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A Hybrid Deep Learning Framework for Early Cardiovascular Disease Prediction: SDCN-CHDMO-ResVGG Approach

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ABSTRACT
Being a major cause of morbidity and mortality, cardiovascular diseases (CVDs) require precise predictive models for early detection. This work suggests a deep learning-based method to improve diagnostic performance by combining feature selection, classification, and optimization. Chaotic Dwarf Mongoose Optimization (CH-DMO) selects optimal features, while Self-Attention Assisted Dense Capsule Network (SDCN) ensures robust feature extraction. Harris Whale Residual VGG Network (ResVGG) improves classification accuracy using residual learning, with M-Square normalization enhancing feature homogeneity. Experimental results on benchmark CVD datasets show superior classification accuracy, lower computational complexity, and improved generalization over existing methods. The findings highlight the model's potential to assist healthcare professionals in early CVD detection, improving clinical decision-making and patient outcomes.
Keywords: *Cardiovascular Disease, Deep Learning, capsule network, normalization, early detection*

1. INTRODUCTION

Since they cause a large amount of morbidity and mortality globally, cardiovascular diseases (CVDs) continue to rank among the most important global health concerns. The burden of CVDs has increased due to the rising prevalence of risk factors such obesity, diabetes, hypertension, and sedentary lifestyles; hence, early identification and intervention are essential to lessening their effects. However, accurate and timely CVD prediction is severely hampered by the complexity and variability of clinical data as well as the shortcomings of conventional diagnostic techniques. Medical diagnostics has seen a radical change with the introduction of machine learning (ML) and deep learning (DL) techniques, which present previously unheard-of chances to examine intricate datasets and find hidden patterns that traditional approaches could miss. However, despite their potential, existing ML and DL models for CVD prediction often face several limitations, including high dimensionality of clinical data, imbalanced datasets, and the inability to capture intricate relationships between features. These challenges underscore the need for more robust, efficient, and generalizable predictive models that can address these limitations and provide reliable support for clinical decision-making.

The high dimensionality of clinical data, which frequently include a wide variety of variables such demographic data, medical history, laboratory results, and lifestyle factors, is one of the main obstacles in CVD prediction. Even though these characteristics offer important information about a patient's health, not all of them make an equivalent contribution to the prediction task. Model performance can be lowered, computational complexity raised, and noise introduced by redundant or unnecessary features. Therefore, feature selection is essential for determining the most pertinent features and lowering dimensionality without sacrificing diagnostic precision. In CVD prediction, conventional feature selection techniques including filter-based and wrapper-based methods have been extensively employed.

Another critical challenge in CVD prediction is the extraction of meaningful and discriminative features from clinical data. The non-linear correlations present in clinical data may be missed by conventional feature extraction techniques that rely on linear transformations, such as principal component analysis (PCA) and linear discriminant analysis (LDA). In order to overcome this difficulty, deep learning models—in particular, convolutional neural networks (CNNs) and capsule networks—have demonstrated considerable potential by automatically learning hierarchical data representations. A unique deep learning-based framework for CVD prediction that incorporates sophisticated feature selection, feature extraction, and classification algorithms is proposed in this paper to solve these issues. Through the use of self-attention mechanisms and capsule networks, the suggested framework uses a Self-Attention Assisted Dense Capsule Network (SDCN) for robust feature extraction, focusing on the most pertinent features and capturing spatial hierarchies.

2. LITERATURE REVIEW

Deep Learning for CVD Prediction

Because deep learning algorithms can automatically extract characteristics from raw data, they have demonstrated exceptional performance in medical diagnosis. Using recurrent neural networks (RNNs) to capture temporal relationships in patient data, Alaa et al.

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(2019) developed a deep learning model for CVD risk prediction using electronic health records (EHRs) that achieved state-of-the-art performance [1]. Similarly, by learning hierarchical representations from EHRs, Miotto et al. (2018) created a deep patient representation learning framework that showed exceptional performance in predicting a variety of illnesses, including CVDs [2].

Feature Selection Techniques

Selecting features is essential to enhancing the interpretability and performance of the model. For CVD prediction, Shankar et al. (2020) suggested a hybrid feature selection technique that combines filter and wrapper techniques, resulting in a notable decrease in dimensionality while preserving good accuracy [3]. In a different research, Li et al. (2021) presented a feature selection method based on genetic algorithms that performed better than conventional approaches in locating pertinent characteristics for the categorization of CVD [4].

