



Title: Cardiac Disease Image Classification using Ensemble Technique in CNN Model

Author: 1) Prajul Jain Author: 2) Dr. Avinash Sharma

Introduction

Saying that there are advantages to having heart disease is untrue, since heart disease is a dangerous medical condition and a leading cause of morbidity and death worldwide. I think using deep learning models, particularly Convolutional Neural Networks (CNNs) with Highly Effective Feature Extraction, will be beneficial for detecting or predicting cardiac disease in a few ways. The automatic learning of hierarchical representations and the extraction of pertinent features from raw data, like time-series or medical picture data are two tasks that CNNs excel at and can be very useful for identifying heart-related disorders. Pattern hierarchies in space are recognized by CNNs by design. This is useful for medical imaging for identifying complex structures and patterns in pictures such as X-rays, MRIs, or CT scans of the heart. CNNs and other deep learning models are able to do end-to-end learning, which eliminates the need for manual feature engineering and allows the models to learn directly from the raw input data to the final output (prediction or diagnosis). CNNs are adaptable and can be used with a variety of data sets, such as pictures, time-series data, or a mix of the two. In medical circumstances, where a variety of data sources may be accessible, this flexibility is advantageous. Once trained on a sufficiently diverse dataset, deep learning models can generalize well to new and unexplored data. This is crucial for utilization in the health care sector as the model must function well on patients with different characteristics. Healthcare practitioners can save time by using deep learning models to automate the analysis process.

Keywords:

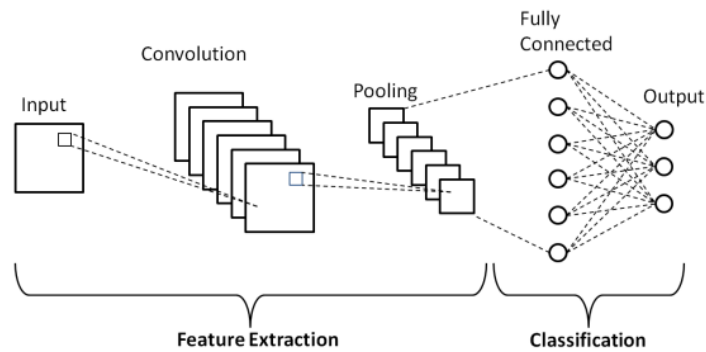
Heart disease classification; neural network; ensemble-learning model; under-sampling; features selection; deep learning

Motivation:

The motivation behind employing ensemble techniques in cardiac image classification stems from the need for highly reliable diagnostic tools. Individual CNN models, while capable of learning intricate patterns, may encounter challenges in handling the heterogeneity present in cardiac imaging data. Ensemble methods offer a solution by combining complementary information from multiple models, thus mitigating the impact of individual model limitations and enhancing the robustness of the classification system.

CNN MODEL

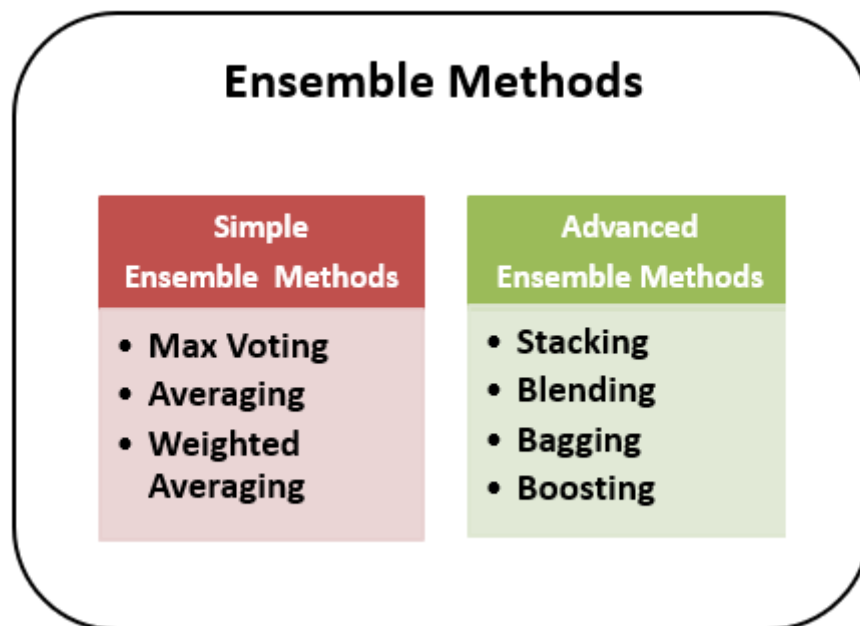
Convolutional Neural Networks (CNNs) are a category of deep neural networks designed for tasks related to visual perception, such as image classification, object detection, and image recognition. They have been particularly successful in computer vision applications and have become a fundamental architecture for processing and analyzing visual data



