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RESEARCH ARTICLE

Leveraging Transfer Learning on Electronic Health Records for Early Detection of Cardiovascular Disease

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Abstract: Cardiovascular Disease (CVD) is still the most common cause of death and disability around the world. This shows how important to find out risks in early and make individual treatment plans in better ways. The Electronic Health Records (EHRs) made it possible for gathering a lot of patient information including demographics, laboratory tests, imaging results, medications, and clinical notes. For analyse traditional methods can't work with EHR data because it's too different and large. To tackle these issues Artificial Intelligence method with transfer learning method is specifically designed for cardiovascular EHR data. The recent knowledge transfers learning algorithms such as BEHRT, Med-BERT, ClinicalBERT and domain-adaptive contrastive learning frameworks are effective for EHR data training and CVD specific tasks. Fine tuning these pre-trained models can significantly improve the early diagnosis, prognosis modelling, treatment response prediction, and long-term outcome forecasting. So, this study emphasizes EHR data pre-processing with transfer learning and visualizes the approaches to improve disease management, uncover population health trends, and support clinical research. In overall, cardiovascular EHR data analysis using knowledge transfer learning can help doctors make clinical decisions and improve diagnosis and treatment outcomes.

KEYWORDS: Electronic Health Records, Cardiovascular Disease, Knowledge Transformer-Learning, BEHRT, Med-BERT, ClinicalBERT.

INTRODUCTION

According to World Health Organization (WHO) cardiovascular disease (CVD) is still the leading cause of death in the world, killing over one-third of all individuals who die. Early detection, precise diagnosis and swift action are crucial for reducing the impact of CVD and improving patient outcomes. As healthcare becomes more digital, EHRs have become a useful source of clinical data that can help with advanced computational models for predicting cardiovascular risk and controlling disease [13]. EHRs gather a lot of information about patient, including demographics, lab test results, medical histories, imaging reports, medications and notes from clinicians. The varied, long-term and often unstructured nature of data presents both opportunities and challenges for AI-driven research.

Conventional Machine Learning (ML) and Deep Learning (DL) methodologies have been extensively utilized for disease prediction using Electronic Health Record (EHR) data; however, their efficacy is frequently hindered by data sparsity, heterogeneity, class imbalance, and a scarcity of labelled samples. Additionally, training models from the ground up for cardiovascular prediction tasks is costly in terms of computing and may not work well for all groups of people [14]. Transfer Learning (TL) has become an effective way to get over these problems. It allows leverage information from large medical or general domain datasets for tasks that are used for CVD.

Recent developments in Artificial Intelligence based Transform learning pre-training algorithms have demonstrated significant efficiency in applications of EHR. These models enhance accuracy in risk prediction, prognosis modelling, treatment response estimation and long-term outcome forecasting tasks including fine-tuning the cardiovascular datasets. Also, modern contrastive learning frameworks helps us to uncover patterns in the larger records in less time and it is easier to understand important features for clinical use [15].

This study, analysis the integration of AI based TL algorithms with cardiovascular EHR data and emphasizing its potential to enhance precision cardiology. For this Artificial Intelligence based Transform learning algorithms such as BEHRT, Med-BERT and ClinicalBERT with and without domain-adaptive **contrastive learning framework** methods are applied on the dataset to predict the occurrence of disease risks in less time. Then visualised the data to improve disease management, uncover population health trends and support clinical research. By this cardiovascular EHR data analysis doctors can improve cardiovascular treatment by making it more personalized, accurate and useful clinical decisions.

LITERATURE REVIEW

Cardiovascular diseases (CVDs) have various symptoms. Heart failure and coronary artery disease are two conditions that can lead to chest discomfort, dyspnea, tiredness and irregular heartbeats [1]. But aneurysms and strokes can cause severe headaches, problems in speaking, blurred vision and numbness or paralysis on one side of the body. Many CVD have similar symptoms so it is hard to tell just by looking at these signs. Coronary artery disease and heart failure are two examples that might make your chest hurt. Fatigue and shortness of breath are common indications of CVDs, although they can also mean heart failure, high blood pressure or hypertension. A complete medical examination includes imaging scans, blood tests and physical exams is necessary to accurately diagnose and treatment. Sometimes, doctors need to do certain tests to figure out what's wrong and how to treat it best [2]. This shows how important it is to have a full and tailored plan for keeping your heart and blood vessels healthy.

