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CASE REPORT

Tackling Overfitting Challenges in CNN Models with Limited Data: A Case Study in ECG Image-Based Disease Detection

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Abstract

Overfitting is a persistent challenge in Convolutional Neural Network (CNN) models when dealing with limited data, as exemplified in our case study focusing on ECG image-based disease detection. In this research, we present a comprehensive approach to mitigate overfitting, resulting in significant performance enhancements. Our modified model achieved remarkable improvements in various metrics, including accuracy (0.85 to 0.92), F1 score (0.81 to 0.93), and AUC-ROC (0.87 to 0.96). Furthermore, the model's robustness was validated on new test data, demonstrating substantial gains in accuracy (0.78 to 0.96), F1 score (0.72 to 0.97), and AUC-ROC (0.82 to 0.98). These findings underscore the effectiveness of our strategies in combating overfitting, ultimately advancing the reliability of CNN-based disease detection models with limited data.

Keywords

CNN; Overfitting; Limited Data;

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INTRODUCTION

Cardiovascular diseases (CVDs) are a leading cause of mortality worldwide. Early and accurate detection of CVDs is paramount for effective treatment and prevention. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in medical image analysis, including the detection of CVDs from electrocardiogram (ECG) images. However, CNNs, known for their ability to learn intricate patterns in data, are susceptible to overfitting when trained on limited datasets, such as those commonly encountered in medical imaging.

Overfitting occurs when a model learns to perform exceptionally well on the training data but fails to generalize to unseen examples. In the context of medical diagnosis, overfitting can have dire consequences, as it may lead to incorrect predictions when applied to real-world cases. This issue is exacerbated when the available dataset is relatively small, which is often the case in medical research due to the challenges of data collection and privacy concerns [1],[2].

This research article addresses the critical challenge of overfitting in CNN models when dealing with a limited dataset of ECG images for disease detection. We present a novel approach that integrates advanced data augmentation techniques with transfer learning to specifically enhance the generalization capability of CNNs, enabling them to make reliable predictions on unseen ECG images. Unlike traditional methods, our approach combines innovative strategies to tackle the overfitting issue effectively.

Our study is motivated by the pressing need for robust and accurate CVD detection tools in the medical field, where misdiagnosis can have life-altering consequences. The novelty of our work lies in its ability to adapt and refine existing CNN architectures with minimal data while ensuring high diagnostic accuracy.

In the subsequent sections, we delve into the methodology employed to mitigate overfitting in CNN models, present experimental results, and discuss the implications of our findings. By developing strategies to enhance the performance of CNNs on small ECG image datasets, this research contributes to the advancement of reliable and accessible CVD diagnostic tools, ultimately improving patient outcomes and healthcare efficiency.

LITERATURE REVIEW

Cardiovascular diseases (CVDs) continue to be a global health challenge, necessitating early and precise diagnostic methods for effective intervention. The advent of deep learning techniques, particularly Convolutional Neural Networks (CNNs), has revolutionized medical image analysis, offering the promise of accurate CVD detection. However, CNNs are notorious for overfitting when confronted with small datasets, a limitation that has spurred significant research efforts to address this issue [3],[4].

Overfitting occurs when a model captures noise or idiosyncrasies in the training data, leading to poor generalization to unseen examples. In medical imaging, where datasets are often limited due to ethical constraints and data privacy issues, mitigating overfitting is crucial for ensuring the reliability of diagnostic tools. This literature review highlights key advancements and strategies in the quest to overcome overfitting in CNN models, focusing on the domain of ECG image-based CVD detection.[5],[6]

Transfer learning has emerged as a powerful technique for leveraging pre-trained CNN models on large datasets, such as ImageNet, to enhance the performance of models on smaller medical imaging datasets. Fine-tuning pre-trained CNNs or using them as feature extractors has shown promise in capturing relevant features from ECG images, effectively reducing overfitting.[5],[8].

Data augmentation involves generating additional training samples by applying various transformations to existing data. In ECG image analysis, techniques like rotation, translation, and scaling can artificially expand the dataset, reducing overfitting and enhancing model generalization.

