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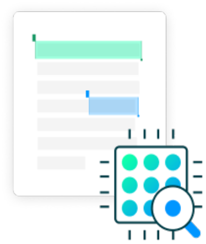

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A Comprehensive Review of Transfer Learning Techniques for Predicting Heart Disease

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***Abstract*— Purpose: This systematic review explores the use of transfer learning techniques in heart disease prediction, assessing the effectiveness of advanced neural network models, such as DGACNN, and their integration with dual-modal data, including electrocardiograms (ECG) and phonocardiograms (PCG).**

Methods: A systematic search was performed in accordance with PRISMA guidelines across databases such as PubMed, IEEE Xplore, and ScienceDirect. Studies published from 2020 to 2024 were selected based on predefined criteria, and metrics like accuracy, sensitivity, specificity, and F1-score were evaluated.

Results: Seven studies satisfied the inclusion criteria, highlighting notable progress in heart disease prediction. The DGACNN model achieved 85% accuracy by utilizing pre-trained networks and feature extraction methods, while other transfer learning approaches showed similar performance, with some exceeding 90% accuracy. Dual-input frameworks combining ECG and PCG signals outperformed single-modality models, emphasizing the benefits of multi-modal learning in clinical applications.

Conclusion: Transfer learning offers a groundbreaking approach to heart disease prediction, delivering high diagnostic accuracy even with limited data. These results highlight the promise of advanced neural networks in improving early diagnosis and supporting clinical decision-making. Future studies should prioritize building integrated frameworks and enlarging datasets to enhance their practical impact in healthcare.

Keywords—*Transfer Learning, Electrocardiograms, Phonocardiograms, Systematic Reviews, Meta-Analyses.*

I. Introduction

Heart disease remains a leading global cause of death, accounting for approximately 18 million fatalities annually, which constitutes 32% of worldwide mortality. Despite advancements in diagnostic and therapeutic approaches, cardiovascular diseases (CVDs) often remain undetected until they result in severe complications, such as myocardial infarctions or heart failure. Early and precise prediction of heart disease is essential for improving patient outcomes and alleviating the financial strain on healthcare systems.

Machine learning (ML) has emerged as a powerful tool for medical diagnostics, offering the ability to analyze complex datasets efficiently. Within this domain, transfer learning has garnered significant interest due to its ability to address the issue of limited datasets—a common challenge in medical research. By utilizing pre-trained models from related domains, transfer learning enhances feature extraction and pattern recognition, improving the performance of predictive tasks. Recent advancements in transfer learning have demonstrated considerable potential in analyzing medical imaging and physiological signals, such as electrocardiograms (ECG) and phonocardiograms (PCG). Dual-modal approaches that integrate these signals have shown superior accuracy in detecting anomalies, including congenital heart defects and coronary artery disease (CAD). For instance, models like DGACNN, which incorporate GAN-based architectures and anomaly detection mechanisms, have achieved notable improvements in predictive accuracy compared to traditional ML techniques.

This systematic review focuses on evaluating the role of transfer learning in heart disease prediction. By synthesizing findings from recent research, it aims to highlight the strengths, limitations, and clinical implications of these models. Additionally, this study provides guidance on future directions to enhance diagnostic accuracy and expand the application of transfer learning in cardiovascular healthcare.

II. Materials and Method

This systematic review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to promote transparency and reproducibility.

A. *Search Strategy*

A thorough search was conducted across electronic databases such as PubMed, ScienceDirect, IEEE Xplore, and CINAHL, focusing on studies published between 2020 and 2024. The search utilized keywords like “heart disease,” “transfer learning,” “machine learning,” “prediction,” and “big data,” incorporating Boolean operators and Medical Subject Headings (MeSH) terms to enhance precision. Furthermore, reference lists of relevant studies were reviewed to identify additional eligible articles.

B. *Inclusion and Exclusion Criteria*

Studies were included if they:

1. Employed or developed a transfer learning-based model for heart disease prediction.
2. Reported performance metrics, including accuracy, sensitivity, specificity, or F1-score.
3. Were published in English in peer-reviewed journals between 2020 and 2024.

