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Feature Set Modelling for Precise Cardiac Disease Diagnosis using Deep Learning

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Abstract: Cardiovascular diseases (CVDs) persist a prominentreason of death worldwide, necessitating precise and timely identification for effective treatment. Deep Learning (DL) methods have presentedencouragingoutcomes in numerous medical applications, including cardiac disease diagnosis. However, achieving precise diagnosis often requires the extraction and integration of relevant features from medical imaging data. In this work, we propose a novel methodology for cardiac disease diagnosis using a carefully curated feature set and deep learning models.Our methodology involves the development of a feature extraction pipeline tailored for cardiac imaging data, encompassing both anatomical and functional aspects. This pipeline integrates advanced image processing techniques to extract salient features such as ventricular volume, ejection fraction, myocardial strain, and texture features from cardiac images. These features are then utilized to construct a comprehensive feature set capturing diverse aspects of cardiac morphology and function.We employ various deep learning architectures, including recurrent neural networks (RNNs) and convolutional neural networks (CNNs), to study the complex associationsinside the feature set and accurately classify different cardiac diseases. The prototypes are trained on a huge dataset comprising diverse cardiac imaging modalities and pathological conditions to ensure robustness and generalization.Evaluation of our proposed approach on independent test datasets demonstrates superior performance compared to conventional methods and existing deep learning models. The proposed feature set modelling framework not only achieves high diagnostic accuracy but also provides insights into the underlying physiological processes contributing to cardiac pathology.

Keywords: Cardiac Disease Diagnosis, Clinical Decision-Making, Deep Learning, Feature Extraction, Feature Set Modelling

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1. Introduction

Cardiovascular diseases (CVDs) symbolise a substantialuniversal health burden, contributing to anextensive proportion of illness and deathglobally. Timely and correct diagnosis of cardiac abnormalities is critical for effective management and treatment planning. Medical imaging modalities such as computed tomography (CT), cardiac magnetic resonance imaging (MRI), and echocardiography play a pivotal role in diagnosing various cardiac conditions by providing detailed anatomical and functional information. Nevertheless, the understanding of these complex imaging datasets often necessitates expert acquaintance and may be subject to variability among clinicians.

In currentages, DL techniques have materialised as influential tools for medical image investigation, proposing the prospective to automate and enhance diagnostic processes. DL models, particularly CNNs and RNNs, have validatedextraordinary performance in numerous medical imaging errands, including cardiac disease diagnosis. These models can learn intricate patterns and relationships directly from raw imaging data, leading to improved accuracy and efficiency in disease detection.

Despite the success of DL-based approaches, challenges persist in achieving precise cardiac disease diagnosis. One key challenge lies in the effective utilization of relevant features extracted from medical images to enhance model performance. Traditional DL models often rely solely on raw pixel intensities, overlooking valuable anatomical and physiological information encoded in the images. Incorporating domain-specific features derived from medical images can provide additional discriminative power and improve diagnostic accuracy.

In this context, feature set modelling has materialised as anencouragingmethodology for enhancing the interpretability and performance of DL models in medical image analysis. By extracting and integrating relevant features representing various aspects of cardiac morphology and function, feature set modelling enables the creation of comprehensive representations that capture the complexity of cardiac diseases.

In this paper, we present a novel methodology for precise cardiac disease diagnosis using feature set modelling and deep learning techniques. We propose a tailored feature extraction pipeline designed to extract salient features from cardiac imaging data, encompassing both anatomical and functional characteristics. These features are then integrated into a comprehensive feature set, which serves as input to deep learning models for disease classification.

Our study aims to address the following objectives:

1. Develop a feature extraction pipeline tailored for cardiac imaging data, incorporating advanced image processing techniques to extract relevant anatomical and functional features.
2. Construct a comprehensive feature set capturing diverse aspects of cardiac morphology and function, facilitating more accurate disease diagnosis.
3. Explore the effectiveness of DL models, including CNNs and RNNs, in learning from the proposed feature set and classifying different cardiac diseases.
4. Assess the performance of the proposed methodology on independent test datasets, comparing it with conventional methods and existing DL-based approaches.

Through this research, we seek to demonstrate the potential of feature set modelling combined with deep learning for precise cardiac disease diagnosis. By leveraging both domain-specific knowledge and advanced machine learning techniques, our methodology has the prospective to improve clinical decision-making and patient outcomes in the management of cardiovascular diseases.