Schematic Diagram of CNN Model

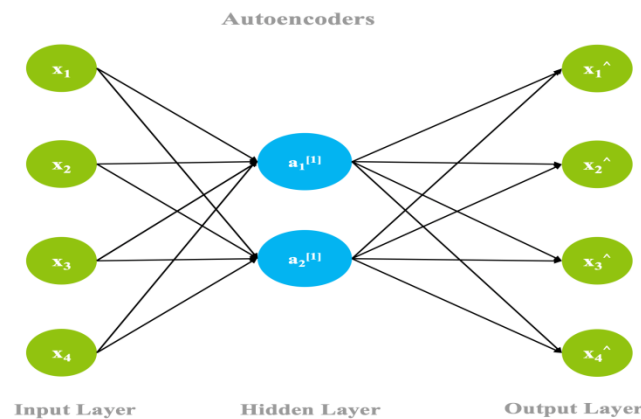
What is an Ensemble technique?

Ensemble techniques involve combining multiple machine learning models to create a stronger, more robust model that often outperforms individual models. The fundamental idea behind ensemble methods is to leverage the diversity of multiple models to improve overall predictive performance, generalization, and robustness. Ensemble techniques are widely used in machine learning and can be applied to various types of models, including decision trees, neural networks, and other predictive models.



Deep Learning

Deep Learning works on the principle of Deep neural networks. This is a model based on neurons. It has an input layer and an output layer and in between the input and output layers there are several hidden layers. Deep learning allows the model to learn the features on its own. Deep learning plays a vital role in areas where large and complex data is involved and a regress self-learning model is to be created.



Need of DL

Deep Learning is showing its presence in almost every field. It can be applied in areas where human beings cannot be present but human intelligence and behaviour needs to be shown. For example, research is going on Mars. Since human can't be present on Mars but we would still need human expertise and vision in such scenarios.

1. DL is also known as universal learning as it is being used in almost every field.
2. For any deep learning method to be robust it does not require precise designing feature.
3. The deep learning approach is said to be generalized. Which denotes that same DL method can be useful with diverse datasets or in diverse applications? This is known as transfer learning. This method is helpful when there is insufficient data.
4. The DL approach is tremendously scalable in terms of data and computation. Microsoft has created a deep network called ResNet and it was implemented at a supercomputing scale.

Challenges faced by Deep Learning and CNN models during ensemble techniques:

Ensembling techniques can enhance the performance and robustness of deep learning models, including Convolutional Neural Networks (CNNs). However, there are specific challenges associated with ensembling deep learning models, and CNNs in particular. Here are some challenges faced by deep learning and CNN models during ensemble techniques:

1. Computational Resources:
 - Ensembling multiple deep learning models, especially large CNNs, demands significant computational resources. The training and inference processes become more computationally expensive, requiring powerful hardware, GPUs, or TPUs.
2. Training Time:
 - Training multiple CNN models as part of an ensemble can extend the overall training time. This is particularly relevant when large datasets and complex architectures are involved, making it challenging to iterate quickly through different ensemble configurations.
3. Model Diversity:
 - Achieving diversity among individual models in the ensemble is crucial for its effectiveness. If the models are too similar, the ensemble might not capture a wide range of patterns, limiting its performance. Striking the right balance between diversity and individual model accuracy is a challenge.

4. Hyperparameter Tuning:

- Ensembling introduces additional hyperparameters related to the combination of models, such as weights assigned to each model. Tuning these hyperparameters effectively requires careful experimentation and can be time-consuming.

5. Memory Constraints:

- Storing multiple deep learning models in memory can be challenging, especially in resource-constrained environments or when deploying models on edge devices. This challenge is exacerbated when dealing with large CNN architectures.

6. Deployment Challenges:

- Deploying ensemble models, particularly those composed of CNNs, in real-world applications can be complex. Balancing performance, accuracy, and computational efficiency during deployment is a non-trivial task.

