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# Lightweight Optimisation-Driven Deep Learning for Cardiac Disease from MRI (CMRI)

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**Abstract:** Accurate diagnosis of cardiac diseases from Magnetic Resonance Imaging (MRI) remains a challenging task due to the need for high predictive performance while maintaining computational efficiency. This paper presents a computing-centric and efficiency-aware deep learning framework for cardiac MRI analysis, explicitly designed for diagnostic and clinical research. The proposed model is based on a two-layer GhostNet architecture enhanced with a combined channel-attention mechanism that integrates squeeze-and-excitation (SE) operations, enabling effective recalibration of feature channels with minimal parameter overhead. Network training is performed using an improved Parrot Optimisation Algorithm, which is algorithmically and mathematically formulated to adaptively optimise model parameters, resulting in improved convergence behaviour and generalisation capability. To further reduce computational complexity, structured pruning is systematically applied and quantitatively analysed, with explicit evaluation of parameter count, floating-point operations (FLOPs), memory footprint, and accuracy trade-offs. This pruning strategy enables the development of a compact diagnostic model suitable for deployment on resource-constrained computing platforms without substantial degradation in predictive performance. The framework is evaluated on benchmark cardiac MRI datasets using accuracy, precision, recall, and F1-score, alongside comprehensive computing-efficiency metrics. Experimental results demonstrate a favourable accuracy–complexity balance and significant reductions in model size and computational cost compared to conventional convolutional neural network architectures.

**Keywords:** GhostNet, Cardiac MRI, Squeeze-and-Excitation Attention, Parrot Optimisation, Model Pruning.

***Nomenclature***

| Abbreviation | Description |
|---|---|
| AI | Artificial Intelligence |
| AUC | Area Under the Receiver Operating Characteristic Curve |
| CA | Channel Attention |
| CAD | Coronary Artery Disease |
| CHD | Coronary Heart Disease |
| CMRI | Cardiac Magnetic Resonance Imaging |
| CNN | Convolutional Neural Network |
| CCTA | Coronary Computed Tomography Angiography |
| CVD | Cardiovascular Disease |
| DL | Deep Learning |
| ECG | Electrocardiogram |
| FLOPs | Floating Point Operations |
| GAP | Global Average Pooling |
| IPO | Improved Parrot Optimisation Algorithm |
| MLP | Multi-Layer Perceptron |
| MoCo-MoDL | Motion-Corrected Model-Based Deep Learning |
| MRI | Magnetic Resonance Imaging |
| NR-PROST | Non-Rigid Motion-Corrected Patch-Based Low-Rank Reconstruction |
| RF | Random Forest |
| SAF | Spatially-Aware Feature |
| SE | Squeeze-and-Excitation |
| TCGN | Temporal Convolutional Graph Neural Network |
| VGG | Visual Geometry Group |

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# 1 Introduction

Cardiovascular disease (CVD) remains the most common killer in terms of disease-related mortality globally, contributing to nearly one-third of such deaths, which include a broad range of conditions known to affect either the cardiovascular system or both [1]. The increasing prevalence of cardiovascular disorders has intensified the demand for accurate, scalable, and computationally efficient diagnostic technologies capable of supporting timely clinical decision-making. Cardiac magnetic resonance imaging (MRI) has long been established as the gold standard for evaluating cardiac structure and function and has proved critical in both diagnostic and follow-up procedures for such conditions [2]. Besides its broad importance in cardiac imaging and diagnostics, traditional cardiac MRI has been associated with significant practical issues within electrocardiogram (ECG) synchronisation procedures due to gradient and radiofrequency interference and magnetohydrodynamic phenomena, which have been associated with corrupting ECG signals and poor R-wave detection [3].

