ECG classification using Deep CNN and Gramian Angular Field

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Motivation

- Growing demand for assistance in the interpretation of ECG recordings in clinical decision-making.
- Need to enhance automated ECG interpretation.
- ECG classification faces several challenges related to feature representation, including signal variability, noise and artifacts, dimensionality, interpretability, and scalability.
- High inter-subject variability makes it challenging to identify relevant features that can be used for classification.
- Study aims to use GAF as a representation model to overcome the limitations.

System Design

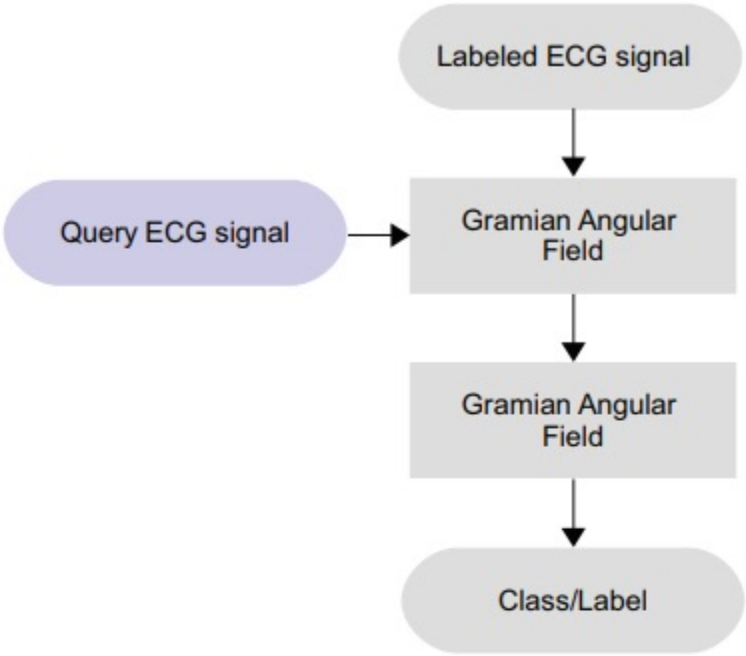
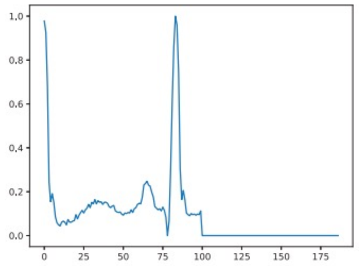
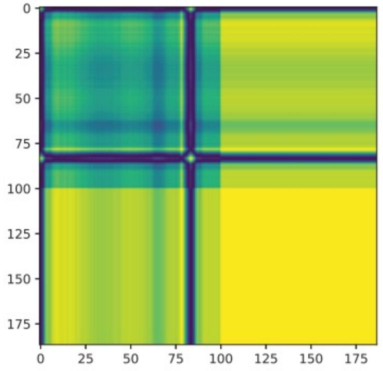


Fig. 1. Architecture of the proposed ECG representation and classification system.

ECG and corresponding GAF image



(a) 1D ECG vector



(b) ECG 2D GAF image

Fig. 2. Example of transforming a 1D ECG signal (of a sample) to a 2D GAF image: (a) 1D vector, and (b) ECG 2D GAF image.

Tested NNs

- Pretained + Transfer learning:
  - VGG16,
  - ResNet50,
  - and EfficientNet methods,

- One Specifically Designed CNN model.