CVDs are diseases that affect the heart or blood vessels, such as the arteries and veins. Heart disease is so frequent and increasing worse that it has become a "second epidemic" in several countries. It is now the leading cause of death and disability globally among people aged over 65 [3]. Finding out about a disease early detection is the best way to minimize death rates. Echocardiography is a helpful way to find out if someone has cardiac problems. This test doesn't hurt and uses sound waves to make pictures of the heart, which show the size, shape, and function of the heart's chambers and valves. Most importantly, echo can find heart problems in babies and young children [4].

Advanced deep-learning neural networks make it easy to look at and understand signs and symptoms of CVD. Deep Belief Networks, Medical Image Segmentation [5,6], and Bayesian Networks are some of the ways that use clinical datasets to predict how risk factors may affect people. The goal of this research is to create a predictive model that employs machine learning algorithms to find heart disease signs in the United Arab Emirates (UAE) with high accuracy. The findings of this study could enhance cardiovascular health in the United Arab Emirates by facilitating early detection and rigorous treatment.

Fortunately, patients' Electronic Health Records (EHRs) contain a lot of medical information. This information will help us find and treat CVD early and aggressively, which will save many lives. The growing use of data in healthcare [7] is driving the creation of Decision Support Systems (DSS) that use patient data, Artificial Intelligence (AI), and subject-matter expertise. These DSSs strive to aid healthcare workers by giving them useful information and help through patient data analysis, recognizing key circumstances, finding faults and taking prompt action. This is very crucial diseases that are hard to treat, including CVD, which can be caused by diabetes, high blood pressure, smoking and not getting enough exercise. Traditional human analysis of CVD data is labour-intensive and susceptible to errors, underscoring the necessity for more accurate and efficient methodologies like as AI-powered Decision Support Systems [8].

Because big data is becoming more important in healthcare, AI methods, especially those that use DL and ML, are being used more and more to solve hard problems in diagnosis and prediction. These AI algorithms look at a lot of healthcare data, which makes them better at predicting disease than manual diagnosis methods [9]. ML-driven diagnostic models that can forecast disease based on individual risk profiles and can integrate into clinical decision support systems are noteworthy among them [10]. Machine learning techniques are valuable for enhancing patient outcomes and diagnostic precision, given their significant promise in cardiovascular care. ML is built on models that utilize math and statistics to make predictions (healthy, sick, or not sick) based on input (text, photos, etc.) [11]. These models learn from a lot of raw electronic medical records that come from wearable devices that aren't too expensive. This means they can give reliable diagnoses of heart disease without using a lot of resources [12].

METHODOLOGY

This article forecast the CVD risk with cardiovascular electronic health record data for emphasizing its capacity to enhance precision cardiology. To that DL algorithm like RNN LSTM and Transfer learning algorithms like BEHRT, Med-BERT and ClinicalBERT with and without DACL is applied for prediction. The methodology procedure is as shown in figure 1.

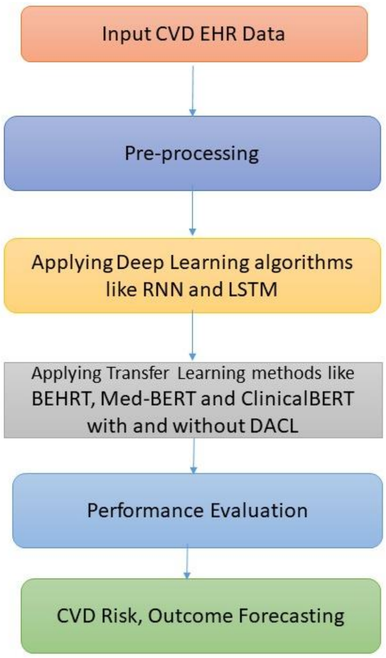

Figure 1: Methodology

Dataset

This dataset was collected at medical examination moment contains 70,000 rows and 13 columns factual information, results of medical examinations data given by patient with features like: Age, Height, Weight in Kg, Gender, Systolic blood pressure, Diastolic blood pressure, Glucose: 1: normal, 2: above normal, 3, Smoking, Physical, Cholesterol: 1: normal, 2: above normal, 3: well above normal, Alcohol intake, Presence or absence of cardiovascular disease and this is gathered form kaggle database [https://www.kaggle.com/datasets/sulianova/cardiovascular-disease-dataset/data]