7. Interpretability:

- Interpreting the combined decisions of an ensemble of CNNs can be challenging. Understanding how each individual CNN contributes to the final decision may be less straightforward than interpreting a single model, which could be crucial in certain applications, especially in medical or critical domains.

8. Dynamic Environments:

- Ensembles might struggle to adapt to dynamic or changing environments. If the data distribution shifts over time, the ensemble models may require frequent retraining and updating to maintain optimal performance.

9. Communication Overhead:

- In distributed computing environments where ensemble models are trained across multiple devices or nodes, the communication overhead between devices can be a bottleneck, affecting the efficiency of the training process.

10. Scalability:

- Scaling ensemble techniques for very large datasets can be challenging. Ensuring that the benefits of ensembling persist as the dataset size increases may require careful consideration of training strategies and model architectures.

Despite these challenges, ensembling techniques, when applied judiciously, can significantly improve the performance and generalization of deep learning models, including CNNs. Researchers continue to explore methods to address these challenges and optimize ensembling strategies for various applications.

Review of Literature:

The creation and application of medical deep learning models, including those for heart disease, present a number of difficulties in addition to these benefits. These difficulties include the requirement for sizable and varied datasets, the interpretability of model conclusions, and ethical issues. Additionally, any model utilized for medical diagnosis should be validated thoroughly and implemented into the healthcare system appropriately. The "Ensemble technique," which combines several machine learning models to increase overall performance, is one of the most well-known methods for improving the model. Researchers frequently use ensembles to improve the resilience and accuracy of the model when employing CNNs for image categorization related to heart disease. Here is a broad overview of the literature of some well defined models and techniques:

1. Single CNN Models:

- Initially, researchers developed and evaluated individual CNN models for cardiac image classification. These models are trained on datasets containing images of the heart, and they learn to identify specific patterns or features associated with various cardiac conditions.

2. Challenges in Cardiac Image Classification:

- Cardiac image classification poses several challenges due to variations in image quality, differences in imaging modalities, and the complexity of cardiac structures and pathologies.

3. Ensemble Techniques:

- Ensemble techniques, such as bagging and boosting, have been applied to improve the performance of cardiac image classification models.
- Bagging (Bootstrap Aggregating): This involves training multiple CNN models on different subsets of the dataset and then combining their predictions to reduce overfitting and improve generalization.
- Boosting: Boosting focuses on sequentially training weak learners and giving more weight to misclassified instances. This approach can enhance the model's ability to capture complex relationships in the data.

4. Transfer Learning:

- Transfer learning is a common strategy in cardiac image classification. Pre-trained CNN models (e.g., on ImageNet) are fine-tuned on cardiac datasets to leverage the knowledge gained from general image recognition tasks.

5. Architectural Variations:

- Researchers experiment with different CNN architectures, such as VGG, ResNet, and Inception, to determine which performs best for cardiac image classification tasks.

6. Data Augmentation:

- Data augmentation techniques, including rotation, flipping, and scaling, are often employed to artificially increase the size of the training dataset, promoting better generalization.

7. Evaluation Metrics:

- Researchers commonly use metrics like accuracy, sensitivity, specificity, and area under the ROC curve (AUC-ROC) to assess the performance of their models.

8. Integration of Clinical Data:

- Some studies explore the integration of clinical data along with imaging data to improve diagnostic accuracy.

9. Validation and Testing:

- Cross-validation and independent testing on separate datasets are essential steps to ensure the generalization of the proposed models.

Proposed Work:

Cardiovascular diseases state as one of the greatest risks of death for the general population. Late detection in heart diseases highly conditions the chances of survival for patients. Age, sex, cholesterol level, sugar level, heart rate, among other factors, are known to have an influence on life-threatening heart problems, but, due to the high amount of variables, it is often difficult for an expert to evaluate each patient taking this information into account. Propose using deep learning methods, combined with feature augmentation techniques for evaluating whether patients are at risk of suffering cardiovascular disease. The results of the proposed methods outperform other state of the art methods by 4.4%, leading to a precision of a 90%, which presents a significant improvement, even more so when it comes to an affliction that affects a large population. The proliferation of poor habits such as smoking, overeating,