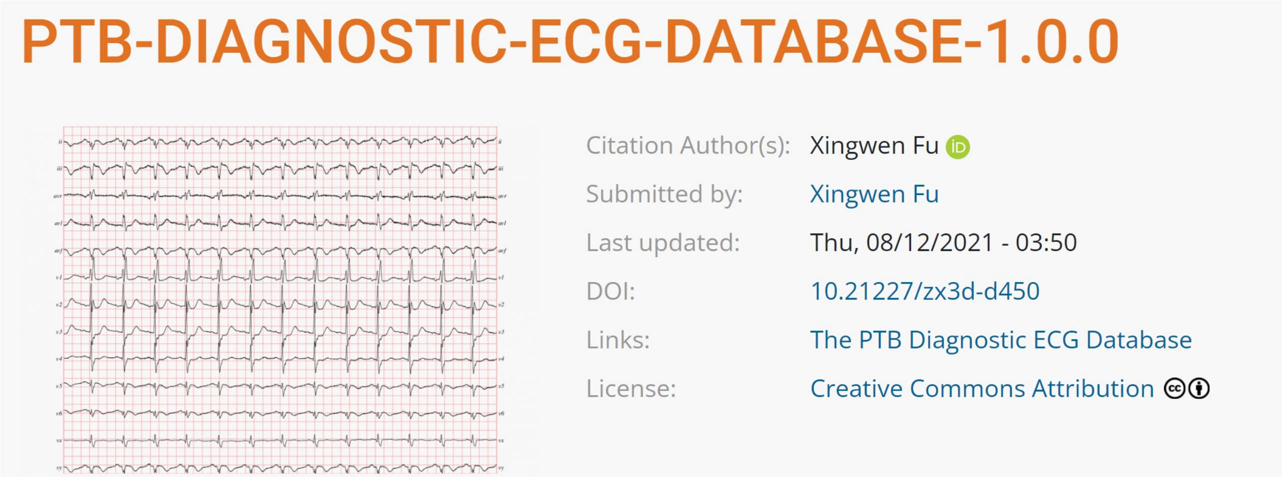
CNN architecture

- Conv2D layer with 32 filters, a kernel size of (3, 3) ’relu’ activation function
- MaxPooling2D layer with a pool size of (2, 2)
- Conv2D layer with 64 filters and a kernel size of (3, 3) with ’relu’ activation function.
- MaxPoo
- Conv2D layer with 64 filters and a kernel size of (3, 3) with ’relu’ activation function.
- Flatten layer, which flattens the 2D feature maps into a 1D vector.
- Dense layer with 64 units and ’relu’ activation function.
- Dense layer with 10 units, which represents the output layer.

Datasets

- MIT-BIH Arrhythmia Dataset3:
  - 109,446 samples
  - 5 classes for normal beat and 4 classes of heart conditions

- The PTB Diagnostic ECG Database:
  - Only Two classes for normal beat and abnormal conditions.
  - 14,552 samples

