SUPPLEMENTAL MATERIAL
Supplemental Methods

VGGNet-16 was designed for 2-dimensional image classification and had a kernel size of $3 \times 3$. Some modifications to the traditional VGGNet-16 were required to accommodate the one-dimensional input signal in this study. First, the convolution and max-pooling layers were revised to be one-dimensional, with the kernel size being $1 \times 3$. Second, the number of filters was reduced from 64, 128, 256, and 512 to 32, 64, 128, and 256, respectively. Third, the number of fully connected layers was reduced from 4 to 2. These steps were taken because when processing one-dimensional physiological signals, reducing the number of filters and fully connected layers can increase the training speed without affecting the performance of deep learning models. Finally, the deep convolutional neural network (DCNN) model employed in this study consists of 13 one-dimensional convolutional (Conv1d) layers, five one-dimensional max-pooling (MaxPool1d) layers, and two fully connected layers. Each convolutional layer was followed by a one-dimensional batch normalization (BatchNorm1d) layer and a rectified linear unit (ReLu) function. A ReLu layer and a dropout ($p = 0.5$) layer were applied between the fully connected layers. The detailed configuration of our DCNN model is provided in Table S1.

In the model, the weights were initialized by using the Kaiming initializer. The model was trained using Adam optimizer with default parameters and a mini-batch size of 128.
The learning rate was set to 0.001 at the beginning and then decayed exponentially (gamma = 0.95) during the training. The construction and evaluation of the DCNN in this paper are implemented based on Pytorch in the CentOS7.3 operating system.

**Data S2**

The process of building the machine learning (ML)-based models for arrhythmia detection is shown in Figure S1. First, the position of peaks in the PPG waveform was detected (Figure S1A, left), and then the IPI series was obtained by calculating the time difference between two successive peaks (Supplementary Figure S1A, right). Second, the reported handcrafted features, including eight PPG waveform features (standard deviation value (STD), kurtosis, skewness, sample entropy (SampEn), Shannon entropy (ShEn), Hjorth mobility, Hjorth complexity, and spectral purity index (SPI)) and nine IPI features (mean value, STD, coefficient of variation (CoV), SampEn, ShEn, coefficient of sample entropy (COSEn), normalized root mean square of successive differences (nRMSSD) and point-care plot SD, and point-care plot SD2) were calculated from the PPG waveform and IPI series (Figure S1B).\textsuperscript{13, 32-35} Third, four ML algorithms that have been used for PPG-based arrhythmia detection were applied to construct the ML-based models (Figure S2C). The four ML algorithms include artificial neural network, random forest, k-nearest neighbors, and support vector machine.\textsuperscript{14, 15, 32, 36} All ML algorithms were implemented by using the Scikit-learn library in a Python programming environment.\textsuperscript{37} The extracted features were described as follows:

- Mean value and STD
Mean and standard deviation (STD) values are the most commonly used statistical parameters. We calculated the mean and STD of IPI sequences and the STD of the PPG waveform for arrhythmia detection.

- **CoV**

  CoV is a measure of relative variability.\(^{33}\) It is the ratio of the standard deviation (\(\sigma\)) to the mean (\(\mu\)), i.e.,  
  \[ CV = \frac{\sigma}{\mu} \]

- **Entropy measures**

  Entropy describes the confusion degree of a system. Two common indices, SampEn and ShEn are features of entropy theory. Previous studies have used the SampEn and ShEn to quantify the complexity of IPI sequences and PPG waveforms.\(^{13,34}\) A detailed introduction of ShEn and SampEn can be found in.\(^{38}\)

- **COSEn**

  COSEn is an entropy estimate optimized for the detection of atrial fibrillation.\(^{34}\) For a time series \(X\), its COSEn can be calculated as 
  \[ \text{CosEn} = \text{SampEn} - \ln(2r) - \ln(\mu) \]  
  (1)

  Where \(\text{SampEn}\) and \(\mu\) are the SampEn and mean of \(X\), respectively. \(r\) is the tolerance, usually set as \(0.2 \cdot \text{std}(X)\).

- **nRMSSD**

  nRMSSD is the ratio of root mean square of successive difference to mean of IPI series,\(^{13}\) defined as 
  \[ nRMSSD = \frac{1}{\sum_{i=1}^{N} a(i)} \cdot \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (a(i+1) - a(i))^2} \]  
  (2)

  Where \(N\) is the length of IPI sequences, and \(a(i)\) is the \(i\)th IPI, where \(i = 1, 2, \cdots, N\).
Poincaré plot parameters (SD1/SD2)

Poincaré plot, a scatter graph that shows the correlation between two consecutive data points in a time series, has been widely used for heart rate variability analysis. A Poincaré plot contains two important parameters, the length (SD1) and width (SD2) of the ellipse. Previously, Krivoshei et al. has studied SD1 and SD2 for discrimination of atrial fibrillation from PPG. Given a time series with length N, \( x_1, x_2, \ldots, x_N \), the parameters SD1 and SD2 can be defined as:

\[
SD1 = \frac{std(Y - X)}{\sqrt{2}} \tag{3}
\]

\[
SD2 = \frac{std(Y + X)}{\sqrt{2}} \tag{4}
\]

Where \( X = (x_1, x_2, \ldots, x_{N-1}) \), \( Y = (x_2, x_3, \ldots, x_N) \), and \( std(Y - X) \) and \( std(Y + X) \) refer the standard deviation value of \( Y - X \) and \( Y + X \), respectively.