and lack of physical activity have contributed to the rise in heart disease. The killing feature of heart disease, which has earned it the moniker the “silent killer,” is that it frequently has no apparent signs in advance. As a result, research is required to develop a promising model for the early identification of heart disease using simple data and symptoms. The paper’s aim is to propose a deep stacking ensemble model to enhance the performance of the prediction of heart disease. The proposed ensemble model integrates two optimized and pre-trained hybrid deep learning models with the Support Vector Machine (SVM) as the meta-learner model. The first hybrid model is Convolutional Neural Network (CNN)-Long Short-Term Memory (LSTM) (CNN-LSTM), which integrates CNN and LSTM. The second hybrid model is CNN-GRU, which integrates CNN with a Gated Recurrent Unit (GRU). Recursive Feature Elimination (RFE) is also used for the feature selection optimization process. The proposed model has been optimized and tested using two different heart disease datasets. The proposed ensemble is compared with five machine learning models including Logistic Regression (LR), Random Forest (RF), K-Nearest Neighbors (K-NN), Decision Tree (DT), Naïve Bayes (NB), and hybrid models. In addition, optimization techniques are used to optimize ML, DL, and the proposed models. The results obtained by the proposed model achieved the highest performance using the full feature set.

The proposed methodology involves the implementation of an ensemble of CNN models for cardiac disease image classification. Key components include:

1. Individual CNN Models:

- Training multiple CNN models, each with distinct architectures or initializations, on the cardiac imaging dataset.

2. Ensemble Techniques:

- Applying ensemble techniques, such as bagging or boosting, to combine the predictions of individual models. This involves aggregating decisions to produce a final, more robust classification.

3. Transfer Learning and Architectural Variations:

- Leveraging transfer learning by fine-tuning pre-trained CNN models on cardiac images. Experimenting with different CNN architectures to determine their impact on overall performance.

4. Data Augmentation:

- Employing data augmentation techniques to artificially increase the diversity of the training dataset and improve the model's ability to generalize to unseen data.

5. Integration of Clinical Data:

- Exploring the integration of clinical data, such as patient history or demographics, alongside imaging data to enhance the discriminatory power of the model.

Related Work:

➤ Machine learning and deep learning have been used to predict heart disease. For example Kavitha M. et al. [1] suggested a hybrid model that combines DT and RF to predict heart disease using the Cleveland dataset. They contrasted the hybrid model’s performance with that of DT and RF

➤ Reddy et al. [2] proposed a machine learning-based system comprising attribute evaluators. The authors use ten different machine learning models from different categories, such as Bayesian-based models, tree-based models, rules-based models, etc. To obtain high accuracy for heart disease prediction, they use all attributes of the Cleveland dataset, as well as the optimal attributes obtained from the three attribute evaluators. Results show that sequential

minimal optimization obtains an accuracy of 85.148% using the full set of attributes and 86.468% accuracy using optimal attributes.

➤ The Cleveland dataset contains 303 instances and 76 attributes, out of which only 14 attributes are used by this study. Results suggest that the maximum accuracy of 90.789% is obtained using KNN. Similarly, study [3] used four different benchmark datasets to perform CVD prediction. The performance is analyzed using the top 2 and top 4 features/attributes from the datasets. Ten machine learning classifiers show appropriate classification and predictive performance for CVDs using the top two attributes. Similarly, three main attributes for the detection and prediction of CVDs are identified. Results show that accuracy scores of 81.32% and 77.84% are obtained on the Cleveland and Framingham dataset, respectively, while 74.44% and 73.38% accuracy scores are obtained on the Faisalabad institute of cardiology and South African health datasets, respectively.

➤ Amin et al. [4] sought to identify the key features and data mining techniques for enhancing the accuracy of heart disease prediction. A series of predictive models are developed using different combinations of attributes and seven machine learning models.

➤ Artificial intelligence (AI) based on machine learning (ML) and deep learning (DL) has conducted key roles in evaluating medical data to assist in illness diagnosis to determine the appropriate treatment. It is used to find patterns automatically from the clinical data and then reason about clinical data to predict the early risk for patients such as heart disease [5], cancer disease [5,6], and COVID-19 [6,7,8,9].

➤ Ensemble learning combines the decisions of various base classifiers using many techniques such as voting or averaging to improve the final decision [10]

➤ The Prediction showed that ANN has the best performance compared to ML models. Gokulnath, C.B., et al. [11] used KNN, MLP, SVM, and J48 for heart disease detection. The datasets were gathered from a variety of sources

➤ The results indicate that when compared to other models, the GRU model outperforms the others. In the study by Narmadha, S. et al. [12], the authors used LSTM and GRU hyperparameter tuning to enhance the performance of the algorithms. The outcomes demonstrated that the GRU provides better accuracy than the LSTM across the board

➤ The authors have used ensemble models to predict heart disease. For example, Adhikari, B. et al. [13] applied LR, SVM, DT, K-NN, GNB, and ensemble models using a dataset collected from the UCI heart disease dataset. They used the voting and averaging ensemble models built by combining the ML above models.