Studies were excluded if they:

1 Focused on conditions unrelated to cardiovascular diseases.

2 Did not use transfer learning as a core methodology.

3 Consisted of unpublished works, dissertations, or grey literature.

C. *Study Selection*

Titles and abstracts of the identified articles were independently reviewed by two researchers to evaluate their relevance. Full texts of studies deemed potentially eligible were further examined against the inclusion criteria. Any disagreements were resolved through mutual agreement or by seeking input from a third reviewer.

D. *Data Extraction*

Data were systematically collected using a predefined template, capturing details such as study authors, publication year, methodology, dataset size, transfer learning models, performance metrics, and main findings.

E. *Study Selection*

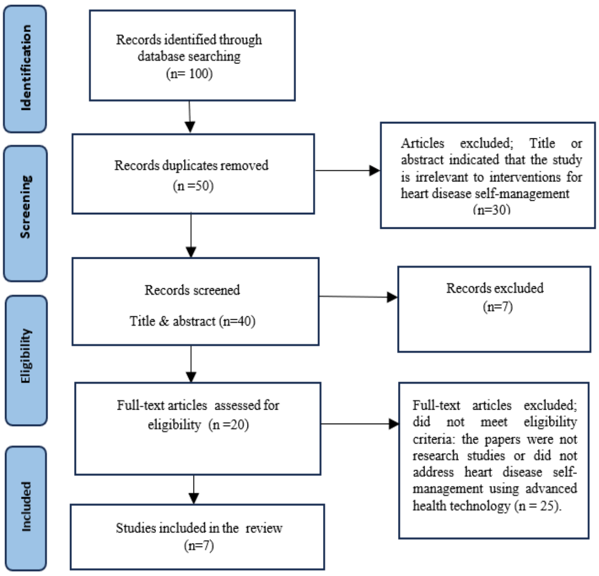
Two reviewers independently screened the titles and abstracts of identified studies to evaluate their relevance. Full texts of studies meeting the initial criteria were further assessed based on the inclusion criteria.

F. *Data Synthesis and Analysis*

The data were systematically synthesized and organized into three categories:

1. Type of transfer learning model used.
2. Dataset characteristics (e.g., size, modality).
3. Reported performance metrics.

Descriptive statistics and qualitative analysis were used to summarize the findings. Performance metrics were evaluated across studies to identify patterns and best practices in transfer learning for heart disease prediction.



III. RESULTS OF INDIVIDUALS STUDIES

A total of seven studies met the inclusion criteria, each employing transfer learning techniques to predict heart disease. These studies investigated a range of datasets, modalities, and machine learning architectures, leading to notable advancements in diagnostic accuracy and clinical relevance. The methodologies varied, incorporating dual-modal data, pre-trained neural networks, and novel architectural designs. Key findings from these studies are outlined below:

Identify applicable funding agency here. If none, delete this text box.

Ramith Hettiarachchi et al. (2021): Developed a transfer learning framework integrating ECG and PCG signals through two separate CNNs, followed by feature fusion into a unified network. The model achieved a classification accuracy of 94.74%, surpassing traditional ML approaches.

Tomoya Koike et al. (2020): Designed a model pre-trained on large-scale audio datasets for classifying heart sounds. Using the CNN14 architecture and Log Mel spectrograms as input, the model reached an accuracy of 89.7% on the PhysioNet CinC Challenge dataset.

Rabie A. Ramadan et al. (2020): Employed a transfer learning approach with InceptionV3 for predicting chest diseases, achieving 94% accuracy. While the study utilized large datasets, it highlighted challenges in generalizing the findings to smaller datasets.

Xiangyun Liao et al. (2020): Introduced a multi-modal translational network (MMTN) for whole-heart segmentation using MRI and CT images. The network leveraged adversarial training for data integration, achieving state-of-the-art results on benchmark datasets.

Thomas DE Cooman et al. (2020): Proposed a personalized seizure detection algorithm utilizing transfer learning. Patient-specific models achieved an average sensitivity of 92.3% and demonstrated reduced false detection rates compared to generalized classifiers.