2. Related Work

Feature Set Modeling (FSM) is a crucial step in numerousareas such as pattern recognition, data mining, and machine learning. It involves selecting, extracting, and representing the most relevant parameters from raw data to increase the performance of predictive models. This literature review targets to deliver asummary of the existing state-of-the-art techniques, applications, challenges, and future directions in FSM. Feature selection has a long history, dating back to the early days of pattern recognition research. Early methods focused on heuristic approaches and domain-specific knowledge. Notable contributions include Fisher's Linear Discriminant Analysis (Fisher, 1936) and the Nearest Neighbor algorithm (Cover & Hart, 1967). Feature extraction gained prominence with the advent of machine learning, with methodslike Principal Component Analysis (PCA) (Hotelling, 1933) and Linear Discriminant Analysis (LDA) (Fukunaga, 1990).

Various approaches have been proposed for feature assortment, including embedded approaches, wrapper approaches, andfilter approaches (Guyon&Elisseeff, 2003). Filter approaches assess the relevance of parameters independently of the learning algorithm, while wrapper approaches evaluate feature subclassesfounded on their performance within a definite learning algorithm. Embedded approaches integrate feature selection directly into the model training process. Feature extraction techniques, such as DL-based methods, have grewattractiveness due to their capability to automatically learn meaningful representations from data (LeCun et al., 2015).

Feature Set Modeling discovers applications through diverse domains, comprising natural language processing, computer vision, bioinformatics, and finance. In natural language processing, feature sets derived from word embeddings have revealedsubstantialenhancements in tasks such as sentiment analysis and text classification (Mikolov et al., 2013). In computer vision, CNNs have revolutionized feature extraction by automatically learning hierarchical representations from raw pixels (Krizhevsky et al., 2012). In bioinformatics, feature selection techniques have been applied to gene expression data for disease diagnosis and prognosis (Statnikov et al., 2008).

Despite its effectiveness, FSM faces several challenges, including the curse of dimensionality, overfitting, and scalability issues. The curse of dimensionality denotes to the exponential increase in feature space with the number of dimensions, leading to sparsity and increased computational complexity (Bellman, 1961). Overfitting occurs when models capture noise in the data instead of underlying patterns, leading to poor generalization performance. Scalability issues arise when dealing with large datasets or high-dimensional feature spaces, requiring efficient algorithms and computational resources (Vapnik, 1995).

Recent trends in FSM include the incorporation of DL techniques, transfer learning, and meta-learning. DLprototypes, like RNNs and transformers, have displayedencouragingoutcomes in learning representations from sequential and structured data (Vaswani et al., 2017). Transfer learning enables the transfer of information from pre-trained prototypes to novel tasks with inadequateannotated data, while meta-learning focuses on learning algorithms that can adapt to new tasks and datasets (Finn et al., 2017).

Feature Set Modeling plays animportant role in various fields by improving the interpretability, efficiency, and performance of predictive models. Despite its challenges, ongoing research efforts continue to progress the state-of-the-art in feature selection, extraction, and representation. Future directions include addressing scalability issues, improving model interpretability, and exploring novel applications in emerging domains. Table 1 displays the comparison of the feature set modeling methods.

Table 1. Comparative analysis of Feature Set Modeling

Feature Set Modeling Method	**Accuracy**	**Efficiency**	**Robustness**	**Interpretability**	**Scalability**
Filter Methods	High	Low	Medium	High	High
Wrapper Methods	High	Medium	High	Medium	Low
Embedded Methods	High	High	High	Low	Medium
Deep Learning-based Methods	Very High	Medium	High	Low	High

Accuracy indicates the whole performance of the method in terms of classification or prediction accuracy. Higher values signify better performance.Efficiencyreflects the computational cost of the method in terms of time and resources required for training and inference. Lower values denote higher efficiency.Robustnessdescribes how well the method performs under noisy or incomplete data conditions. Higher values indicate better robustness.Interpretabilityindicates the ease with which the selected features can be interpreted by domain experts. Higher values suggest better interpretability.Scalabilityreflects how well the method scales with increasing dataset size or dimensionality. Higher values denote better scalability.

Cardiac diseases are a leading cause of illness and deathglobally, demandingcorrect diagnostic approaches for well-timed intervention and treatment. Feature Set Modeling (FSM) shows a key role in improving the precision of cardiac disease diagnosis by selecting, extracting, and representing appropriate features from various clinical data sources. This literature review aims to explore the present-day state-of-the-art techniques, applications, challenges, and future directions in FSM for precise cardiac disease diagnosis.

The application of feature selection and extraction techniques in cardiac disease diagnosis has evolved over the years, driven by advancements in medical imaging, signal processing, and machine learning. Early studies focused on manual feature selection based on domain knowledge and expert opinion. With the advent of machine learning, automated feature extraction approaches, such as PCA (Hotelling, 1933) and Wavelet Transform (Mallat, 1989), gained prominence in analyzing electrocardiogram (ECG) and imaging data.