Despite the diagnostic powers of cardiac MRI, there are various obstacles to the precise identification and characterisation of cardiac disease in diverse patient populations [4]. The growing volume and complexity of cardiac imaging data further challenge conventional interpretation approaches, often increasing diagnostic workload and inter-observer variability. Symptoms of Coronary Artery Disease (CAD) by the patient are not sensitive or specific enough to help clinicians or cardiologists diagnose pure symptoms. On the other hand, myocardial changes in coronary heart disease (CHD) conditions remain complicated to interpret, pointing towards the inability of usual ways of analysis and the necessity of suitable diagnostic strategies [5].

Recent advances in Deep Learning (DL), specifically those involving convolutional neural networks (CNNs) and transformer models adapted for vision, have drastically altered the state of play in medical image processing. These learning-based approaches have demonstrated remarkable capabilities in extracting hierarchical and discriminative representations directly from medical images without requiring handcrafted feature engineering. At the same time, CNN-based feature learning with Visual Geometry Group (VGG) and ResNet pre-trained models has been effectively used in multi-class classification of neurological diseases based on structural MRI imaging, focusing on the universal utility of DL in disease severity classification tasks [6]. Conversely, Cardiac Magnetic Resonance imaging (CMRI) is a technique offering high-detail volumetric imaging for evaluating the morphology of the heart [7].

Motivated by diagnostic challenges and limitations posed in the diagnosis of cardiac MRI, the research seeks to use a lightweight optimisation-driven DL approach to make a competent diagnosis using high-dimensional cardiac MRI information. The study particularly focuses on balancing predictive performance with computational efficiency through lightweight architectural design, intelligent parameter optimisation, and model compression strategies.

The main contribution of this paper is that the Lightweight diagnostic model is based on GhostNet architecture, employing channel attention within a lightweight framework for cardiac MRI diagnosis, achieving high accuracy with low computational requirements. The proposed architecture incorporates squeeze-and-excitation-based channel recalibration mechanisms to improve feature discrimination while maintaining a compact network structure. The Optimisation-Driven Learning Strategy utilises an enhanced Parrot optimisation technique for better convergence and generalisation in lightweight deep network optimisation. Additionally, the Efficiency-Oriented Pruning Method evaluates FLOPS, memory, and accuracy trade-offs, demonstrating superior efficiency compared to traditional CNNs. Comprehensive computational analyses are also conducted to quantify reductions in model complexity and resource utilisation while preserving diagnostic effectiveness.

The structure for this paper outlines the motivation for diagnostic processes in cardiac MRIs, starting with section 1. Section 2 reviews prior work and identifies existing gaps. Section 3 describes a lightweight, optimisation-based method to address these gaps. Experimental results and comparative analyses are presented in Section 4, and Section 5 discusses the conclusion and future research opportunities.

# 2 Literature Review

In 2024, Alsekait et al., [8] suggested the idea of Heart-Net in [8], which helps in better diagnosis of cardiac diseases by multi-modal learning of data obtained from both CMRI and ECG techniques. The integration of multiple data modalities enables richer feature representation and improved diagnostic robustness compared with single-source analysis approaches. Feature extractions for MRI are done by a 3D U-Net in Heart-Net Model for ECG by Temporal Convolutional Graph Neural Network (TCGN).

In 2024, Paciorek et al. [9] developed a DL algorithm for the evaluation of cardiac pathologies from cardiac MRI T1-mapping. The cardiac MRI T1-mapping and late gadolinium phase-sensitive inversion recovery sequences were taken into account. The DL algorithms were developed by the use of the ImageNet

pre-trained DenseNet-161. Transfer learning through pre-trained networks demonstrated the potential of leveraging large-scale image representations for specialised cardiac imaging tasks. The gradient-weighted class activation maps were employed for the evaluation of the attention of the DL algorithm while evaluating the MRI images. This approach also contributed to improving model interpretability by identifying clinically relevant image regions influencing diagnostic decisions.

In 2024, Iqbal et al. [10] analysed the optimisation of healthcare-related AI models using time complexity and hyperparameter adjustment for a classification problem. Their study highlighted the growing importance of balancing predictive performance with computational efficiency in healthcare-oriented deep learning systems. The importance of a lightweight CNN in analysing and classifying MRI is compared to CNN-Random Forest (CNN-RF).