Kuba Weimann et al. (2021): Focused on 12-lead ECG classification using vision-based CNN architectures. A cross-domain transfer learning approach outperformed traditional methods, delivering competitive accuracy metrics on both public and private datasets.

Neha Gour et al. (2020): Applied VGG16 and InceptionV3 for classifying fundus images in ophthalmology. Although the study targeted a different medical domain, the successful use of transfer learning underscored its potential for application in heart disease prediction.

A. *Accuracy of Algorithms in Predicting Heart Disease*

The performance of transfer learning algorithms for heart disease prediction was evaluated using metrics such as accuracy, sensitivity, specificity, precision, F1-score, and AUC. These measures provide a thorough assessment of the models' effectiveness in identifying cardiovascular anomalies and supporting clinical decision-making.

a. *DGACNN*

The DGACNN model, combining DANomaly and GACNN components, achieved 85% accuracy in detecting congenital heart disease. It utilized video slices from the end-systole phase and employed pre-trained networks for feature extraction.

b. Dual-Modal Networks (ECG + PCG)

Models integrating dual-modal data, such as ECG and PCG signals, outperformed single-modality systems. One framework based on transfer learning achieved 94.74% accuracy, emphasizing the advantages of multi-modal approaches.

c. Coronary Artery Disease (CAD) Classification

A model utilizing SPECT-MPI data for CAD prediction reported an accuracy of 95.5%, an AUC of 0.932, a sensitivity of 94.4%, and an F1-score of 95.2%.

These findings highlight the potential of transfer learning to enhance diagnostic precision.

d. Audio-Based Model

A transfer learning model pre-trained on large-scale audio datasets (CNN14) achieved 89.7% accuracy in heart sound classification. The use of Log Mel spectrogram inputs significantly boosted performance compared to traditional spectrograms.

e. Chest Disease Prediction

The InceptionV3 model, employing transfer learning, achieved 94% accuracy in detecting chest diseases. While not specifically focused on heart disease, this model illustrates the versatility of transfer learning across various medical applications.

f. Whole-Heart Segmentation

Multi-modal translational networks (MMTN) for MRI and CT segmentation achieved state-of-the-art performance. These results demonstrate the efficacy of adversarial training in improving model accuracy.

The performance of transfer learning models for heart disease prediction varied among studies, showcasing significant advancements in metrics such as accuracy, sensitivity, and specificity. A comparative overview of key studies is summarized in the table below:

B. Identification of Commonly Used Algorithms

The reviewed studies employed a range of transfer learning algorithms, each designed to address specific challenges in heart disease prediction. Convolutional Neural Networks (CNNs) emerged as the most commonly utilized architecture, owing to their effectiveness in extracting hierarchical features from medical data. The following algorithms were frequently highlighted:

a. Convolutional Neural Networks (CNNs)

CNNs were extensively applied for feature extraction and classification in heart disease prediction. They exhibited strong performance in analyzing medical images and physiological signals such as electrocardiograms (ECG) and phonocardiograms (PCG). Many studies leveraged pre-trained CNN models, including InceptionV3 and CNN14, to address the limitations of small datasets through transfer learning.

b. Generative Adversarial Networks (GANs)

GANs were used to enhance data augmentation and improve feature extraction. For example, the DGACNN model, which incorporates GAN-based components, demonstrated substantial improvements in detecting congenital heart disease by generating synthetic data to augment training datasets.