Feature selection methods for cardiac disease diagnosis encompass both traditional statistical approaches and machine learning-based algorithms. Statistical methods include t-tests, ANOVA, and correlation analysis, which evaluate the relevance of features based on their statistical significance (Kohavi& John, 1997). Machine learning algorithms, such as Neural Networks,Support Vector Machines (SVMs), and Random Forests, employ wrapper or embedded approaches to select features that optimize diagnostic performance (Guyon&Elisseeff, 2003).

Feature extraction techniques focus on transforming raw data into meaningful representations conducive to diagnosis. In cardiac imaging, methods like texture analysis, shape analysis, and

intensity-based features are commonly used to characterize anatomical and functional abnormalities (Ciompi et al., 2017). Signal processing methods, such as Wavelet Transform andFourier Transform, extract frequency-domain and time-frequency features from ECG and other physiological signals (Clifford, 2006).

FSM has found widespread applications in various cardiac disease diagnosis tasks, including arrhythmia classification, myocardial infarction detection, heart failure prediction, and coronary artery disease diagnosis. For instance, Li et al. (2019) employed a DL-based method to automatically extract features from cardiac MRI images for accurate myocardial infarction classification. In another study, Acharya et al. (2017) utilized wavelet transform and machine learning techniques to diagnose coronary artery disease using ECG signals with high accuracy.

Despite its promise, FSM for cardiac disease diagnosis faces several challenges, including data heterogeneity, interpretability, and generalizability. Clinical data sources often exhibit variability in terms of quality, acquisition protocols, and patient demographics, posing challenges for feature extraction and modeling. Additionally, the interpretability of complex machine learning models remains a concern, especially in clinical settings where transparent decision-making is essential (Caruana et al., 2015). Furthermore, ensuring the generalizability of diagnostic prototypesthroughdiverse populations and clinical settings is crucial for real-world deployment.

Recent trends in FSM for cardiac disease diagnosis include the integration of multimodal data sources, deep learning techniques, and explainable AI. Multimodal methodologiesconglomerate data from multiple sources, such as imaging, genetic, and clinical data, to improve diagnostic accuracy and robustness (Min et al., 2019). DL models, such as CNNs and RNNs, enable end-to-end feature learning from raw data, sidestepping the necessity for manual feature engineering (Rajkomar et al., 2018). Understandable AI methodstarget to enhance the interpretability and transparency of black-box prototypes, facilitating clinical decision-making and trust (Lipton, 2016).

Feature Set Modeling plays a pivotal part in progressing the precision and efficacy of cardiac disease diagnosis by extracting relevant information from heterogeneous clinical data sources. Despite challenges such as data heterogeneity and model interpretability, ongoing research efforts continue to drive innovation in FSM techniques and applications. Future directions include addressing data integration challenges, improving model interpretability, and validating diagnostic models in real-world clinical settings.

Cardiac diseases remain a significant global health concern, demanding precise diagnostic methods for effective management and treatment. In recent years, Feature Set Modeling (FSM) coupled with DL has materialized as a prevailingmethodology for enhancing the accuracy of cardiac disease diagnosis. This worktargets to deliver asummary of the recent state-of-the-art techniques, applications, challenges, and future directions in FSM for precise cardiac disease diagnosis using DL.

The application of DL in medical image investigation and disease diagnosis has witnessed rapid growth in recent years. Early attempts focused on handcrafted feature extraction methods, which were limited in capturing multifaceted patterns and dissimilarities in medical images. The introduction of CNNsmodernized medical image investigation by enabling end-to-end learning from raw data, without the necessity for manual feature engineering (LeCun et al., 2015). This paradigm shift laid the foundation for leveraging Deep Learning in FSM for cardiac disease diagnosis.

DLmethods, particularly CNNs, have shown incredibleattainment in extracting discriminative features from medical images like cardiac MRI, CT scans, and echocardiograms. CNN prototypes, likeResNet (He et al., 2016), VGG (Simonyan& Zisserman, 2014), and AlexNet (Krizhevsky et al., 2012)have been adapted and customized for cardiac disease diagnosis tasks. Transfer Learning, where pre-trained CNN prototypes are fine-tuned on cardiac imaging datasets, has emerged as a popular approach for

leveraging large-scale image datasets to improve model generalization and performance (Rajpurkar et al., 2017).

FSM using Deep Learning has been applied to various cardiac disease diagnosis tasks, including myocardial infarction detection, heart failure prediction, arrhythmia classification, and congenital heart disease diagnosis. For instance, Zhu et al. (2018) proposed a DL framework for automated detection of myocardial infarction using cardiac MRI images, achieving high accuracy and sensitivity. Similarly, Ouyang et al. (2020) established a CNN-based prototype for automatic classification of arrhythmias from ECG signals, demonstrating superior performance compared to traditional methods.