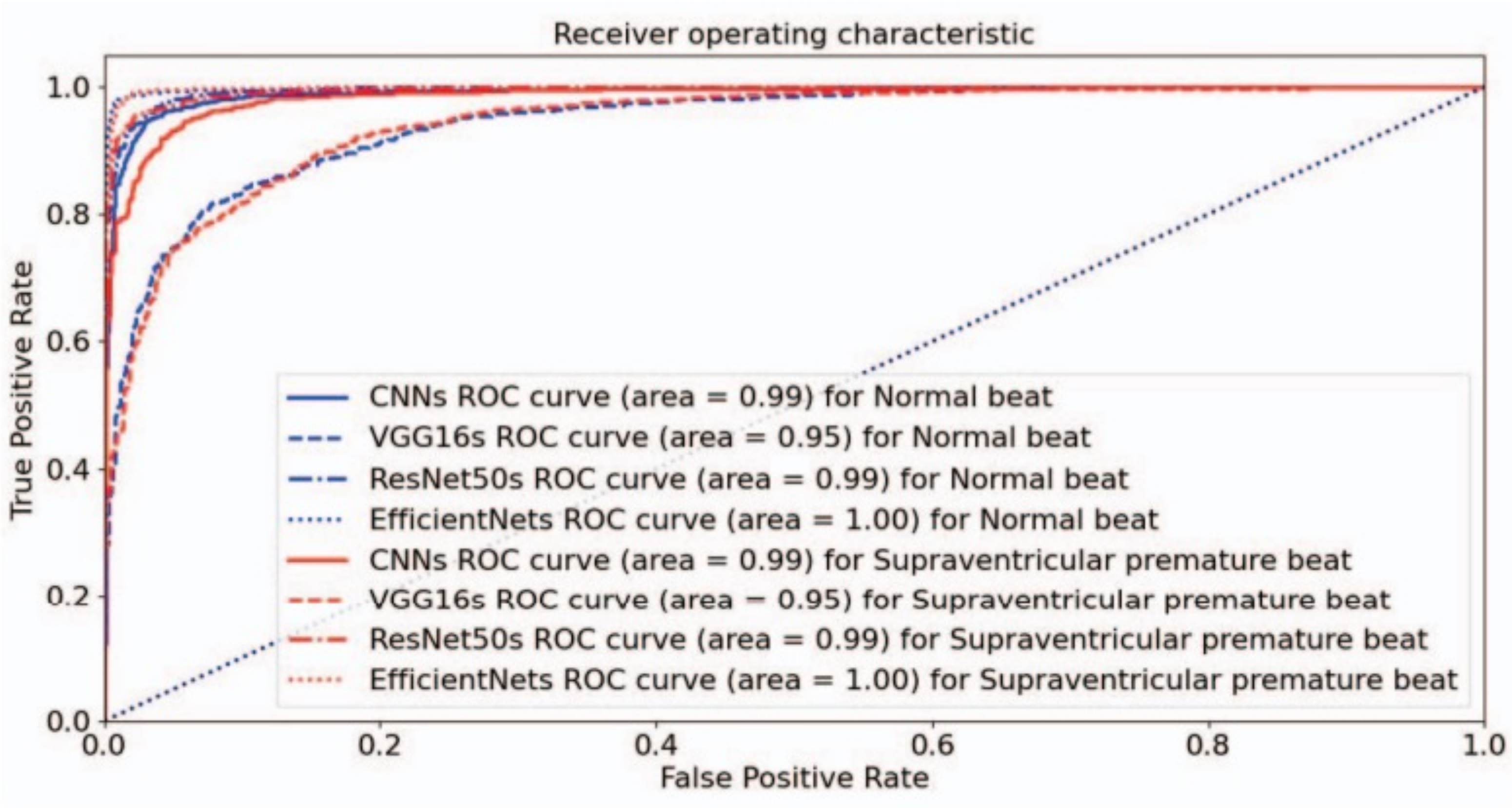


5-class and 2-class classification

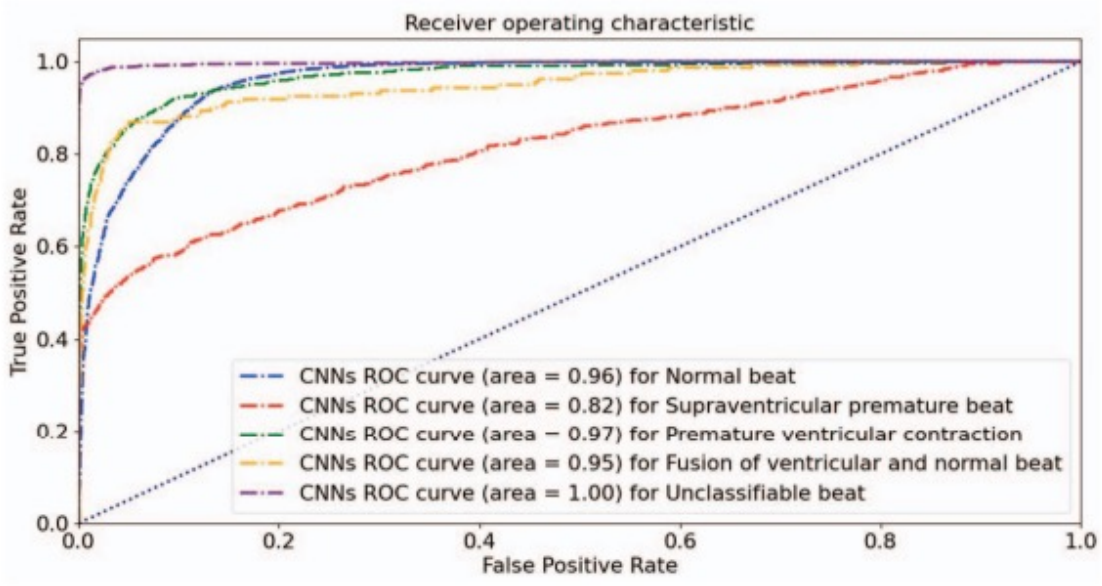
TABLE I
COMPARISON OF RESULTS ON TWO ECG CLASSIFICATION DATASETS

Dataset	*Number of Samples (train, test)*	*Number of Categories (classes)*	*Method*	*Accuracy (%)*	*F1-score (%)*
Arrhythmia	109446 (87554/21892)	5	CNN	97.47	97.34
			VGG16	97.32	97.18
			ResNet50	97.07	96.92
			EfficientNet	96.78	96.64
The PTB Diagnostic	14552 (11642/2910)	2	CNN	97.56	97.56
			VGG16	89.17	88.98
			ResNet50	95.84	95.90
			EfficientNet	98.65	98.65