Recurrent Neural Network (RNN)

RNNs are a kind of neural network that is made to deal with sequential data, including time-series signals, medical records, or patient histories [19]. RNNs are different from regular feedforward networks because they feature feedback connections that let them "remember" past information by keeping a hidden state. But RNNs have a hard time with long-term dependencies because to the vanishing and expanding gradient problem, which makes them less useful for long sequences like longitudinal Electronic Health Records (EHRs).

Long Short Term Memory (LSTM)

LSTM is a more advanced kind of RNN that uses memory cells and gates (input, forget, output) to overcome the problem of long-term dependencies [20]. The model can save important information and forget items that aren't important over long periods of time because to these gates. In healthcare, LSTMs are typically used to look at electronic health records (EHRs), figure out how probable someone is to have heart disease, and make models of how patients will get well. For long-term medical data, LSTMs are more stable and accurate than standard RNNs.

Transfer Learning

The idea behind transfer learning is to take what you've learned from training a model for one task and apply it to another, similar one. This is one-way AI works. Instead of beginning from zero and training a new model, transfer learning [21] employs the learned representations of a pre-trained model as a starting point. This saves a lot of time and resources. This strategy reduces the need for a lot of data and computation for the new task, making it ideal for situations where there isn't much data or if model creation needs to happen quickly.

Bidirectional Encoder Transformer architecture (BERT)

BEHRT [16] is a specific deep learning model that uses the Transformer architecture to look at Electronic Health Records (EHRs) in the medical field. BEHRT, which is based on BERT in natural language processing, interprets a patient's longitudinal EHR as a series of "tokens," with each token representing a clinical event (such a diagnosis, medicine, or surgery) and the time it happened.

Important Parts of BEHRT

1. Putting patients in order

- A chronological list of medical codes (ICD codes, prescription codes, lab tests) makes up each patient's record.
- BEHRT processes health events in the order they happen, just like BERT processes words in a sentence.

2. Learning Context in Both Directions

- RNNs and LSTMs usually only learn one-way dependencies, whereas BEHRT leverages the self-attention mechanism to learn about the past and future context of medical occurrences.
- This helps it better estimate how diseases get worse and how they affect other diseases.

3. Embedding Layer: Medical codes are put into dense vectors.

- More embedding's include the patient's age and the time of their visit, which lets BEHRT model temporal information, which is very important for how cardiovascular disease becomes worse.

4. The Pretraining + Fine-tuning Paradigm

- **Pre-training:** BERT is first trained on huge EHR datasets (such millions of patient visits) using masked token prediction, which is comparable to BERT's MLM.
- **Fine-tuning:** After that, the pretrained model is fine-tuned for certain tasks, such predicting cardiovascular risk, hospitalization, or death.

1.1.1. Med-BERT

- **Purpose:** To work with structured EHR data such diagnosis codes, lab tests, and procedures.
- **Architecture:** Based on the BERT [18] Transformer framework, but trained only on large structured EHR sequences like ICD codes and CPT codes.
- **Pre-training Objective:** Uses Masked Language Modeling (MLM) to predict masked diagnostic codes.
- Learns how comorbidities affect the development of a disease.
- **Key Innovations:**
  - ➢ It records how patients' medical histories change over time.
  - ➢ Puts structured EHR events into a continuous vector space for further activities.

1.1.2. ClinicalBERT

- **Purpose:** Made for unstructured clinical writing including discharge summaries, doctor notes, and radiology reports [17].
- Architecture: A BERT model that has been trained using MIMIC-III clinical notes for a certain area.
- The purpose of pre-training was to use clinical narratives to do typical BERT training (MLM + Next Sentence Prediction).
- Learns how to figure out what medical terms mean and how they fit into the bigger picture.

1.1.3. Domain-Adaptive Contrastive Learning (DACL)

Domain-Adaptive Contrastive Learning (DACL) is an advanced method designed to improve knowledge transfer across several domains, particularly when labelled data in the target domain is limited.