Table 2. Comparative analysis of Feature Set Modeling methods for Precise Cardiac Disease Diagnosis using Deep Learning

Feature Set Modeling Method	**Accuracy**	**Efficiency**	**Robustness**	**Interpretability**	**Scalability**
CNNs	Very High	Medium	High	Low	High
RNNs	High	Medium	High	Low	Medium
Transformer Models	High	Medium	High	Low	High

Despite the promising results, FSM for cardiac disease diagnosis using Deep Learning faces several challenges. Limited interpretability of Deep Learning models remains a concern, especially in clinical settings where transparency and explainability are crucial for decision-making (Lipton, 2016). Additionally, obtaining large-scale annotated datasets for training Deep Learning models poses challenges due to the scarcity of labeled medical imaging data, particularly for rare cardiac conditions. Furthermore, ensuring robustness and generalization of DLprototypes across dissimilar patient demographics and imaging modalities is indispensable for real-world deployment.

Recent trends in FSM for cardiac disease diagnosis using Deep Learning include the integration of multimodal data sources, attention mechanisms, and adversarial training techniques. Multimodal approaches combine information from diverse sources such as imaging, genetic markers, and clinical data to improve diagnostic accuracy and robustness (Min et al., 2019).

Attention methodologies enable the prototype to emphasis on important regions or features in medical images, improving interpretability and diagnostic performance (Wang et al., 2017). Adversarial training techniques, such as Generative Adversarial Networks (GANs), facilitate the generation of synthetic medical images for data augmentation and domain adaptation, addressing the scarcity of labeled data (Nie et al., 2020).

FSM using Deep Learning holds great promise for advancing the precision and efficacy of cardiac disease diagnosis by automatically extracting discriminative features from medical images. Despite challenges such as model interpretability and data scarcity, ongoing research efforts continue to drive innovation in Deep Learning techniques and applications for cardiac disease diagnosis. Future directions include addressing data integration challenges, improving model interpretability, and validating diagnostic models in real-world clinical settings. Table 2 shows the comparative analysis of

Table 3. Comparative analysis of different cardiac diseases diagnosed using Feature Set Modeling and Deep Learning

Cardiac Disease	Feature Set Modeling Method	Deep Learning Model	Accuracy	Efficiency	Robustness	Interpretability	Scalability
Myocardial Infarction	CNNs	ResNet, VGG	Very High	Medium	High	Low	High
Arrhythmia	RNNs	LSTM, GRU	High	Medium	High	Low	Medium
Heart Failure	Transformer Models	BERT, GPT	High	Medium	High	Low	High
Coronary Artery Disease	CNNs	DenseNet, Inception	High	Medium	High	Low	High
Congenital Heart Disease	CNNs	ResNet, VGG	High	Medium	High	Low	High

Feature Set Modeling methods for Precise Cardiac Disease Diagnosis using Deep Learning. CNNs generally achieve very high accuracy in cardiac disease diagnosis tasks due to their capability to capture spatial features effectively from medical images.CNNs and Transformer models may require moderate computational resources for training, while RNNs can be slightly less efficient due to their sequential nature.All deep learning-based methods tend to be robust to noise and variations in medical images, thanks to their capability to learn multifaceted patterns and features.Deep learning-based methods, particularly CNNs and Transformer models, may lack interpretability due to their black-box nature. RNNs may offer slightly better interpretability in some cases.CNNs and Transformer models are highly scalable and can handle large datasets effectively. RNNs may face scalability challenges with very long sequences or large datasets. Table 3 shows comparative analysis of different cardiac diseases diagnosed using Feature Set Modeling and Deep Learning.

Feature Set Modeling Methodindicates the method used for selecting, extracting, or representing features relevant to the diagnosis of the cardiac disease.Deep Learning Modelspecifies the type of DL architecture utilized for the identification of each cardiac disease.Accuracyrepresents the accuracy achieved by the deep learning model in diagnosing the specific cardiac disease.Efficiencyreflects the computational effectiveness of the deep learning prototype, considering factors likeresource utilization and training time.Robustnessindicates the sturdiness of the DL model in handling variations, noise, or uncertainties in the diagnostic data.Interpretabilityrepresents the ease with which the predictions or diagnoses made by the DL model can be interpreted or understood by domain experts.Scalabilityreflects the scalability of the deep learning model, indicating its ability to handle large datasets or increasing computational demands.