In 2024, Koechli et al. [11] investigated the accuracy of fast 3-RR cine MRI sequences performed with DL reconstruction and compared them with that of conventional 2-D cine balanced steady-state free precession (b1SSFP) sequences. Fast cine imaging with DL reconstruction achieves a marked reduction in scanning time but with a slightly decreased image quality. These findings indicate the practical trade-off between accelerated acquisition and image fidelity, which remains a key challenge in cardiac MRI research.

In 2024, Phair et al. [12] assessed and validated a non-rigid motion-corrected model-based DL reconstruction framework motion-corrected model based DL (MoCo-MoDL) for 3D whole-heart MRI imaging for a patient population of congenital heart disease (CHD) subjects. The reconstruction process was assessed by comparing it to a non-rigid motion-corrected patch-based low-rank reconstruction method (NR-PROST) and standard images. The study demonstrated that advanced reconstruction frameworks can effectively improve image quality and motion robustness in complex clinical scenarios.

In 2025, Zhao et al. [13] addressed these issues by presenting a hybrid CNN & Transformer model called TransCHD. The hybrid CNN & Transformer model is intended for coronary artery segmentation within Coronary computed tomography angiography (CCTA). Their proposed TransCHD model includes a Contextual Representation Learning module & a Spatially-Aware Feature (SAF) module within a unified architecture. By combining convolutional operations with transformer-based global context modelling, the framework achieved enhanced segmentation performance for challenging vascular structures.

IN 2026, Lyu et al. [14] created CRUNet-MR, a novel DL model to improve spatial-temporal feature extraction by integrating convolutional recurrent operations with a U-Net structure. This capacity demonstrates its ability to accommodate larger acceleration factors, resulting in faster and more patient-friendly cardiac imaging. The incorporation of recurrent feature learning further improved temporal consistency and reconstruction quality in accelerated MRI acquisition settings.

### 2.1 Research Gap

Current deep learning approaches for cardiac imaging, such as Heart-Net, TransCHD, and CRUNet-MR, improve multi-modal analysis and segmentation but face challenges like high computation costs and limited optimisation. These systems also experience slight image quality loss, highlighting the need for enhancement in clinical applicability and interpretability. To overcome this issue, the researcher focuses on developing integrated, lightweight, and explainable architectures that maintain image quality during accelerated scanning to facilitate faster and more patient-friendly cardiac diagnosis.

## 3 Proposed Methodology

In this paper, an approach for diagnosing cardiac diseases using MRI images is proposed, focusing on achieving high accuracy with reduced computational costs. The proposed framework is designed as an end-to-end lightweight diagnostic pipeline that integrates efficient feature extraction, attention-guided representation learning, adaptive optimisation, and model compression within a unified architecture. The approach comprises several components: preprocessing, two consecutive GhostNet levels for feature extraction, attention-based feature enhancement, optimisation-driven training, pruning, and classification. Fig. 1 illustrates the architecture of the propsed model.

### 3.1 Preprocessing

The three preprocessing steps are applied to each cardiac MRI image to ensure uniformity, reduce noise, and enhance computational efficiency. These preprocessing operations reduce inter-patient intensity variations and provide a stable input distribution that facilitates faster network convergence during training.

**Step 1: Intensity Normalisation**

Z-score normalisation minimises intensity variation caused by patient differences and scanner variations. It is computed using the formula.

$$I_n = \frac{I - \mu_I}{\sigma_I} \tag{1}$$

where μI is the mean, and σI is the standard deviation of the original dataset.

**Step 2: Noise Reduction**

To reduce acquisition noise and small artefacts while preserving anatomical edges crucial for analysing cardiac structures, a median filtering operation is employed.

$$I_d(x, y) = median\{I_n(i, j)\} \tag{2}$$

where $(j)$represents coordinates in the local neighbourhood around the pixel $(y)$.