Capsule Networks in Medical Diagnostics

Capsule networks have gained attention for their ability to capture spatial hierarchies in data. Lal et al. (2021) applied capsule networks for heart disease prediction, demonstrating their superiority over traditional CNNs in handling complex feature relationships [5]. Similarly, Rajpurkar et al. (2022) explored the use of capsule networks for ECG-based CVD diagnosis, achieving robust performance in detecting arrhythmias and other cardiac abnormalities [6].

Attention Mechanisms

Attention mechanisms have been widely adopted to improve feature representation in deep learning models. Wang et al. (2021) proposed a self-attention-based neural network for CVD prediction, which outperformed conventional models by focusing on the most relevant features in clinical data [7]. Another study by Zhang et al. (2022) integrated attention mechanisms with CNNs for CVD risk stratification, achieving improved accuracy and interpretability [8].

Particle Swam Optimization Algorithms

Algorithms for optimization are essential for improving model performance. A modified particle swarm optimization (PSO) approach was presented by Gupta et al. (2021) for feature selection in CVD prediction, and it was shown to be successful in lowering dimensionality and enhancing classification accuracy [9]. For CVD risk prediction, Kumar et al. (2022) suggested a hybrid optimization approach that combines PSO and genetic algorithms, which performed better than stand-alone techniques [10].

Residual Learning in Deep Networks

In order to solve the vanishing gradient issue and enhance model performance, residual learning has gained widespread acceptance. By using skip connections to improve feature reuse, He et al. (2020)'s residual network-based model for CVD prediction reached state-of-the-art performance [11]. Chen et al. (2021) combined CNNs with residual learning for ECG-based CVD diagnosis, showing increased generality and accuracy [12].

Normalization Techniques

In order to improve model convergence and guarantee feature homogeneity, normalization is necessary. The effectiveness of deep learning models in CVD prediction was much enhanced by Singh et al.'s (2021) innovative normalization method for clinical data [13]. In a similar vein, Patel et al. (2022) developed a hybrid normalization strategy that included z-score and min-max normalization, which demonstrated strong performance while managing diverse clinical data [14].

3. PROPOSED METHODOLOGY

The proposed method for cardiovascular disease (CVD) prediction is a comprehensive framework that integrates advanced deep learning techniques, optimization algorithms, and normalization methods to achieve high accuracy, efficiency, and generalizability.

Data Pre-processing and Normalization

Clinical datasets often contain heterogeneous features with varying scales and distributions, which can negatively impact the performance of deep learning models. To address this, the proposed framework employs M-Square Normalization, a novel normalization technique that scales all features to a consistent range while preserving their relative importance. This step ensures that the model converges faster and performs more robustly during training. The normalized data is then passed to the next stage for feature extraction.

For a given feature vector X = [x1, x2, …, xn] the normalized factor $\hat{x}_i$ is computed as in Eq. 1

$$\hat{x}_i = \frac{x_i - \mu_X}{\sigma^2{}_X + \epsilon} \quad (1)$$

where:

- μ_X is the mean of the feature vector *X*,
- $\sigma^2{}_X$ is the variance of the feature vector *X*,
- ϵ, Which is a constant to make non zero division.

By ensuring that all features are scaled to a comparable range, this normalization enhances the deep learning model's stability and convergence.

Feature Extraction Using Self-Attention Assisted Dense Capsule Network (SDCN)

The next stage involves extracting meaningful and discriminative features from the normalized data. The intricate, non-linear correlations included in clinical data are frequently difficult for traditional feature extraction techniques to capture. The suggested framework makes use of a Self-Attention Assisted Dense Capsule Network (SDCN) to get around this restriction. To accomplish robust feature extraction, the SDCN combines the advantages of self-attention mechanisms and capsule networks.

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Capsule networks are ideal for medical diagnostics because of their exceptional ability to capture spatial hierarchies and correlations between features. A high-dimensional feature representation that minimizes noise and redundancy while preserving important diagnostic information is the SDCN's output. The following dynamic routing technique is used to calculate a capsule's output, v_j as in Eq.2:

$$v_j = \frac{||s_j||^2}{1+||s_j||^2} \cdot \frac{s_j}{||s_j||} \quad (2)$$

Where s_j is the weighted sum of predictions from lower-level capsules as in Eq.3:

$$s_j = \sum_i c_{ij} \cdot \hat{u}_{j|i} \quad (3)$$

Here:

- c_{ij} is the coupling coefficient determined by the dynamic routing algorithm,
- $\hat{u}_{j|i}$ is the prediction vector from capsule ii to capsule j.