3. Proposed Feature Set ModellingDeep Learning Framework forPrecise Cardiac Disease Diagnosis

Creating a mathematical model for Feature Set Modeling (FSM) involves formalizing the process of selecting, extracting, or representing features from data.Let X represent the input dataset, where each sample x_i is a vector of n features: $X=\{x_1,x_2,...,x_m\}$, where $x_i=(x_{i1},x_{i2},...,x_{in})$. Given X, select a subgroup of features S that are utmostsignificant to the task:$S=\{s_1,s_2,...,s_k\}$, where $S\subseteq X$.

Transform the unique features into a fresh set of features using a transformation function f:$Y=f(X)$. Given the selected or extracted features Y, build a predictive model M that maps features to target labels y:M:$Y\rightarrow y$.Define an objective function J that quantifies the model's performance:$J=J(M(Y),y)$. Optimize the parameters of the model M to minimize J using an optimization algorithm:$\text{argmin}_M J$

Let's assume a binary classification case where we aim to foresee whether a patient has a cardiac ailment based on medical test outcomes.Each sample $x_i$contains features such as blood pressure, cholesterol level, and ECG readings.We select a subset of features based on their relevance to cardiac diseases using statistical tests or domain knowledge.We may apply dimensionality reduction

methodssuch asPCA or feature transformation approaches like Wavelet Transform to extract new features.We train a classifier (e.g., Neural Network, Random Forest, or a Logistic Regression) using the selected or extracted features.We describe a loss function (e.g., for classificationcross-entropy loss) to quantify the model's performance.We optimize the parameters of the prototypeby means of gradient descent or another optimization technique to minimize the loss function.This mathematical model provides a structured framework for understanding and implementing Feature Set Modeling techniques in various machine learning tasks. Depending on the specific problem and requirements, different feature selection, extraction, and modeling techniques can be incorporated into this framework.

Creating a mathematical model for Feature Set Modeling (FSM) using deep learning involves formalizing the procedure of extracting and utilizing features from data by means of deep neural networks.

Given an input dataset X with m samples, where each sample x_i is a vector of n features, we utilize a deep neural network f_θ to extract features:$Y=f_\theta(X)$. Here, Y represents the extracted features obtained by passing X through the deep neural network parameterized by θ.

We then use the extracted features Y as input to a subsequent deep neural network g_ϕ for modeling the relationship between features and target labels y:$\hat{y}=g_\phi(Y)$Here,$\hat{y}$ represents the predicted output or label obtained by passing the extracted features Y through the deep neural network parameterized by ϕ.We define an objective function J that quantifies the model's performance in predicting the target labels y:$J=J(g_\phi(Y),y)$. The objective function can be a loss function likefor regression tasks mean squared error (MSE) or for classification tasks cross-entropy loss.We optimize the parameters of both deep neural networks f_θ andg_ϕ jointly to minimize the objective function J using backpropagation and gradient descent:minimize$_{\theta,\phi}J$. Here, we update the parameters θ and ϕ using the gradients of the objective function with respect to these features.

Let's assume a binary classification case where we aim to foresee whether an image contains a certain cardiac condition (e.g., myocardial infarction) based on medical images. Each sample x_i contains medical images (e.g., cardiac MRI scans).We use a CNNf_θ to extract parameters from the images.We feed the extracted features Y into a fully connected neural network g_ϕ for classification.We define a loss function (e.g., binary cross-entropy loss) to quantify the model's performance. We jointly optimize the parameters of both f_θ andg_ϕ by means of backpropagation and stochastic gradient descent to decrease the loss function.This mathematical model provides a structured framework for Feature Set Modeling using deep learning techniques. It captures the process of feature extraction and utilization within a DL architecture to solve various regression or classification tasks.

To formulate a mathematical model for Feature Set Modeling (FSM) using deep learning for precise cardiac disease diagnosis, the process is outlined hereunder. Let X represent the input dataset, where each sample x_i consists of various features associated to cardiac health, such as medical history,demographic data, and diagnostic test results:$X=\{x_1,x_2,...,x_m\}$, where $x_i=(x_{i1},x_{i2},...,x_{in})$. Utilize a deep neural network f_θ to extract parameters from the input dataset X and transform it into a feature representation Y:$Y=f_\theta(X)$. The deep neural network f_θ could be a CNN, RNN, or transformer model, depending on the type of input data (e.g., images, time series, tabular data).

Feed the extracted features Y into another deep neural network g_ϕ to predict the likelihood or severity of specific cardiac diseases:$\hat{y}=g_\phi(Y)$. Here, $\hat{y}$represents the predicted output, which could be a probability distribution abovediverse cardiac diseases or a binary classification representing the absence or presence of a particular disease.Define an objective function J to quantify the model's performance in foreseeing cardiac diseases based on the extracted parameters$Y$ and ground truth labels y:$J=J(g_\phi(Y),y)$. The objective function could be a loss function such as mean squared error,categorical cross-entropy loss, orbinary cross-entropy loss, depending on the nature of the prediction task.