Regularization methods, such as dropout and weight decay, have proven effective in preventing overfitting. Dropout randomly deactivates neurons during training, while weight decay penalizes large weight values. These techniques promote network simplicity and encourage the learning of essential features.

Hyperparameter Optimization: Tuning hyperparameters, such as learning rates and batch sizes, is critical for preventing overfitting. Automated methods like Bayesian optimization can efficiently search for optimal hyperparameter configurations.[9]

METHODOLOGY

Data Collection and Preprocessing

Data Acquisition: A dataset of ECG images for ISA detection was obtained, comprising a limited number of samples, 250 images where 47% is of sick patients.

- Data Split: The dataset was divided into three subsets: a training set, a validation set, and a test set. The training set was used to train the CNN model, the validation set for hyperparameter tuning and model selection, and the test set for final evaluation.

- Data Augmentation: To artificially expand the training dataset and mitigate overfitting, data augmentation techniques were applied. These included random rotations, translations, and flips of ECG images.

Model Architecture

• The Mitigated Model

The Mitigated Model used in this study refers to a modified convolutional neural network (CNN) architecture designed to overcome the challenge of overfitting when dealing with very small data, specifically in the context of detecting sickness from ECG (Electrocardiogram) images. The goal of this model is to enhance its ability to generalize from a limited dataset, reducing the risk of overfitting.[11]

Here are some key components and strategies incorporated into the Mitigated Model:

•**Data Augmentation:** Data augmentation techniques involve applying random transformations to the training images, such as rotations, flips, zooms, and shifts. This artificially increases the effective size of the training dataset, providing the model with more diverse examples to learn from. Data augmentation helps prevent overfitting by exposing the model to variations it may encounter in real-world scenarios.[12]

• **Dropout Layers**: Dropout layers are a regularization technique used during training. They randomly deactivate a fraction of neurons (nodes) in a neural network during each training iteration. This prevents any single neuron from becoming overly specialized and forces the network to learn more robust and general features. In the Mitigated Model, dropout layers are strategically placed to encourage better generalization.[13]

• **Transfer Learning:** Transfer learning involves using pre-trained neural network models as a starting point for a new task. In this study, a pre-trained CNN model, VGG16 was used as a base model. The pre-trained model's weights were fine-tuned, and additional layers were added to adapt it to the specific ECG image classification task. Transfer learning leverages the knowledge acquired by the pre-trained model on large datasets to improve performance on the smaller ECG dataset.[14]

• **Regularization Techniques:** The Mitigated Model includes regularization techniques: L2 regularization, to prevent excessive weight values. Regularization helps in controlling the complexity of the model and reduces the risk of fitting noise in the training data.[15]

Justification for the Mitigated Model

The mitigated model was developed to address the inherent limitations of working with a small dataset. Given the high risk of overfitting in such scenarios, the model incorporates several advanced techniques to enhance its generalizability and robustness. Data augmentation significantly increases the variety of training examples, while dropout layers and L2 regularization reduce the likelihood of overfitting by preventing the model from becoming overly dependent on any single feature or subset of data [16].

Transfer learning allows the model to leverage the knowledge from a large pre-trained network (VGG16), providing a strong starting point and reducing the amount of new data required for effective training [17],[18]. These strategies collectively aim to create a more reliable and accurate model for detecting sickness from ECG images, addressing the critical need for effective diagnostic tools in medical imaging.

• Baseline Model

Baseline Model used in this study serves as a reference for evaluating the performance of more advanced models, such as the Mitigated Model, in the context of detecting sickness from ECG (Electrocardiogram) images. The purpose of the Baseline Model is to provide a benchmark against which improvements can be measured. [19]

Here are the key characteristics of the Baseline Model:

• **Simplicity**: The Baseline Model is typically a simple and straightforward neural network architecture, such as a basic convolutional neural network (CNN) with a minimal number of layers and parameters. It may consist of only essential layers like convolutional layers, pooling layers, and fully connected layers.

• **Limited Complexity:** Unlike more complex models used in the study, the Baseline Model is intentionally kept less sophisticated. It may not include advanced architectural elements or techniques designed to mitigate overfitting or enhance performance on a small dataset.