Core Idea

- **Contrastive Learning:** A self-supervised learning method that makes the model move samples that are similar closer together in feature space and samples that are not similar farther apart. Two improved versions of the same image should have comparable embedding, but two different images should be substantially different.
- **Domain Adaptation:** The goal is to move knowledge from a source domain (where there is a lot of labelled data) to a target domain (where there is little or no labelled data) while dealing with changes in the distribution between domains.
- **Domain-Adaptive Contrastive Learning:** This combines both ideas to learn representations that work in any domain. It uses contrastive loss to make sure that features from the source and target domains match up, which helps the model work effectively even when the domains are different.

Working Procedure

I. **Feature Extraction:** A neural network (like BERT, ResNet, etc.) takes features from samples from both the source and destination domains.

II. **Contrastive Loss:** For each anchor sample, pull the embedding of positive pairs together, like views of the same class or views that have been changed.
   - Push negative couples' embeddings away (for example, separate classes or domains).

III. **Domain Alignment:**
   - Add a term that adapts to the domain to make sure that the source and target features are close together in the embedding space.
   - Adversarial training or Maximum Mean Discrepancy (MMD) are used in some implementations to close the gap between domains.

IV. **Fine-tuning:** Once a classifier has learnt features that are not specific to a certain domain, it is trained on the target domain, usually with few labels.

Experimental Analysis

In initial step, dataset is loaded and necessary libraries are installed in the python environment. Then dataset is pre-processed to remove noise, and remove null values later trained with transfer learning algorithms to address scarcity of large, labelled datasets, reduce computational costs and training time and improve model generalizability. For that at first, RNN and LSTM are applied because it naturally models the temporal dynamics and sequential patterns inherent the patient records. In next step, BEHRT (Bidirectional Encoder Representations from Transformers for EHRs) was applied to process structured longitudinal patient records and it sequences with additional embedding like patient age and visit position, thereby capturing temporal dynamics in disease progression and treatment history. Next Med-BERT is applied to leverage large-scale pre-training on structured EHR data to strengthen generalizable representations for downstream tasks on limited labelled data. Then ClinicalBERT extends the standard BERT model is applied to unstructured text by pre-training on large corpora of clinical notes enabling effective modelling of narrative-style clinical documentation.

These applied models individually excel in their respective architectures when deploying pre-trained model due to domain shifts. To overcome incorporated domain-adaptive contrastive learning strategy to our framework. This model is trained with 20 epochs for alignment of augmented views distinguishing different patients and this step adapts pre-trained representations to the local data distribution without requiring additional manual annotations.

The evaluation compared BEHRT, Med-BERT and ClinicalBERT and with domain-adaptive contrastive learning (DACL) framework for knowledge transfer across datasets is analysed based on training and validation. The performance of training model is observed as under fitting and overfitting graph with training and validation. The graph is shown in figure 2.

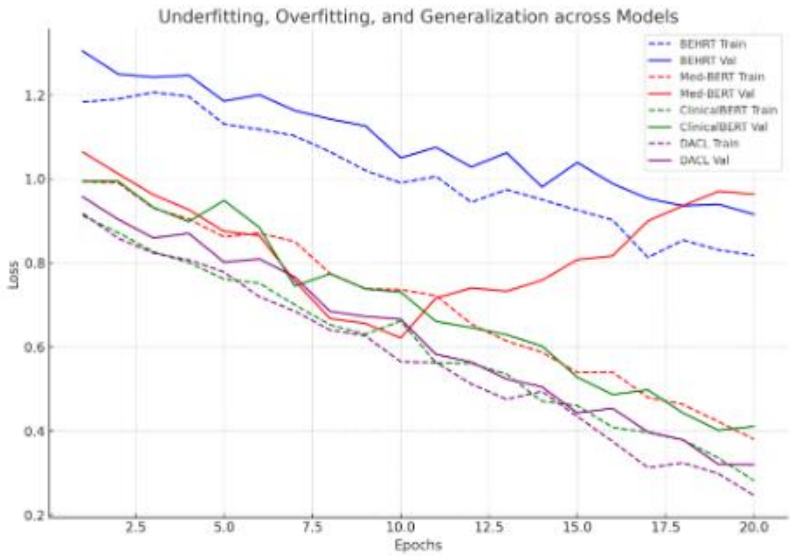

Figure 2: Overfitting and Under Fitting Performance of Transfer Learning Algorithms