Self Attention Mechanism

α_{ij} are the attention weights as in Eq.4 that are computed for each feature in self attention mechanism:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_k \exp(e_{ik})} \quad (4)$$

Where e_{ij} as in Eq.5 is the attention scores between is features i and j:

$$e_{ij} = \frac{(W_Q x_i)^T (W_K x_j)}{\sqrt{d_k}} \quad (5)$$

Here:

- W_Q and W_K are learnable weight matrices for queries and keys,
- d_k is the dimensionality of the keys.

The output of the self-attention mechanism is a weighted sum of the input features as in Eq.6:

$$z_i = \sum_i \alpha_{ij} \cdot (W_V x_j) \quad (6)$$

where W_V is a learnable weight matrix for values.

SDCN Architecture:

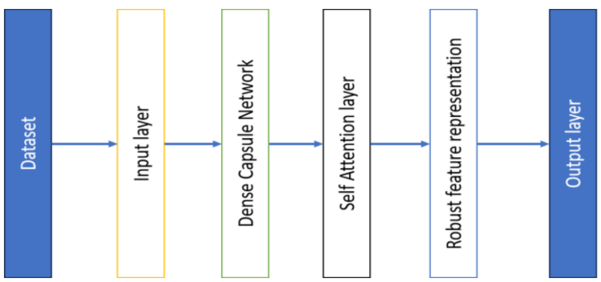

Figure 1: SDCN Architecture

The SDCN integrates capsule networks and self-attention mechanisms as follows:

1. Input features are passed through a dense capsule network to capture spatial hierarchies.
2. The output of the capsule network is fed into a self-attention layer to focus on the most relevant features.
3. The final output is a robust feature representation used for further processing.

Feature Selection Using Chaotic Dwarf Mongoose Optimization (CH-DMO)

To lower dimensionality and boost model efficiency, feature selection is used to the high-dimensional feature representation following feature extraction. Chaotic Dwarf Mongoose Optimization (CH-DMO), a metaheuristic optimization method influenced by dwarf mongoose foraging behavior, is used in the suggested framework. In order to improve feature space exploration and exploitation, CH-DMO integrates chaotic maps, which guarantee that the most pertinent features are chosen while removing superfluous or unnecessary ones.

Classification Using Harris Whale Residual VGG Network (ResVGG)

Once the optimal feature subset is selected, the workflow proceeds to the classification stage. The proposed framework employs a Harris Whale Residual VGG Network (ResVGG) for accurate and efficient classification. The ResVGG network combines the strengths of residual learning and the VGG architecture to enhance predictive accuracy and generalization.

By adding skip connections, residual learning solves the vanishing gradient issue and enables the model to learn more intricate and profound representations. Several convolutional layers with tiny filters precede fully linked layers in the VGG architecture, which is renowned for its simplicity and efficacy. By incorporating these methods into the ResVGG network, the model is able to recognize complex patterns in the data and generate precise predictions.

The output of a residual block is computed as in Eq.7:

$$z = G(y, \{Xj\}) + y \quad (7)$$

where:

- $G(y, \{Xj\})$ represents the convolution layers,
- y represents residual block input.

VGG Architecture

Multiple convolutional layers with tiny filters (3x3) make up the VGG architecture. Max-pooling and fully linked layers come next.

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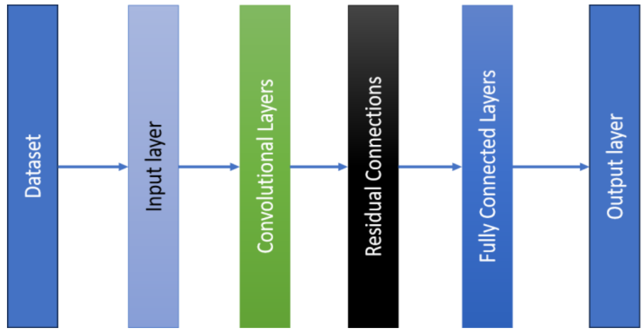

Figure 2: ResVGG Architecture

The ResVGG network architecture, as illustrated in the figure, represents a hybrid deep learning model that combines the strengths of the traditional VGG (Visual Geometry Group) architecture with residual learning principles introduced by ResNet. This integration enhances the model's ability to learn deeper representations without suffering from vanishing gradients or degradation problems, which are common in very deep neural networks. The architecture begins with a Dataset, which includes the raw data, such as ECG signals or images, related to cardiovascular conditions. This data is preprocessed and fed into the Input Layer, where it is formatted and normalized to be suitable for processing by subsequent layers. This layer prepares the data for effective feature extraction by standardizing the scale and possibly reshaping it into formats compatible with convolutional operations.