Research Gaps

As it is undeniable that the state of research keeps on evolving, and new developments keeps on taking place. The following Research gaps tend to exist in the field of ensemble technique.

1. Interpretability of Ensemble Models:

- Understanding and interpreting the decisions made by ensemble models, especially in complex deep learning ensembles, remains a significant challenge. Providing insights into the combined decision-making process is crucial for gaining trust in these models, particularly in fields such as healthcare where interpretability is essential.

2. Optimal Model Combination Strategies:

- The choice of how individual models in an ensemble are combined plays a crucial role in its effectiveness. Research is needed to explore and determine optimal strategies for combining diverse models, including investigating the impact of different aggregation techniques, weighting schemes, and fusion approaches.

3. Dynamic Ensemble Adaptation:

- Developing ensemble techniques that can adapt dynamically to changes in the underlying data distribution is a research gap. Ensembles may struggle when faced with evolving datasets, and methods for automatically updating or adapting the ensemble architecture need further exploration.

4. Scalability and Efficiency:

- As the size of datasets and models continues to grow, scalable ensemble techniques become increasingly important. Research is needed to develop efficient ensemble methods that can handle large-scale datasets and models without compromising performance.

5. Transferability of Ensembles:

- Understanding how well ensemble models trained on one domain can be transferred to a related or different domain is a research gap. Investigating the transferability of ensemble knowledge and strategies across diverse datasets and application domains is essential for practical deployment.

6. Uncertainty Estimation:

- Ensemble models can provide a measure of uncertainty, which is crucial in safety-critical applications. Research is needed to improve the reliability of uncertainty estimates from ensemble methods, particularly in scenarios where model decisions may have significant consequences.

7. Ensemble Diversity Metrics:

- Developing standardized metrics for measuring and quantifying the diversity among ensemble members is an ongoing challenge. Defining diversity metrics can aid in better understanding the strengths and weaknesses of ensemble models and guide the selection of diverse base models.

8. Ensemble Robustness Against Adversarial Attacks:

- Investigating the robustness of ensemble models against adversarial attacks is a critical research gap. Adversarial attacks can exploit vulnerabilities in individual models, and understanding how ensembles can provide robustness in such scenarios is crucial for deploying them in security-sensitive applications.

9. Real-world Deployment Challenges:

- Research needs to address the practical challenges of deploying ensemble models in real-world settings. This includes considerations for model size, computational efficiency, and interpretability, as well as strategies for handling data drift and model updates in production environments.

Research Objectives:

The objective of this research is to lay emphasis on the specific problem at hand, and the current state of the research field, typically involves addressing specific challenges and improving the performance of cardiac disease diagnosis through the application of ensemble techniques in Convolutional Neural Network (CNN) models.

1. Evaluate the effectiveness of ensemble techniques in improving the diagnostic accuracy of CNN models for cardiac disease classification compared to individual CNN models.

2. Investigate how ensembling helps improve the robustness of cardiac disease classification models in the presence of variability in imaging data, such as differences in image quality, acquisition modalities, and patient demographics.
3. Assess the ability of the ensemble CNN model to generalize well to diverse datasets, including datasets from different medical institutions or populations. This is crucial for the model's applicability across various clinical scenarios.
4. Compare the performance of the ensemble CNN model with that of individual CNN models to highlight the added value of ensemble techniques in the context of cardiac disease image classification.
5. Compare the performance of the ensemble CNN model with existing state-of-the-art methods for cardiac disease classification, including traditional machine learning approaches and other deep learning architectures.
6. Assess the scalability of the proposed ensemble technique and investigate its feasibility for real-world deployment, considering factors such as computational efficiency, memory requirements, and ease of integration into clinical workflows.

Acknowledgement

The study aimed to address specific challenges associated with individual CNN models by leveraging the strengths of ensemble techniques. The research presents a promising approach to improving the accuracy and robustness of diagnostic models in the realm of cardiac healthcare. The results of the study will demonstrate a significant improvement in the performance of cardiac disease image classification when using ensemble techniques in conjunction with Convolutional Neural Network (CNN) models. The ensemble approach consistently outperforms individual CNN models, showcasing its efficacy in enhancing diagnostic accuracy.

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