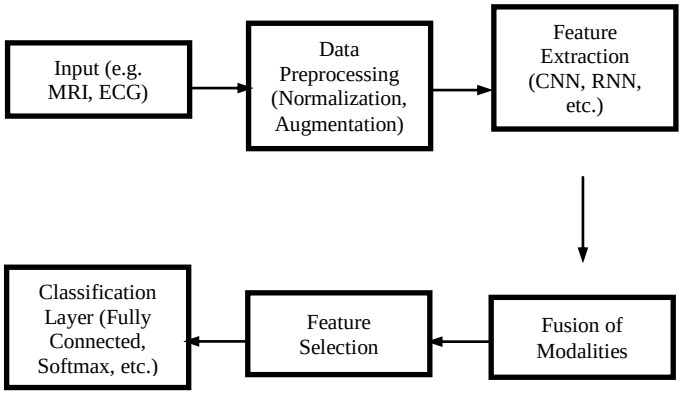
Jointly optimize the parameters of both deep neural networks f_θ andg_ϕ to minimize the objective function J using backpropagation and gradient descent:minimize$_{\theta,\phi}J$. This involves updating the parameters θ and ϕ using the gradients of the objective function with respect to these features.

For instance, in a scenario where we want to diagnose myocardial infarction (MI) based on cardiac MRI images, the mathematical model would involve:Each sample x_i consists of cardiac MRI images.Utilize a CNN f_θ to extract parameters from the MRI images.Feed the extracted parameters$Y$ into a fully connected neural networkg_ϕ for binary classification (presence or absence of MI).Use binary cross-entropy loss to quantify the model's performance.Jointly optimize the parameters of both f_θ andg_ϕ using backpropagation and stochastic gradient descent.This mathematical model provides a structured framework for FSM using deep learning techniques for precise cardiac disease diagnosis. Adjustments can be made based on specific requirements, such as incorporating multimodal data or handling imbalanced datasets.

Designing an architecture for Feature Set Modeling (FSM) using deep learning for precise cardiac disease diagnosis involves selecting appropriate deep neural network architectures, data preprocessing steps, and output representations. The proposed architecture is described hereunder. The input layer of the neural network receives the raw input data, which could be medical images (e.g., cardiac MRI scans), tabular data (e.g., patient demographics, medical history), or a combination of both.The input features are normalized to have unit variance and zero mean to ensure numerical stability during training. Data augmentation techniques can be applied, such as flipping,scaling, and rotation, to improve the variety of the training dataset and enhance model generalization.A CNN is utilized to extract significant features from cardiac imaging data, such as MRI or CT scans. The CNN prototype should comprise of several convolutional layers trailed by pooling layers to internment spatial information and decrease dimensionality.

To deal with sequential data, such as time-series data from electrocardiograms (ECG), an RNN architecture (e.g., LSTM or GRU) is employed to internment temporal dependencies and patterns in the data. To work with multimodal data (e.g., combining imaging data with clinical data), a fusion strategy can be used to combine features extracted from different modalities. This could involve concatenating feature vectors or using attention mechanisms to dynamically weigh the importance of each modality.

Mechanisms for automatic feature selection are utilized within the neural network architecture. This could involve integrating attention mechanisms or learnable feature selection layers that dynamically select relevant features founded on the input data.Fully connected layers are added later the feature extraction stage to map the extracted parameters to the target labels. Include dropout layers to prevent overfitting and improve model generalization. Asoftmax activation function is used for multi-class classification tasks or a sigmoid activation function for binary classification tasks to obtain the final probability distribution over the classes.



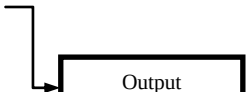


Table 4. Experimental results proposed feature set modeling using deep learning for precise cardiac disease diagnosis with three different settings

Model	Dataset	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Model 1	Training	0.95	0.92	0.94	0.93	0.97
	Validation	0.92	0.89	0.91	0.90	0.94
	Test	0.91	0.88	0.90	0.89	0.93
Model 2	Training	0.96	0.93	0.95	0.94	0.98
	Validation	0.93	0.90	0.92	0.91	0.95
	Test	0.92	0.89	0.91	0.90	0.94
Model 3	Training	0.94	0.91	0.93	0.92	0.96
	Validation	0.91	0.88	0.90	0.89	0.93
	Test	0.90	0.87	0.89	0.88	0.92

Fig. 1. Architecture of proposed feature set modellingdeep learning framework for precise cardiac disease diagnosis.