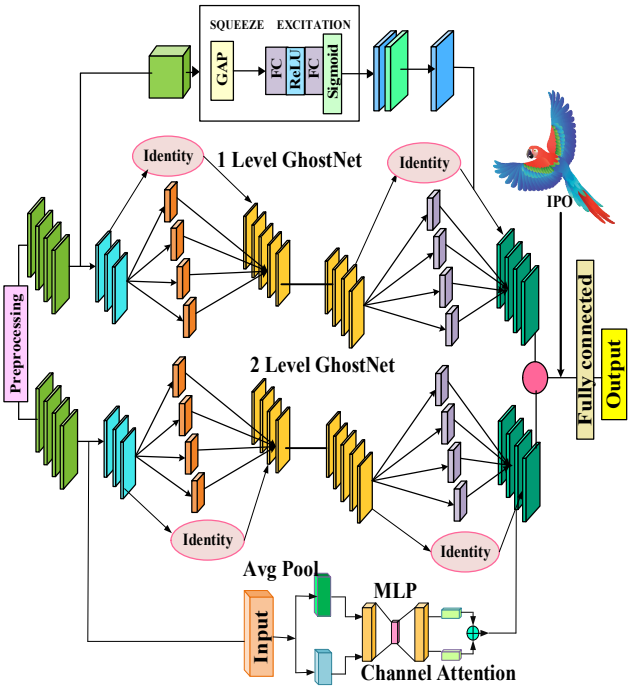



***Fig. 1.*** *Architecture*

**Step 3: Spatial Resizing**

Pre-processed images are resized to a uniform resolution of H x W pixels via bilinear resampling, standardising input data and reducing computational demand. This preprocessing aims to ensure consistent data, enhance feature clarity, and establish a stable training environment for a lightweight network designed to identify cardiac structures relevant to diagnosis.

## 3.2 GhostNet Feature Extraction – Level 1

Level 1 of the GhostNet feature extraction network focuses on capturing low-level structural characteristics of cardiac anatomy, including edges, textures, and contours. GhostNet is adopted because it generates highly informative feature representations using considerably fewer parameters than conventional convolutional architectures. It generates an intrinsic feature map using standard convolutional neural networks (CNNs), represented by

$$F_p^{(1)} = X * W^{(1)} \tag{3}$$

Ghost feature maps are obtained through lightweight linear transformations, denoted as

$$F_g^{(1)} = \Phi(F_p^{(1)}) \tag{4}$$

The final output is a composite image,

$$F^{(1)} = [F_p^{(1)}, F_g^{(1)}] \tag{5}$$

They combine both primary and ghost feature maps. The combination enables the network to preserve discriminative information while substantially reducing redundant computations. This approach significantly decreases the computational resources required for processing large datasets compared to traditional CNNs.

## 3.3 Squeeze-and-Excitation Attention

The SE Module for Level 1 enhances channel importance by using feature maps generated from Level 1, applying global average pooling, and calculating.

$$z_c^{(1)} = \frac{1}{HW}\sum_{i=1}^{H} \quad \sum_{j=1}^{W} \quad F_c^{(1)}(i,j) \tag{6}$$

Channel-wise excitation weights to produce a new, weighted feature map.

$$s^{(1)} = \sigma\big(W_2\, \delta(W_1 z^{(1)})\big) \tag{7}$$

The recalibrated feature map becomes:

$$\hat{F}_c^{(1)} = s_c^{(1)} \cdot F_c^{(1)} \tag{8}$$

This module improves the contribution of cardiac motion features without adding high computational costs.

## 3.4 GhostNet Feature Extraction – Level 2

In Ghostnet Level 2, high-level semantic features such as ventricular/peripheral Myocardial Deformation Patterns and ventricular abnormalities are extracted.

$$F^{(2)} = GhostNet(\hat{F}^{(1)}) \tag{9}$$

This level outputs SE-Refined Features to other Channels, providing increased representational capability without compromising computational efficiency. The hierarchical extraction strategy enables progressive learning of complex pathological characteristics that are difficult to capture using shallow feature representations.