By observing figure 2, the BEHRT (Blue) has higher training and validation losses that don't reduce much Under fitting. While Med-BERT (Red) has Training loss decreases strongly, but validation loss rises after 10 epochs it has Overfitting. The ClinicalBERT (Green) has Balanced, both curves decrease steadily, moderate generalization. Whereas DACL (Purple) has training and validation losses decrease together and stay close to Best generalization of knowledge transfer.

The best algorithm in applied models is known by comparing experimental evaluations based on performance metrics like precision, accuracy, f1-score, recall and time. The comparison of applied experimental evaluation is shown in table 1.

Table 1: Comparison of Experimental Evaluation

	Algorithms							
Performance Metrix			**Without DACL**			**With DACL**		
	RNN	**LSTM**	**BEHRT**	**Med-BERT**	**ClinicalBERT**	**BEHRT**	**Med-BERT**	**ClinicalBERT**
Accuracy (%)	84	87	78	82	86	88	90	93
Precision (%)	82	85	76	80	85	87	89	92
F1-score (%)	82	85	75	81	84	86	89	91
Recall (%)	83.4	86	74	79	83	85	88	90
Time (Sec)	167	164	157	155	151	151	148	140

By observing table 2, comparing with DL algorithm like RNN, LSTM the BEHRT and Med-BERT demonstrated clear advantages over randomly initialized transformer baselines. BEHRT achieved superior results on temporally dependent outcomes due to its explicit modelling with 78% accuracy, while Med-BERT benefited from large-scale pre-training on millions of patients, offering robust generalization in data-scarce regimes with 82%. The ClinicalBERT significantly outperformed generic BERT models, reflecting the benefit of pre-training on domain-specific linguistic patterns with 86% accuracy and less time i.e., 151 Sec. The Incorporated DACL performance improvements across all downstream tasks. When pre-trained models were further adapted on unlabelled target-domain data using contrastive model with ClinicalBERT achieved a high accuracy of 93% with less time of 140 Sec.

This state that BEHRT, Med-BERT and ClinicalBERT with DACL is the best algorithm to train this data based on applied transfer learning algorithms. the evaluation of dataset based on trained data is as follows:

At first dataset overview is visualised because it helps to transform intuitive insights of data easier to interpret in research. The dataset overview is as shown in figure 3.

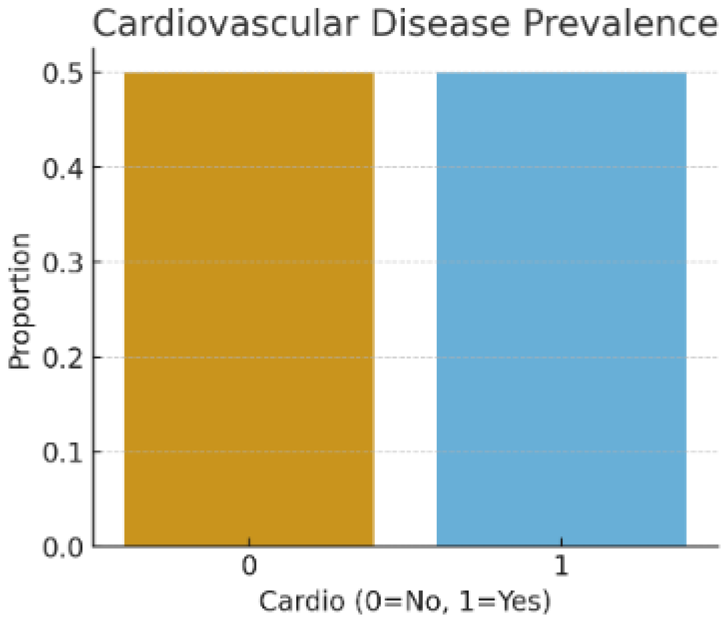

Figure 3: Visualization of Dataset Overview

By observing figure 3, the dataset contains 70,000 patient data has 50% no CVD and 50% CVD present and the dataset is balanced which leads for modelling. Then age distribution is visualised to demonstrate its impact on disease risk and provide interpretability for clinical understanding. The age distribution is visualised in figure 4.