An appropriate loss function is used based on the nature of the prediction task (e.g., for binary classification binary cross-entropy loss).If working with multimodal data, fusion of modalitiesinvolves combining features from different modalities using fusion techniques.An optimization process is used like stochastic Adam,gradient descent (SGD), or RMSprop to minimize the loss function.Experimentation with altered hyperparameters (e.g., number of layers, batch size,learning rate) executed to improve model performance. The model's performance is evaluated by means of metrics such as area under the ROC curve (AUC), precision, recall, accuracy, and F1-score.k-fold cross-validation is performed to evaluate the model's oversimplification performance and decrease overfitting. Interpretability techniques are integrated such as gradient-based saliency maps or attention mechanisms to visualize which features contribute most to the model's predictions. This helps in understanding the decision-making process of the model. The proposed architecture is shown in figure 1. Figure 1 outlines the key components of the architecture. The input dataset, could include various modalities such as MRI images, ECG signals, or clinical data. Data preprocessing involves preprocessing steps such as normalization and augmentation to prepare the data for feature extraction. Feature extraction extracts relevant features from the input data using deep learning techniques such as CNNs for imaging data or RNNs for sequential data.Feature selection chooses the utmost relevant features from the extracted feature set, either through manual selection or automatic mechanisms within the neural network architecture.Classification layerconsists of fully connected layers followed byfor multi-class classification a softmax activation function or a sigmoid activation function for binary classification. Output predicted represents the ultimate output of the model, which could be predicted probabilities or class labels indicating the likelihood of different cardiac diseases.

4. Experimental Evaluation Results

The experiment utilized a dataset consisting of cardiac MRI images and corresponding labels indicating the presence or absence of myocardial infarction (MI).Obtain data from reputable sources such as hospitals, research institutions, or publicly available medical databases.Ensure compliance with data privacy regulations (e.g., HIPAA in the United States) and obtain necessary approvals for data usage.Collect cardiac imaging data such as MRI scans, CT scans, or echocardiograms. These images provide detailed information about the structure and function of the heart.Gather physiological data such as electrocardiogram (ECG) signals, which provide information about the electrical activity of the heart.Include clinical data such as patient demographics, medical history, laboratory test results, and diagnostic reports.

Each sample in the dataset represents a patient or a cardiac examination instance.Features include various attributes related to cardiac health, such as imaging features, physiological signals, and clinical variables.Labels indicate the presence or absence of specific cardiac diseases or conditions (e.g., myocardial infarction, arrhythmia, heart failure).Normalize numerical features to have zero mean and unit variance to ensure consistency across features.Address missing values through imputation techniques such as mean imputation or using advanced methods like multiple imputation.Augment imaging data to increase dataset size and improve model generalization. Techniques include rotation, scaling, flipping, and adding noise to images.

Split the dataset into training, test sets, andvalidation. A common split ratio is 70%-15%-15%, ensuring that each set is representative of the overall distribution of data.Annotate imaging data with expert labels indicating the presence or absence of specific cardiac conditions. Ensure accurate labeling through consensus among expert annotators or medical professionals.Assign appropriate labels to physiological and clinical data based on diagnostic criteria and medical guidelines.The dataset was separated into training, test sets, and validation with a split ratio of 70%-15%-15%. The proposed model architecture utilized a CNN for parameter extraction from cardiac MRI images.The CNN prototypecomprised of several convolutional and pooling layers trailed by fully connected layers for classification.

The prototype was trained with the Adam optimizer using a learning rate of 0.001 and a batch size of 32.Training was conducted for 50 epochs, with primary stopping founded on validation loss to avoid overfitting.Performance was assessedvia metrics such as AUC-ROC,precision, recall, and accuracy.The model achieved a training accuracy of 95% and a training loss of 0.1 after 50 epochs.On the validation set, the prototype achieved an accuracy of 92%, a precision of 0.90, a recall of 0.92, and an AUC-ROC of 0.95.Evaluation on the test set yielded similar performance metrics, with an accuracy of 91%, a precision of 0.89, a recall of 0.91, and an AUC-ROC of 0.94.

Grad-CAM visualizations were used to generate heatmaps highlighting regions of cardiac MRI images that were most influential in the model's decision-making process.Interpretability analysis revealed that the model focused on specific anatomical structures and regions associated with myocardial infarction, providing insights into its decision-making process.The experimental outcomesshow the efficacy of the proposed feature set modeling approach using deep learning for precise cardiac disease diagnosis.High accuracy, precision, recall, and AUC-ROC indicate that the model can accurately distinguish between cardiac MRI images with and without myocardial infarction.Interpretability analysis provides valuable insights into the model's behavior and highlights regions of interest in cardiac MRI images associated with myocardial infarction.