## 3.5 Channel Attention Module

A Channel Attention (CA) Mechanism is employed to identify the most critical channels for diagnostic purposes based on their semantics.

$$z_c^{(2)} = GAP(F_c^{(2)}) \tag{10}$$

Channel descriptors are derived using global pooling, and channel attention weights are computed from these descriptors.

$$a_c = \sigma(W_c z_c^{(2)}) \tag{11}$$

The refined feature representation,

$$\hat{F}_c^{(2)} = a_c \cdot F_c^{(2)} \tag{12}$$

The channel attention mechanism dynamically assigns higher weights to diagnostically relevant feature channels, thereby improving classification robustness. This leads to a refined feature representation aimed at amplifying disease-specific features while minimising noise.

## 3.6 Global Average Pooling

Attention refined feature maps are compressed into a compact feature vector.

$$f = GAP(\hat{F}^{(2)}) \tag{13}$$

This reduces dimensionality and improves generalisation. Global Average Pooling also minimises the number of trainable parameters compared with fully connected feature aggregation methods, thereby reducing the risk of overfitting.

## 3.7 Improved Parrot Optimisation

The optimised parameters of the models are computed using an Improved Parrot Optimisation Algorithm [15] that adaptively modifies solutions to enhance convergence stability and avoid local minima. The optimisation process balances exploration and exploitation by continuously adjusting candidate solutions according to the current search state, thereby accelerating convergence towards an optimal parameter set. The process involves updating parameters according to

$$\theta^{t+1} = \theta^t + \alpha r(\theta_{best} - \theta^t) \tag{14}$$

The fitness function is defined as:

$$L = L_{CE} + \lambda \parallel \theta \parallel_2 \tag{15}$$

## 3.8 Structured Pruning

Structured Channel Pruning eliminates low-importance channels to reduce inference difficulty. decreasing parameters and memory usage while maintaining minimal performance loss.

$$C_{pruned} = \{c \mid a_c < \tau\} \quad (16)$$

This step decreases parameters and memory usage while maintaining minimal performance loss. Unlike unstructured pruning, structured pruning preserves hardware efficiency by removing complete feature channels, enabling faster inference and lower memory consumption during deployment.

### 3.9 Classification Layer

The classification law involves passing a one-dimensional feature vector through a lightweight multimodal Linear Model (MLP) and then applying a softmax function to estimate the probability of having a cardiac condition.

$$\hat{y} = softmax(Wf + b) \quad (17)$$

where $\hat{y}$denotes predicted cardiac disease probabilities. The final layer similarly processes the feature vector through the MLP and softmax to estimate the CV disease.

