated over and over again, and the goal of SGD is to find a set of optimum parameters to minimize the loss and enhance the performance of the model.

SGD is used to classify lung diseases by developing machine learning models that allow accurate classification of medical images, such as X rays and CT scans, into various types of pulmonary diseases. The rationale for using SGD in this context is to provide an efficient optimization approach that can deal with the complexity and scale of medical imaging data.

2.1 SGDRE

Early diagnosis of childhood pneumonia is essential for early treatment. Stochastic Gradient Descent with Warm Restarts Ensemble (SGDRE) was developed by the authors. The SGDRE algorithm solves the generalization problem by using the average ensemble method, and the SGDR mechanism is used to obtain the various classifiers required to assemble the ensemble. Using the average ensemble method, a variety of classifiers are obtained by using the SGDR mechanism of SGDRE method. The multimodal character of the cost function can be solved by Stochastic Gradient Descent with Restart (SGDR) design. Learning speed can be abruptly increased to search for a global minimum, but SGDR may drop to a local minimum in the course of training(Vrbančič, 2022). In SGDRE there are four phases, beginning with the initial training phase, then progressing to SGD reboot 1, SGD reboot 2, and integration phase. Using different learning rate annealing functions (cosine annealing, linear reduction, and sine-based annealing), the maximum number of different models can be obtained. In a limited training budget, the first phase of training is done, and the rest of the budget is spent on SGD reboot 1 and SGD reboot 2(Loshchilov,2017). Finally, the collected models are evaluated at the integration stage, and the three best performance models are chosen to construct the final integrated model.

2.2 Automated Pneumonia Detection

Using deep transfer learning to streamline and boost detection accuracy, researchers have developed a unique deep learning technique for the autonomous identification of pneumonia. This study aims to preprocess input chest X-ray images, classify pneumonia as bacterial or viral using pre-trained models on the ImageNet dataset (e.g., ResNet50, InceptionV3, InceptionResNetV2), and use segmentation based on the U-Net architecture to identify the presence of pneumonia (Manickam, 2021).

Two optimizers were employed to extract useful features and raise the pre-trained model's accuracy. Adam computes individual adaptive learning rates for various parameters by combining the benefits of two SGD extensions: adaptive gradient algorithm (AdaGrad) and root mean square propagation

(RMSProp). Despite Adam's widespread appeal, new research indicates that he might not always be able to "converge to the optimal solution" in particular situations. AdaBound, a novel optimizer that convergence occurs to SGD at indefinite bounds, is well-defined, well-structured, and was proposed by Liangchen et al. (Luo, 2019). It can generalize more effectively and converges more quickly. These two optimization methods were employed in this work, and the performance of each at batch counts of 16 and 32 was examined independently. The performance of the pre-trained model was examined and contrasted with other convolutional neural network (CNN) models based on the values that were acquired.

2.3 Automated LUS Scoring of COVID-19 Pneumonia Patients

In order to thoroughly analyze the entire dataset, the researchers utilized 5-fold cross validation along with a secondary selection approach based on the ResNet-50 model (He, 2016). For the secondary selection of LUS images, a combination of five deep neural network models rooted in ResNet-50 were applied, complemented by a SoftMax classifier (Luo, 2021) and SGDM (Jayalakshmy, 2020) optimizer.

The predominant components of this model consist of convolutional and identity blocks. The former primarily focuses on adjusting the network dimensions, while the latter aims to enhance the network's depth. In networks with fewer layers, normalizing data in the intermediate layer enables the utilization of a stochastic gradient descent algorithm during backpropagation. By introducing a residual module incorporating a convolutional neural network model, the direct transmission of input data to the output layer, bypassing the convolutional layer, is made possible. This module has the capability to retain original information and effectively combat the challenge of gradient vanishing during backpropagation. Through this process, deep network training and feature extraction can be accomplished. The incorporation of a zero-pad layer prior to the convolutional layer ensures that the dimensions of the input image and the feature map after the remain consistent (Xing, 2022).