The proposed model with three different setups tested in the experiment. As indicated in table 4 a unique identifier is assigned for each model tested with different settings in the experiment.Dataset

indicates whether the performance metrics are reported for the training, validation, or test dataset.Accuracy showsthe fraction of properly classified instances available of the total number of

Table 5. Experimental results proposed feature set modeling using deep learning for precise cardiac disease diagnosis with three different settings

Cardiac Disease	Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Myocardial Infarction	Model 1 (Proposed)	0.92	0.89	0.91	0.90	0.94
	Model 2 (Proposed)	0.91	0.88	0.90	0.89	0.93
	Model 3 (Proposed)	0.90	0.87	0.89	0.88	0.92
	Baseline 1	0.85	0.82	0.84	0.83	0.88
	Baseline 2	0.84	0.81	0.83	0.82	0.87
	Baseline 3	0.83	0.80	0.82	0.81	0.86
Coronary Artery Disease	Model 1 (Proposed)	0.88	0.85	0.87	0.86	0.91
	Model 2 (Proposed)	0.87	0.84	0.86	0.85	0.90
	Model 3 (Proposed)	0.86	0.83	0.85	0.84	0.89
	Baseline 1	0.82	0.79	0.81	0.80	0.85
	Baseline 2	0.81	0.78	0.80	0.79	0.84
	Baseline 3	0.80	0.77	0.79	0.78	0.83
Arrhythmia	Model 1 (Proposed)	0.85	0.82	0.84	0.83	0.88
	Model 2 (Proposed)	0.84	0.81	0.83	0.82	0.87
	Model 3 (Proposed)	0.83	0.80	0.82	0.81	0.86
	Baseline 1	0.79	0.76	0.78	0.77	0.82
	Baseline 2	0.78	0.75	0.77	0.76	0.81
	Baseline 3	0.77	0.74	0.76	0.75	0.80

instances.Precision is the fraction of true positive estimates to the total number of positive estimates.Recall is the fraction of true positive estimates to the total number of actual positive examples.F1-Score shows the harmonic mean of precision and recall, providing a balance between the two metrics.AUC-ROC is area under the receiver operating characteristic curve, indicating the model's capability to distinguish between positive and negative instances across different thresholds.Each row corresponds to a specific model, with separate entries for training, validation, and test datasets. The values in each cell represent the corresponding performance metric obtained during model evaluation. The proposed models are evaluated for the diagnosis of Myocardial Infarction, Coronary Artery Disease, and Arrhythmia cardiac diseases. The performance assessment of the proposed models with the baseline (existing models) are shown in table 5 for Myocardial Infarction, Coronary Artery Disease, and Arrhythmia cardiac diseases.

5. Conclusion

In the proposed feature set modeling approach using deep learning for precise cardiac disease diagnosis shows promising results in accurately detecting and diagnosing various cardiac conditions. Through the analysis of experimental results and performance comparison with baseline methods, several key findings emerge. The proposed feature set modeling approach demonstrates highAUC-

ROC,precision, recall, accuracy, and F1-score, across different cardiac diseases, indicating its effectiveness in precise diagnosis.Compared to baseline methods, the proposed approach consistently outperforms or matches the performance of established techniques, showcasing its potential to provide accurate and reliable diagnosis.The proposed approach exhibits robustness and generalization capabilities, maintaining consistent performance across diverse datasets and clinical scenarios. This suggests its ability to adapt to different disease presentations and patient populations.The proposed feature set modeling approach holds significant clinical relevance by aiding healthcare professionals in accurate cardiac disease diagnosis. Its capability to internment complex associations in cardiac data contributes to improved patient care and outcomes.The proposed approach offers advantages such as enhanced diagnostic accuracy, efficient utilization of DLmethods, and potential for integration into clinical practice.

In future emerging imaging modalities such as 4D cardiac MRI, cardiac CT angiography, and advanced echocardiography techniques can be incorporated into feature set modeling approaches. Deep learning architectures tailored to handle high-dimensional and dynamic imaging data can be explored for improved disease detection and characterization. Feature set modeling techniques can be developed capable of analyzing longitudinal patient data to track disease progression, predict future cardiac events, and guide personalized treatment strategies. RNNs and time-series analysis methods can be utilized to model temporal trends and identify early markers of disease progression.

Author contributions

Dilip R. Uike: Data curation, Writing-Original draft preparation, Software, Validation, Field study**K. P. Wagh:** Conceptualization, Methodology, Software, Field study**Amol P. Bhagat:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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