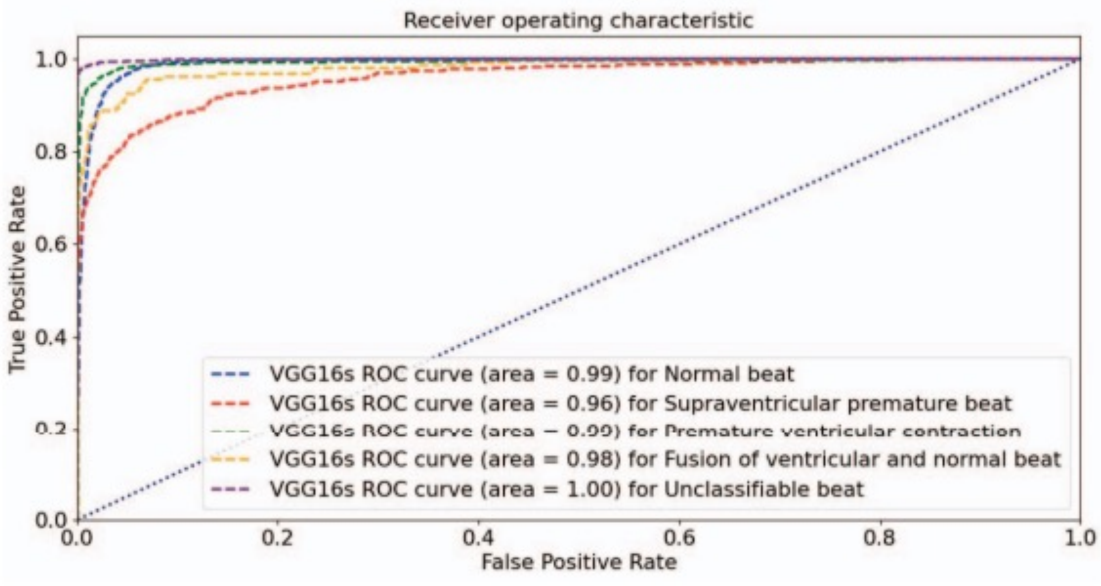
PTB dataset Results



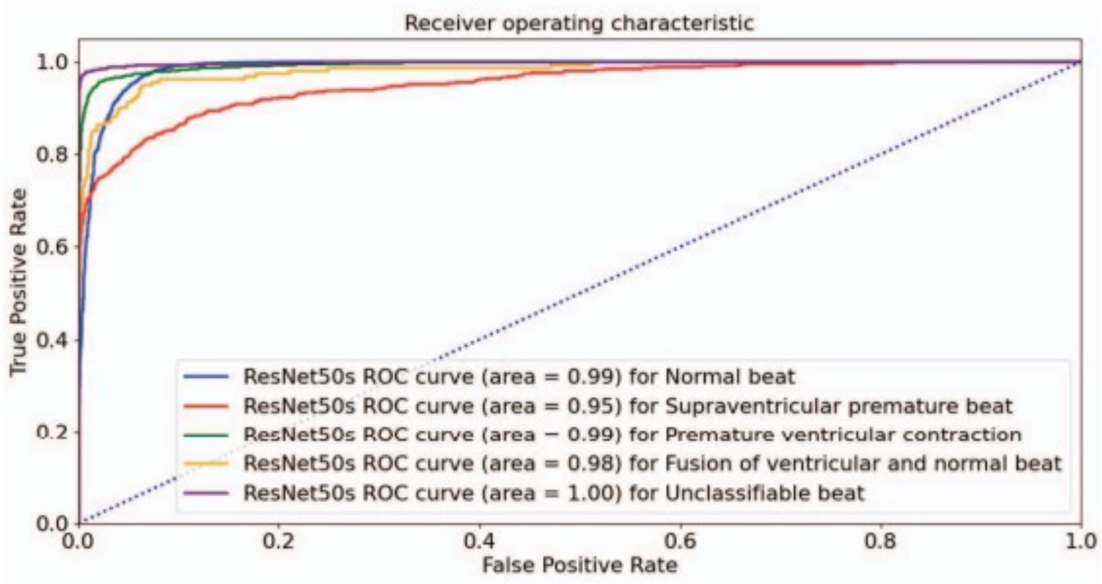
(e) The PTB Diagnostic


Receiver operating characteristic
True Positive Rate
False Positive Rate
CNNs ROC curve (area = 0.96) for Normal beat
CNNs ROC curve (area = 0.82) for Supraventricular premature beat
CNNs ROC curve (area = 0.97) for Premature ventricular contraction
CNNs ROC curve (area = 0.95) for Fusion of ventricular and normal beat
CNNs ROC curve (area = 1.00) for Unclassifiable beat