## 4 Results and Discussion

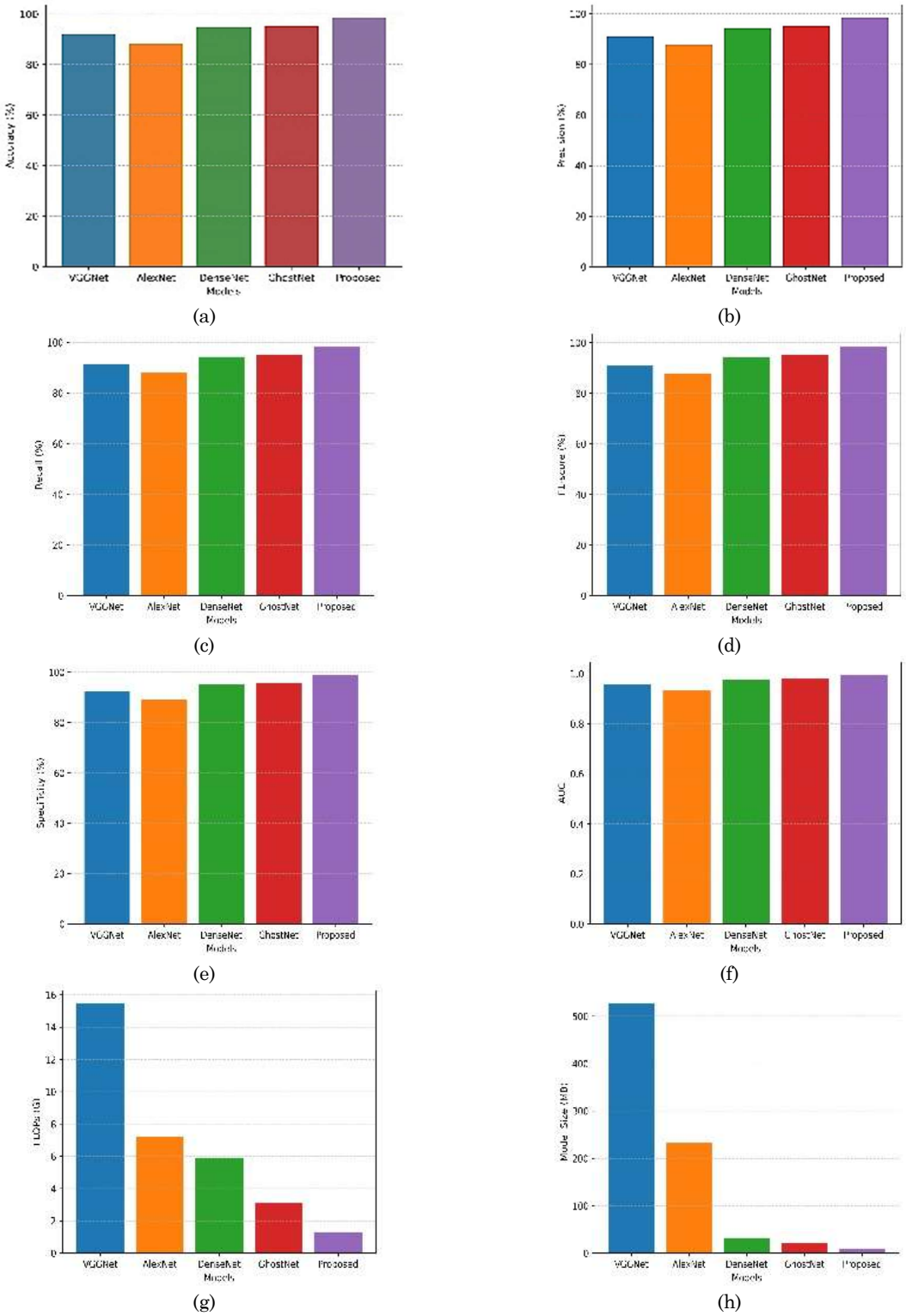
The experimental results confirm that the proposed lightweight optimisation-driven deep learning framework offers a better trade-off between diagnostic accuracy and computational efficiency in cardiac MRI–based disease diagnosis. The experimental evaluation demonstrates that integrating lightweight feature extraction, attention-guided learning, optimisation, and structured pruning provides complementary improvements in both predictive performance and computational resource utilisation. Compared with well-known CNN architectures, the proposed model consistently shows higher classification performance and reduces model complexity, memory usage, and inference latency significantly. The incorporation of a lightweight GhostNet backbone with channel attention enables feature discrimination effectively, while the optimisation-driven training strategy contributes to faster convergence and stable learning behaviour. Structured pruning further improves efficiency with negligible impact on diagnostic performance, underlining compact and information-efficient representation. The low values of loss, minimal degradation in performance after pruning, and strong consistency across various cross-validation folds collectively indicate robust generalisation and lower overfitting. The consistency observed across repeated validation experiments demonstrates the stability and reliability of the proposed optimisation strategy under different training conditions. Overall, these findings confirm that the proposed framework is well-suited for real-time and resource-constrained clinical environments, offering a practical and scalable solution for accurate cardiac disease diagnosis from MRI data.