• **Fewer Hyperparameters:** The Baseline Model may have fewer hyperparameters to tune compared to the Mitigated Model. This makes it easier to establish a reasonable starting point for experimentation.

• **No Advanced Regularization:** Unlike the Mitigated Model, which incorporates techniques like data augmentation, dropout, and transfer learning, the Baseline Model may not utilize these advanced regularization strategies. Instead, it relies on basic training procedures.

• **Quick Training:** The Baseline Model is typically quick to train since it has fewer layers and parameters. This allows researchers to rapidly assess its performance and make decisions about whether more complex models are warranted.

Justification for the Baseline Model

The baseline model was chosen for its simplicity to provide a clear contrast with the mitigated model's performance. This allows for a straightforward demonstration of the effectiveness of the advanced techniques employed in the mitigated model. Additionally, a slightly more complex baseline model incorporating basic regularization techniques was evaluated to ensure a fair comparison.

RESULTS

Model Performance

In our study, we employed several performance metrics to assess the effectiveness of both the Mitigated and Baseline Models.Accuracy was used as the primary metric to gauge the proportion of correctly classified ECG images within the test dataset. Additionally, we calculated the F1 score, which balances precision and recall, offering valuable insights into the models' proficiency in correctly classifying both positive and negative cases. Furthermore, we utilized the Area Under the Receiver Operating Characteristic (ROC) Curve (AUC-ROC) to evaluate the models' discriminative capabilities in distinguishing between positive and negative cases. These comprehensive metrics collectively provided a thorough assessment of the models' performance and discriminatory power (Table 1) [20].

Table 3. Performance metrics of mitigated and baseline models

Metrics	Mitigated Model	Baseline Model
Accuracy	0,93	0,85
F1 Score	0,94	0,81
AUC-ROC	0,96	0,87

The Mitigated Model consistently outperformed the Baseline Model across all performance metrics. It achieved higher accuracy, a superior F1 score, and a significantly improved AUC-ROC score. These results indicate that the overfitting mitigation strategies successfully enhanced the model's generalization ability, even when dealing with a very small dataset of ECG images.

Comparative Analysis

In our study, we conducted a comprehensive comparison of the experimental results to evaluate the effectiveness of overfitting mitigation strategies on model performance. Firstly, we aimed to enhance accuracy, anticipating that the Mitigated Model would demonstrate superior performance on the test dataset compared to the Baseline Model. Additionally, we focused on improving the F1 score, aiming for the Mitigated Model to achieve a better balance between precision and recall in comparison to the Baseline Model. Furthermore, we conducted an AUC-ROC analysis to assess the discriminatory ability of both models, with a higher score indicating improved performance in this crucial metric (Table 2).

Table 3. Confusion matrix metrics for mitigated and baseline models

Metrics	Mitigated Model	Baseline Model
True Positives	23	14
False Positives	2	11
True Negatives	25	15
True Negatives False	0	10
Accuracy	92%	56%
F1 Score	96%	57%
Area Under ROC Curve	96%	58%

The Mitigated Model demonstrated superior performance in detecting interatrial septal aneurysms in ECG images. It was particularly effective in correctly identifying true positive and true negative cases while maintaining a low false positive and false negative rate. This comparison underscores the Mitigated Model's robustness and its ability to generalize better when faced with limited data.

DISCUSSION

The results of this study offer valuable insights into the challenges of training convolutional neural network (CNN) models with very small datasets, particularly when applied to the task of detecting diseases from electrocardiogram (ECG) images. Overfitting is a common concern in such scenarios, where the limited amount of data can lead to models that perform well on the training set but fail to generalize effectively to unseen data. The experiments conducted in this research demonstrate the effectiveness of various overfitting mitigation strategies.

The Mitigated Model, which incorporated data augmentation, dropout layers, and transfer learning, consistently outperformed the Baseline Model across all performance metrics. This suggests that these strategies effectively counteract overfitting, enabling the model to make more accurate predictions on unseen ECG images. The improved accuracy, F1 score, and AUC-ROC score of the Mitigated Model indicate its superior generalization ability.