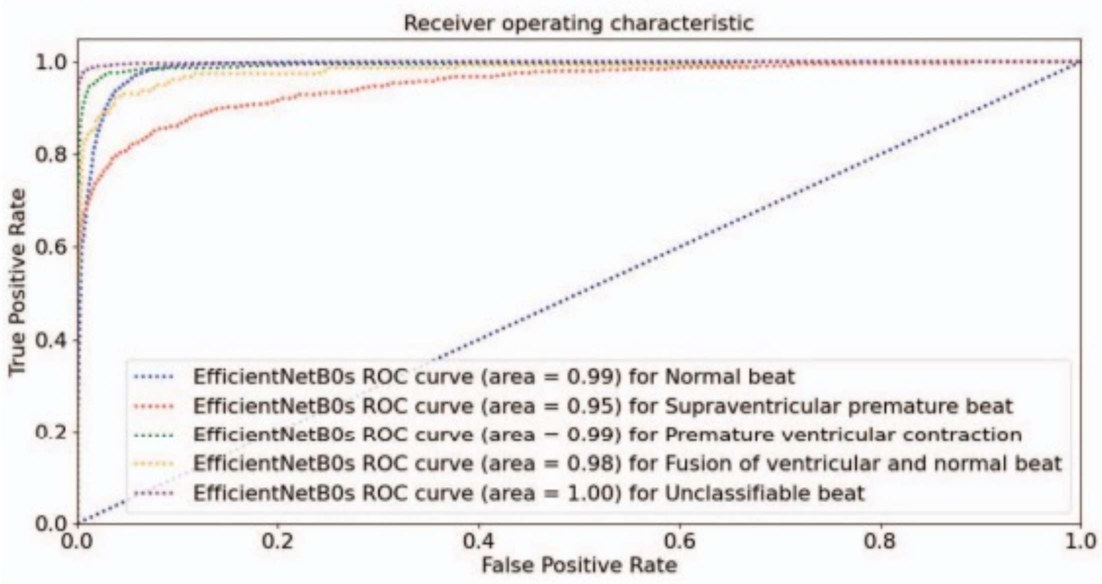
(a)


Receiver operating characteristic
True Positive Rate
False Positive Rate
VGG16s ROC curve (area = 0.99) for Normal beat
VGG16s ROC curve (area = 0.96) for Supraventricular premature beat
VGG16s ROC curve (area = 0.99) for Premature ventricular contraction
VGG16s ROC curve (area = 0.98) for Fusion of ventricular and normal beat
VGG16s ROC curve (area = 1.00) for Unclassifiable beat

(b)


Receiver operating characteristic
True Positive Rate
False Positive Rate
ResNet50s ROC curve (area = 0.99) for Normal beat
ResNet50s ROC curve (area = 0.95) for Supraventricular premature beat
ResNet50s ROC curve (area = 0.99) for Premature ventricular contraction
ResNet50s ROC curve (area = 0.98) for Fusion of ventricular and normal beat
ResNet50s ROC curve (area = 1.00) for Unclassifiable beat

(c)


Receiver operating characteristic
True Positive Rate
False Positive Rate
EfficientNetB0s ROC curve (area = 0.99) for Normal beat
EfficientNetB0s ROC curve (area = 0.95) for Supraventricular premature beat
EfficientNetB0s ROC curve (area = 0.99) for Premature ventricular contraction
EfficientNetB0s ROC curve (area = 0.98) for Fusion of ventricular and normal beat
EfficientNetB0s ROC curve (area = 1.00) for Unclassifiable beat

(d)