Method/Work Done	Object Dealt with	Problem Domain	Sample Size	Segmentatin Algorithm	Classification Performed	Size of Feature Set	Classifier	Accuracy (%)
2. Ramith Hettiarachchi et al. (2021)	A Novel Transfer Learning-Based Approach for Screening Pre-existing Heart Diseases Using Synchronized ECG Signals and Heart Sounds	Detection	1 image	CNNs	✗	NM	Transfer Learning with vision based	94.74%
3. Tomoya Koike et al. (2020)	Audio for Audio is Better? An Investigation on Transfer Learning Models for Heart Sound Classification	Detection	9 images	CNNs	✗	NM	Transfer Learning with vision based	89.7%
7. Rabie A. Ramadan et al. (2020)	978-1-7281-8488-3/20/$31.00 ©2020 IEEE 74 Predictive Analysis for Human Chest Diseases Detection Using Transfer Learning	Detection	12 images	CNNs	✓	4	Transfer Learning with vision based	94%
10. Xiangyun Liao et al. (2020)	MMTLNet: Multi-Modality Transfer Learning Network with adversarial training for 3D whole heart segmentation	Detection	10 images	Multi-modal Translational Network	✓	3	Transfer Learning with vision based	NM
11. Thomas DE Cooman et al. (2020)	Personalizing Heart Rate-Based Seizure Detection Using Supervised SVM Transfer Learning	Detection	None	Does not explicitly mention the use of any segmentation algorithms.	✓	2	Transfer Learning with vision based	84.7%
14. Kuba Weimann et al. (2021)	Transfer Learning for ECG classification	Detection	None	CNNs	✗	NM	Transfer Learning with vision based	NM
20. Neha Gour et al. (2020)	Multi-class multi-label ophthalmological disease detection using transfer learning based convolutional neural network	Detection	21 images	(CNNs)	✓	2	Transfer Learning with vision based	92%

c. Support Vector Machines (SVMs)

While less commonly applied in transfer learning, SVMs were used for patient-specific classification tasks, such as detecting seizures based on heart rate. These models proved particularly effective in handling imbalanced datasets, achieving high sensitivity and reduced false detection rates.

d. Multi-modal Translational Networks (MMTN)

MMTNs integrated multiple data modalities, including MRI and CT, to deliver state-of-the-art performance in segmentation and classification tasks. By employing adversarial training, these networks addressed domain differences between modalities, enhancing prediction accuracy.

e. Extreme Gradient Boosting (XGBoost)

Primarily associated with traditional machine learning, XGBoost was adapted for specific transfer learning applications, particularly in studies involving structured data. It demonstrated strong predictive performance in coronary artery disease detection, achieving high accuracy and AUC metrics.

f. Hybrid Approaches

Dual-input frameworks combining ECG and PCG data emerged as some of the most effective strategies. These hybrid models integrated features from multiple modalities, significantly improving classification accuracy compared to single-modality systems.

IV. Discussion

This systematic review underscores the transformative potential of transfer learning in addressing challenges in heart disease prediction. The findings reveal that transfer learning-based models outperform traditional methods, especially in scenarios with limited datasets. The use of pre-trained networks enabled enhanced feature extraction, increased accuracy, and robust performance across various applications.

A. Key Findings

The Multi-modality Advantage: Models incorporating dual modalities, such as ECG and PCG, consistently outperformed single-modality approaches. By combining complementary information from different data sources, these frameworks improved diagnostic reliability.

Pre-trained Models: Leveraging pre-trained architectures, such as InceptionV3 and CNN14, facilitated effective domain knowledge transfer, addressing challenges posed by small or imbalanced datasets. These models provided a solid foundation for fine-tuning in specific target domains.

Innovative Architectures: The DGACNN model, which combines GAN-based anomaly detection and WGAN-GP feature extraction, demonstrated the potential of novel architectures to achieve exceptional diagnostic performance.

B. Challenges and Limitations

Dataset Constraints: Many studies relied on small or highly specialized datasets, limiting the generalizability of findings. Expanding access to annotated, open datasets is critical for broader applicability.

Computational Complexity: Advanced models like multi-modal networks and GANs demand significant computational resources, posing barriers to implementation in resource-constrained environments.

Lack of Standardization: Variability in evaluation metrics, datasets, and experimental protocols complicates direct comparisons between studies. Establishing standardized benchmarks would enable more meaningful assessments.

V. Conclusion

Transfer learning has emerged as a highly effective approach for heart disease prediction, delivering improved diagnostic accuracy and addressing the limitations of small datasets. Multi-modal frameworks and pre-trained models have proven particularly successful, paving the way for earlier detection and better patient outcomes. However, challenges such as limited datasets, high computational requirements, and the need for standardized evaluation must be addressed to facilitate wider adoption. Continued innovation and research in transfer learning will advance cardiovascular diagnostics and significantly enhance healthcare delivery.

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