One noteworthy aspect of this study is the successful application of transfer learning, where a pre-trained CNN model's knowledge was leveraged to enhance performance. Transfer learning allowed the model to extract relevant features from ECG images, even with limited data. This finding has significant implications for medical image analysis tasks with constrained datasets.

When comparing our results with other studies, our findings align with the work of Zhang et al. (2021), who demonstrated the effectiveness of overfitting suppression strategies in deep learning-based atrial fibrillation detection. Zhang et al. achieved a significant improvement in model performance by incorporating techniques like data augmentation and dropout, similar to our approach. Their model achieved an accuracy of 88%, an F1 score of 90%, and an AUC-ROC of 92% [21]. Our Mitigated Model, which achieved an accuracy of 93%, an F1 score of 94%, and an AUC-ROC of 96%, shows comparable yet slightly superior results, indicating that our additional use of transfer learning may provide incremental benefits.

Similarly, the study by Ahmed et al. (2023) on classifying cardiac arrhythmia from ECG signals using a 1D CNN model supports our approach of using advanced techniques to improve model generalization under limited data conditions. Ahmed et al. reported an accuracy of 91%, an F1 score of 89%, and an AUC-ROC of 90%. Again, our results are favourable in comparison, suggesting that the integration of multiple overfitting mitigation strategies can yield better generalization and performance [22].

Despite the promising results, our study has several limitations. The primary limitation is the small dataset size, which, while useful for testing overfitting mitigation strategies, does not fully represent the diverse range of ECG patterns seen in larger, more heterogeneous populations. Additionally, our baseline model was relatively simplistic, which might have exaggerated the effectiveness of the mitigated model. Future work should focus on testing these strategies on larger, more diverse datasets and comparing the results with more sophisticated baseline models.

The superior performance of the Mitigated Model highlights the critical importance of employing overfitting mitigation strategies in medical imaging tasks, especially when data is scarce. The use of data augmentation and dropout layers provided regularization that reduced overfitting, while transfer learning leveraged pre-existing knowledge from large datasets to improve feature extraction.

Future research could explore the integration of additional overfitting mitigation techniques, such as adversarial training and ensemble methods, to further enhance model robustness. Additionally, a more extensive comparative analysis with a broader range of existing methods could provide deeper insights into the relative strengths and weaknesses of different approaches. Incorporating domain-specific knowledge into the model training process might also improve performance and generalization.

In summary, this study underscores the importance of addressing overfitting in CNN models for ECG image analysis and highlights the potential of data augmentation, dropout layers, and transfer learning as effective strategies. These findings contribute to the ongoing efforts to improve the reliability and accuracy of AI-driven diagnostic tools in the medical field.

CONCLUSION

This research article delved into the critical challenge of mitigating overfitting in convolutional neural network (CNN) models when dealing with a limited dataset of ECG images for the detection of interatrial septal aneurysms. Through a comprehensive analysis, we demonstrated that employing advanced mitigation strategies, including data augmentation, dropout layers, and transfer learning, significantly enhanced the performance of the Mitigated Model.

Our experimental results, based on a novel dataset of 50 new ECG images, showcased the remarkable capabilities of the Mitigated Model. It achieved an outstanding accuracy of 93%, an impressive F1 score of 0.94, and a high AUC-ROC of 0.96. These results indicate the model's superior ability to make accurate predictions and effectively discriminate between positive and negative cases.

In contrast, the Baseline Model, lacking these advanced mitigation techniques, showed inferior performance with an accuracy of 56%, an F1 score of 0.57, and an AUC-ROC of 0.58. Although it demonstrated reasonably good results, it fell short of the Mitigated Model's robustness.

These findings underscore the critical role of mitigation strategies in addressing the overfitting challenge when working with limited datasets, particularly in the context of cardiovascular disease detection from ECG images. The superior performance of the Mitigated Model highlights its potential for practical applications in healthcare, where accurate disease detection is paramount.

As we look ahead, further research can explore additional strategies to enhance model performance and generalize these findings to other medical imaging tasks. Ultimately, this study contributes to the broader objective of improving the accuracy and reliability of machine learning models in healthcare, ultimately benefiting patient care and diagnosis.

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