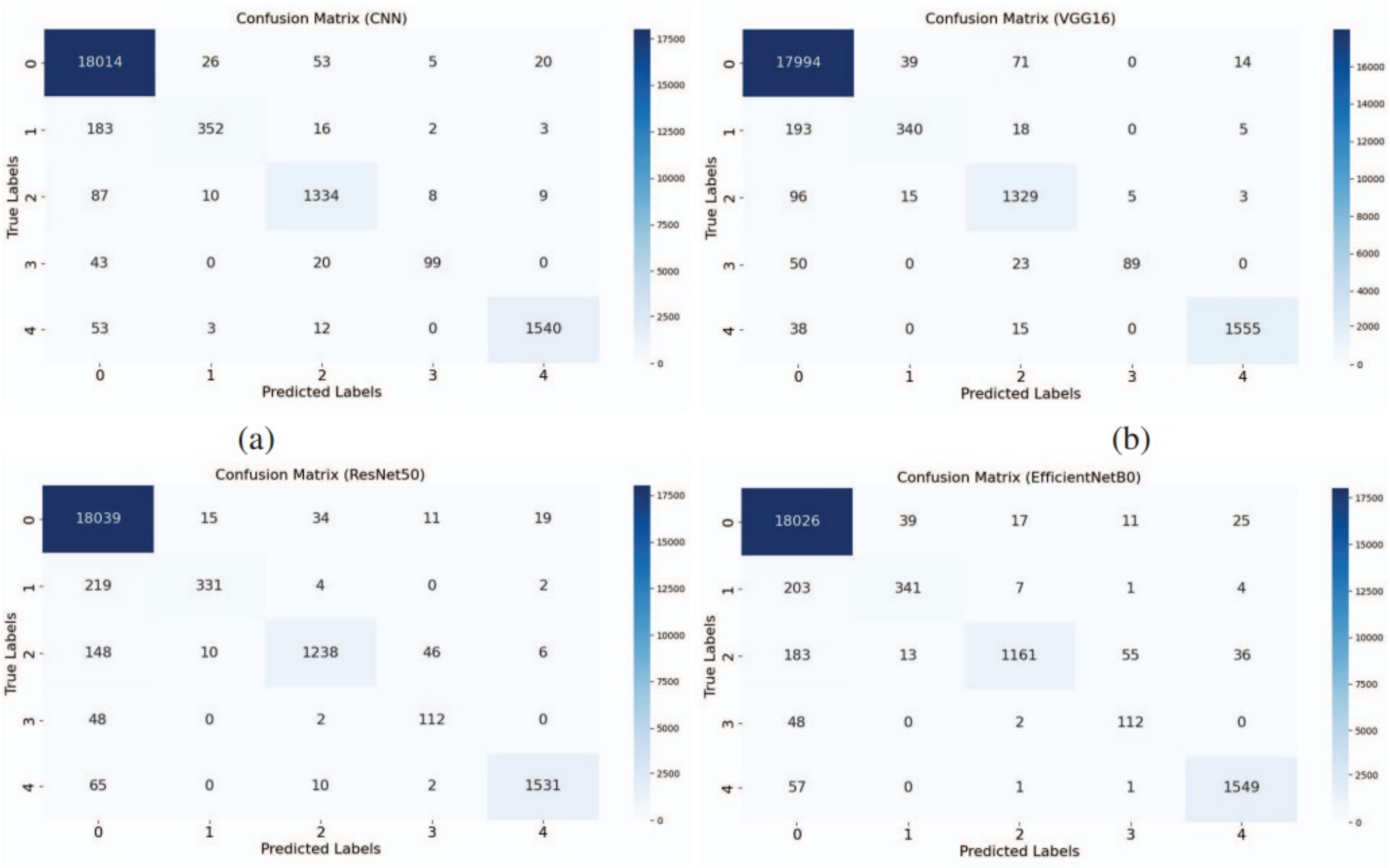


Fig. 5. Confusion matrices under the Arrhythmia dataset using (a) CNN, (b) VGG-16, (c) ResNet-50 and (d) EfficientNet.

Discussion

- GAF is a highly effective method for ECG classification, regardless of dataset size and class complexity.
- Use of pretrained models did not result in significant improvement in the current experiments,
- Finetuning may require further optimization and resources to fully leverage potential for ECG classification.
- Future research could explore comparing GAF-based classification with other approaches, such as time-frequency based methods, or fusing time-frequency features.