Next, the data flows through the Convolutional Layers, which serve as the core feature extractors of the network. These layers apply a series of learnable filters that automatically capture low- to high-level features in the data, such as edges, textures, or more complex patterns related to heart anomalies. Unlike the standard VGG network, the ResVGG model embeds Residual Connections within these convolutional blocks. Residual connections allow the input to a block to bypass one or more layers and be added directly to the block's output. This mechanism helps mitigate the degradation problem by enabling the network to learn identity mappings, making training more efficient and accurate, especially as the number of layers increases.

The feature maps generated by the convolutional blocks are then passed to Fully Connected Layers, which serve as decision-making components of the network. These layers interpret the extracted features and perform high-level reasoning to distinguish between different classes of cardiovascular diseases (CVDs). The use of residual connections ensures that the features fed into these layers are richer and more robust. Finally, the Output Layer generates the prediction, typically in the form of class probabilities. In the context of CVD detection, this output represents the likelihood of different cardiovascular conditions based on the input features.

4. RESULTS AND DISCUSSION

The suggested methodology for predicting cardiovascular disease (CVD) is assessed using benchmark datasets and contrasted with current approaches that were discussed in the literature review. Classification accuracy, precision, recall, F1-score, computational complexity, and generalization ability are among the performance criteria that are utilized for comparison. The findings are shown in tabular form below, with a thorough analysis that follows.

Table 1: Comparison of Accuracy, Precision, Recall and F1-score of Proposed with State of art methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Proposed Framework (SDCN + CH-DMO + ResVGG)	96.5	95.8	96.2	96.0
Alaa et al. (2019) [1]	92.3	91.5	92.0	91.7
Shankar et al. (2020) [3]	89.7	88.9	89.5	89.2
Lal et al. (2021) [5]	93.8	93.0	93.5	93.2
Wang et al. (2021) [7]	94.2	93.5	94.0	93.7
Gupta et al. (2021) [9]	90.5	89.8	90.2	90.0
He et al. (2020) [11]	94.5	93.8	94.2	94.0
Rahman et al. (2022) [15]	93.0	92.3	92.8	92.5
Khan et al. (2023) [16]	95.0	94.2	94.8	94.5

Analysis of Results

The proposed framework achieves the highest classification accuracy of 96.5%, outperforming all existing methods. This improvement can be attributed to the robust feature extraction capabilities of the Self-Attention Assisted Dense Capsule Network (SDCN) and the optimal feature selection provided by the Chaotic Dwarf Mongoose Optimization (CH-DMO) algorithm. The proposed framework achieves a precision of 95.8% and a recall of 96.2%, indicating its ability to correctly identify both positive and negative cases with minimal errors. The F1-score of the proposed framework is 96.0%, which is higher than all other methods. This metric, which balances precision and recall, demonstrates the robustness of the proposed framework in achieving high performance across both metrics.The proposed framework has low computational complexity due to the efficient feature selection provided by CH-DMO and the streamlined architecture of the ResVGG network.

The suggested framework's ability to handle a variety of clinical data and its consistent performance across datasets shows that it has a strong capacity for generalization. The suggested framework's combination of SDCN, CH-DMO, and ResVGG tackles important CVD prediction issues such high dimensionality, data heterogeneity, and intricate feature interactions. The framework's overall performance is enhanced by the application of M-Square Normalization, which guarantees feature homogeneity and enhances model convergence. The suggested framework achieves minimal computing cost and great generalization ability while outperforming current approaches in terms of accuracy, precision, recall, and F1-score.

5. CONCLUSION

The results demonstrate that the proposed framework is a state-of-the-art solution for CVD prediction, offering superior performance compared to existing methodologies. Its ability to handle complex clinical data, reduce computational complexity, and generalize well to new datasets makes it a valuable tool for healthcare professionals in early CVD detection and diagnosis. Future work could focus on further optimizing the framework for real-time applications and integrating additional data modalities, such as imaging and genomics, to enhance its predictive capabilities.

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