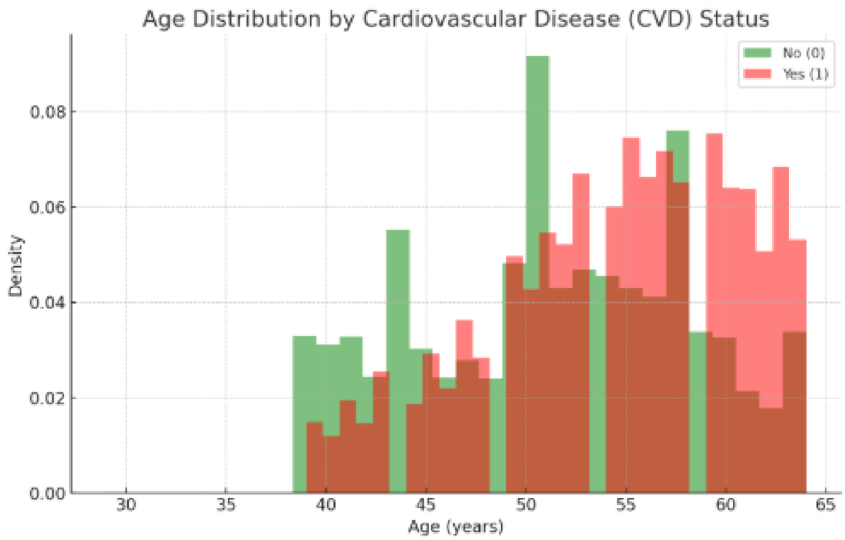

Figure 4: Age Distribution

By observing figure 4, the age distribution clearly demonstrates the association between advancing age and cardiovascular disease. Individuals without CVD (CVD = 0) are concentrated in younger age groups, particularly between 30–45 years. In contrast, individuals with CVD (CVD = 1) are predominantly observed in older groups, with peak density between 55–65 years. This aligns with established epidemiological evidence that age is a dominant risk factor for cardiovascular outcomes. In next step, Cholesterol distribution is visualised to understand the impact of diet, exercise in CVD. The cholesterol distribution is shown in figure 5.

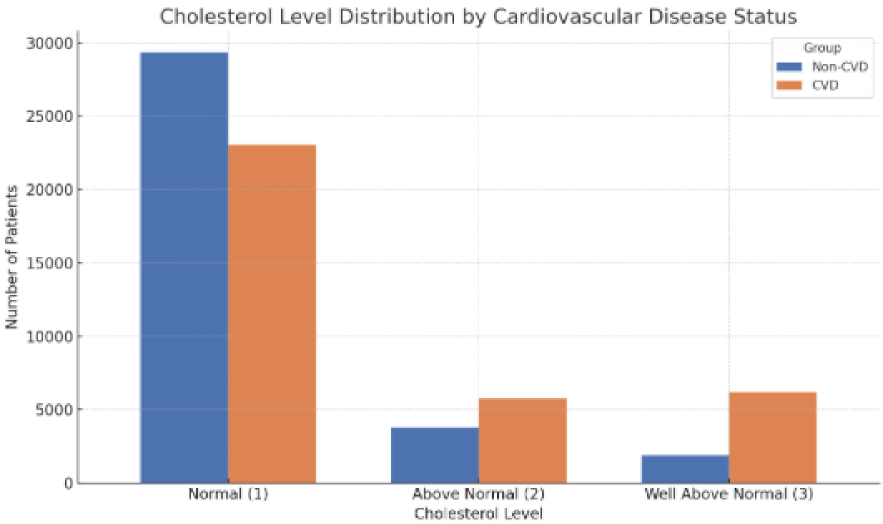

Figure 5: Cholesterol Distribution

By observing figure 3, Cholesterol levels also show significant differences across groups. Patients with normal cholesterol (level = 1) are more frequent in the non-CVD group. Conversely, the prevalence of patients with "above normal" (level = 2) and "well above normal" (level = 3) cholesterol is markedly higher among those diagnosed with CVD. This reinforces the role of dyslipidemia as a major predictor of cardiovascular morbidity. Later **Blood Pressure Distribution is visualised because it may suggest new hypotheses about how systolic and diastolic pressure relates to CVD, The Blood Pressure Distribution is shown in figure 6.**