3 DISCUSSIONS

When using SGD for lung disease classification, there are several limitations and challenges to consider, including interpretability, applicability, and privacy issues.

In terms of interpretability, SGD-based neural network model can be considered as a "black box" model, meaning that the inner workings of the algorithm can be Lack of transparency. The inner workings of SGD-based model involve numerous layers and parameters, making it challenging to interpret how each parameter contributes to the final prediction. This lack of transparency can undermine trust in the model's reliability and robustness, especially in critical healthcare applications where transparency and accountability are essential.

For the applicability, in medical image analysis, it is challenging to use the same type of classification algorithm on different subsets of datasets due to poor generalization ability, the necessity for large datasets, and the time complexity of the learning process. When applying the same algorithm to different subsets of medical image datasets, these challenges make it difficult to achieve consistent and accurate results (Vrbancic, 2019).

In terms of model privacy, training machine learning models on patient data can lead to issues related to data privacy and security, and there is a risk of unintentional disclosure of confidential information. It is crucial to implement powerful privacy protection technologies, such as data anonymization and encryption, to protect patient privacy.

These limitations and challenges must be addressed through careful model selection, validation, and ethical considerations to ensure responsible deployment of machine learning models in healthcare applications. As a classic optimization algorithm, SGD-based neural network models have broad application prospects in lung disease classification tasks, such as grad-CAM, SHAP, Transfer learning and Federated learning.

The decision-making process of convolutional neural networks (CNNs) in image classification tasks can be visualized and understood using Gradient-weighted Class Activation Mapping (Grad-CAM). Visualizing the regions in lung images that contribute the most to model predictions is possible when using Gradient CAM for lung disease classification. Enhance the explanatory and interpretable nature of the proposed deep learning model by utilizing grad CAM technology (Panwar, 2020). By assigning an importance score to every feature in a complex machine learning model, Shapley Additive Explanations (SHAP) is a powerful method for interpreting predictions. The trust and confidence in classification results is enhanced by the transparency and explanatory power of SHAP, which leads to better decision-making and more accurate treatment strategies (Nahiduzzaman, 2024).

Transfer learning involves leveraging knowledge gained from solving one problem and applying it to a different but related problem. In the classification of lung diseases, the data set of lung diseases may be small or unbalanced, and migration learning can solve this problem by using the information in other large data sets. If a well-trained model has been used for the classification of a certain lung disease, it can be used as a pre training model, and then applied to solve the problem of new lung disease classification through fine-tuning.

Federated learning is a machine learning method designed to train models without sending raw data from devices to a central server. On the contrary, the model is trained on the local device, and then only updates or gradients of the model are sent to the central server, which updates the global model after aggregation. Federated learning provides a solution to protect user data privacy, such as medical records and personal preferences, by training models on local devices and aggregating updates. In addition, the developed algorithms should rely on more advanced hardware or transmission mechanisms to achieve higher processing speeds and more accurate identification capabilities (Deng, 2023; Sugaya, 2019).

4 CONCLUSIONS

Through this research, a systematic summary and analysis have been conducted on the use of SGD algorithm for lung disease classification. Through a comprehensive evaluation of multiple cases and research results such as SGDRE, Automated pneumonia detection, automated LUS, The SGD algorithm has shown good performance and effectiveness in lung disease classification tasks.

The SGD algorithm has strong scalability and generalization ability, can adapt to different types and scales of lung disease datasets, and has a certain degree of noise resistance and robustness. It can achieve high accuracy and stability on medical imaging datasets, providing strong support for the accurate diagnosis of lung diseases. Compared with other traditional machine learning algorithms and deep learning methods, SGD algorithm has significant advantages in computational efficiency and model convergence speed. This makes SGD an important choice for processing large-scale medical imaging data.

Although the SGD algorithm has made significant progress in lung disease classification, it still faces some challenges and limitations, such as the quality of data annotations and user privacy, which require further improvement and exploration. Future research can focus on improving the accuracy and interpretability of the SGD algorithm in lung disease classification and promoting its widespread application in clinical practice.

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