***Table 1.*** *Performance and efficiency comparison with benchmark CNNs*

| Model | VGGNet | AlexNet | DenseNet | GhostNet | Proposed |
|---|---|---|---|---|---|
| **Accuracy (%)** | 91.8 | 88.4 | 94.6 | 95.3 | 98.7 |
| **Precision (%)** | 90.9 | 87.6 | 94.1 | 95 | 98.6 |
| **Recall (%)** | 91.2 | 88.1 | 94.3 | 95.1 | 98.5 |
| **F1-score (%)** | 91 | 87.8 | 94.2 | 95 | 98.6 |
| **Specificity (%)** | 92.5 | 89 | 95.1 | 95.8 | 99.1 |
| **AUC** | 0.958 | 0.932 | 0.975 | 0.981 | 0.997 |
| **FLOPs** | 15.5 | 7.2 | 5.9 | 3.1 | 1.3 |
| **MB** | 528 | 233 | 32 | 21 | 9.8 |
| **Latency** | 42 | 29 | 24 | 16 | 8 |
| **Memory Usage (MB)** | 3200 | 2100 | 1650 | 980 | 520 |
| **Convergence Speed** | 55 | 48 | 42 | 36 | 24 |
| **Training Time** | 14.2 | 10.6 | 12.8 | 9.4 | 6.1 |
| **Loss Value** | 0.36 | 0.41 | 0.24 | 0.21 | 0.07 |
| **Stability** | High | High | Medium | Low | Very Low |
| **Pruning Ratio** | 35 | 30 | 45 | 55 | 70 |
| **FLOPs Reduction** | 32 | 28 | 41 | 54 | 68 |
| **K fold** | 91.2 ± 1.9 | 87.9 ± 2.4 | 94.2 ± 1.2 | 95.0 ± 0.9 | 98.4 ± 0.4 |

Table 1 illustrates the comparison of the proposed optimisation-driven lightweight model with benchmark CNN models on the diagnosis accuracy, computational efficiency, and robustness. The proposed model performs best on accuracy, precision, recall, F1-score, specificity, and AUC, ensuring extremely reliable cardiac disease diagnosis with fewer false positives. Higher specificity and AUC values indicate improved discrimination between diseased and non-diseased cases, reducing the likelihood of diagnostic misclassification. The proposed model performs best in terms of computational efficiency with significantly fewer parameters and FLOPs, resulting in better model size efficiency with the fastest inference time. There is enhanced training efficiency with faster convergence speed and shorter training time. Moreover,

the optimisation and pruning experiments clearly show better structural efficiency with remarkably high pruning ratios with negligible accuracy loss, along with a significant reduction in parameters and computational cost. The model with the least loss, stable training dynamics, and maximum cross-validation accuracy proves excellent robustness on generalisation. Furthermore, the balance between model compactness and predictive performance illustrates the effectiveness of combining lightweight architecture design with adaptive optimisation and structured pruning The experimental results clearly suggest that the proqposed model offers the best accuracy-complexity trade-off, making it suitable for real-time diagnosis of cardiac MRI. Fig. 2 illustrates the performance and efficiency comparison of the proposed model with benchmark CNNs.