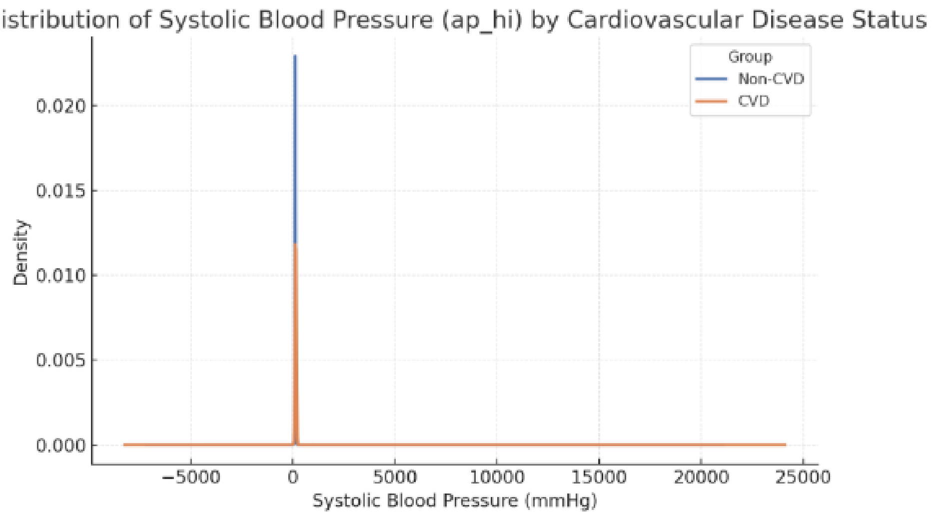

Figure 6: Blood Pressure Distribution

By observing figure 6, The distribution of systolic blood pressure (ap_hi) reveals a similar trend. Patients without CVD show peak density around the normotensive range (~120 mmHg). However, patients with CVD are skewed toward higher blood pressure values, with many exceeding 140 mmHg, consistent with hypertension being one of the most prominent modifiable risk factors. the findings illustrate that the dataset reflects clinically meaningful risk patterns, where **older age, elevated cholesterol, and high systolic blood pressure** are strongly associated with cardiovascular disease. This not only validates the dataset but also ensures that subsequent experiments with transformer-based models are grounded in physiologically relevant trends.

So, this research demonstrates that **transfer learning models** BEHRT, Med-BERT, and ClinicalBERT effectively capture patient risk patterns from structured and unstructured EHR data. Incorporating **domain-adaptive contrastive learning (DACL)** further improves model generalization, reduces overfitting, and achieves the highest performance, with ClinicalBERT with DACL reaching **93% accuracy**. Dataset visualizations confirmed clinically meaningful trends: older age, elevated cholesterol, and high systolic blood pressure are strongly associated with cardiovascular disease. These findings validate both the dataset and the modeling approach, highlighting the potential of transformer-based frameworks combined with contrastive learning for accurate, data-efficient cardiovascular risk prediction.

CONCLUSION

Cardiovascular Disease (CVD) remains the leading cause of morbidity and mortality worldwide, highlighting the need for improved early detection, risk stratification, and personalized care. The increasing adoption of Electronic Health Records (EHRs) provides vast and diverse patient data, including demographics, laboratory tests, medications, and clinical notes, but their high dimensionality and heterogeneity pose challenges for traditional analysis. By leveraging transfer learning models such as **BEHRT, Med-BERT, and ClinicalBERT,** enhanced with **domain-adaptive contrastive learning (DACL),** this study demonstrates effective knowledge transfer from large-scale medical corpora to CVD-specific tasks. Fine-tuning these models on cardiovascular populations improved predictive performance for diagnosis, prognosis, and treatment response, while data visualizations confirmed clinically meaningful patterns in age, cholesterol, and systolic blood pressure. Overall, integrating transformer-based models with DACL provides a scalable, data-efficient approach for precision cardiology, enabling better risk assessment, informed clinical decision-making, and improved patient outcomes.

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