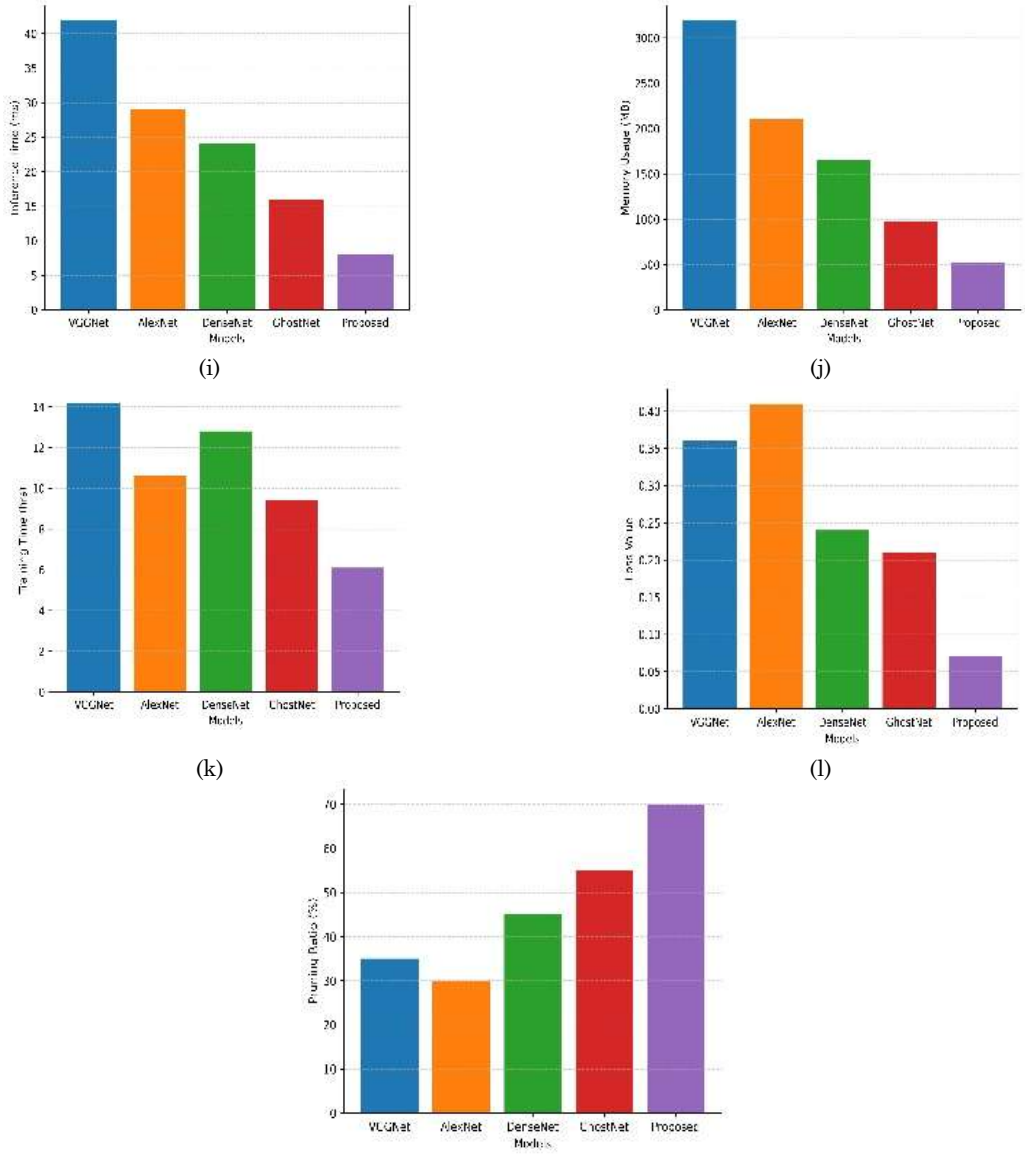



***Fig. 2.*** *Performance and efficiency comparison of the proposed model with benchmark CNNs.*

# 5 Conclusion

This paper presents a lightweight, optimisation-driven deep learning framework for the diagnosis of cardiac diseases from MRI images. The proposed framework effectively integrates lightweight feature extraction, attention-guided representation learning, adaptive optimisation, and model compression into a unified diagnostic architecture suitable for intelligent medical image analysis. Utilising a two-level GhostNet architecture with hierarchical attention mechanisms, including Squeeze-and-Excitation and Channel Attention, it enhances diagnostically significant features while maintaining low computational complexity. The IPO Algorithm ensures stable convergence and improved generalisation, and structured channel pruning significantly reduces model size, memory needs, and computational latency with minimal performance loss. Furthermore, the optimisation and pruning strategies demonstrate that substantial reductions in computational cost can be achieved without compromising diagnostic effectiveness, making the framework appropriate for deployment in resource-constrained healthcare environments. Experimental results demonstrate that the framework outperforms standard CNN models in accuracy, robustness, and efficiency, achieving a favourable balance between accuracy and complexity.

## Compliance with Ethical Standards

**Conflicts of interest:** Authors declared that they have no conflict of interest.

**Human participants:** The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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