Kurtosis and Skewness

Kurtosis is a measure of the heavy or light tails of a normal distribution, and skewness measures the symmetry or asymmetry of data distribution. Kurtosis and skewness are defined as:

\[
Kurtosis = E \left[ \left( \frac{x - \mu}{\sigma} \right)^4 \right] \tag{5}
\]

\[
Skewness = E \left[ \left( \frac{x - \mu}{\sigma} \right)^3 \right] \tag{6}
\]

Hjorth parameters

Hjorth parameters called mobility (\( H_1 \)), complexity (\( H_2 \)), and spectral purity index (SPI) have been used for PPG-based atrial fibrillation detection. The parameters are calculated from the spectral moment of the signal. Let’s define the \( n \)th order spectral moment as
\[ m_n = \int_{-\pi}^{\pi} \omega^n S(\omega) d\omega \quad (7) \]

where \( S(\omega) \) is the power spectrum. From the moment with different orders, \( \mathcal{H}_1, \mathcal{H}_2, \) and SPI are defined as the following formula:

\[ \mathcal{H}_1 = \sqrt{\frac{m_2}{m_0}} \quad (8) \]
\[ \mathcal{H}_2 = \sqrt{\frac{m_4 - m_2}{m_2 - m_0}} \quad (9) \]
\[ SPI = \frac{m_2^2}{m_4 m_0} \quad (10) \]

Our study calculated the Hjorth parameters using a free MATLAB Toolkit provided by Kugiumtzis et al.\textsuperscript{40}
| Layers | Type              | Output Size    | Filters | Kernel-size | Strides | Padding | Number of Parameters |
|--------|-------------------|----------------|---------|-------------|---------|---------|----------------------|
| 1      | Conv1d            | BS\times32\times1000 | 32      | 3           | 1       | 1       | 128                  |
| 2      | BatchNorm1d+ReLU  | BS\times32\times1000 | -       | -           | -       | -       | 64                   |
| 3      | Conv1d            | BS\times32\times1000 | 32      | 3           | 1       | 1       | 3 104                |
| 4      | BatchNorm1d+ReLU  | BS\times32\times1000 | -       | -           | -       | -       | 64                   |
| 5      | MaxPool1d         | BS\times32\times333 | -       | 3           | 3       | 0       | 0                    |
| 6      | Conv1d            | BS\times64\times333 | 64      | 3           | 1       | 1       | 6 208                |
| 7      | BatchNorm1d+ReLU  | BS\times64\times333 | -       | -           | -       | -       | 128                  |
| 8      | Conv1d            | BS\times64\times333 | 64      | 3           | 1       | 1       | 12 352               |
| 9      | BatchNorm1d+ReLU  | BS\times64\times333 | -       | -           | -       | -       | 256                  |
| 10     | MaxPool1d         | BS\times64\times111 | -       | 3           | 3       | 0       | 0                    |
| 11     | Conv1d            | BS\times128\times111 | 128     | 3           | 1       | 1       | 24 704               |
| 12     | BatchNorm1d+ReLU  | BS\times128\times111 | -       | -           | -       | -       | 256                  |
| 13     | Conv1d            | BS\times128\times111 | 128     | 3           | 1       | 1       | 49 280               |
| 14     | BatchNorm1d+ReLU  | BS\times128\times111 | -       | -           | -       | -       | 256                  |
| 15     | Conv1d            | BS\times128\times111 | 128     | 3           | 1       | 1       | 49 280               |
| 16     | BatchNorm1d+ReLU  | BS\times128\times111 | -       | -           | -       | -       | 256                  |
| 17     | MaxPool1d         | BS\times128\times37 | -       | 3           | 3       | 0       | 0                    |
| 18     | Conv1d            | BS\times256\times37 | 256     | 3           | 1       | 1       | 98 560               |
| 19     | BatchNorm1d+ReLU  | BS\times256\times37 | -       | -           | -       | -       | 512                  |
| 20     | Conv1d            | BS\times256\times37 | 256     | 3           | 1       | 1       | 196 864              |
| 21     | BatchNorm1d+ReLU  | BS\times256\times37 | -       | -           | -       | -       | 512                  |
| 22     | Conv1d            | BS\times256\times37 | 256     | 3           | 1       | 1       | 196 864              |
| 23     | BatchNorm1d+ReLU  | BS\times256\times37 | -       | -           | -       | -       | 512                  |
| 24     | MaxPool1d         | BS\times256\times12 | -       | 3           | 3       | 0       | 0                    |
| 25     | Conv1d            | BS\times256\times12 | 256     | 3           | 1       | 1       | 196 864              |
| 26     | BatchNorm1d+ReLU  | BS\times256\times12 | -       | -           | -       | -       | 512                  |
| 27     | Conv1d            | BS\times256\times12 | 256     | 3           | 1       | 1       | 196 864              |
| 28     | BatchNorm1d+ReLU  | BS\times256\times12 | -       | -           | -       | -       | 512                  |
| 29     | Conv1d            | BS\times256\times12 | 256     | 3           | 1       | 1       | 196 864              |
| 30     | BatchNorm1d+ReLU  | BS\times256\times12 | -       | -           | -       | -       | 512                  |
| 31     | MaxPool1d         | BS\times256\times4 | -       | 3           | 3       | 0       | 0                    |
| 32     | Fully-connected   | BS\times256        | -       | -           | -       | -       | 262 400              |
| 33     | Fully-connected   | BS\times6           | -       | -           | -       | -       | 1 542                |

Total parameters: 1 496 102

Each conv1d layer is followed by a one-dimensional batch normalization (BatchNorm1d) layer and a rectified linear unit (ReLU) function. A ReLU layer and a dropout (p = 0.5) layer are applied between the fully connected layers. DCNN, deep convolutional neural network; Conv1d, one-dimensional convolutional; MaxPool1d, one-dimensional max-pooling; BS: batch size.
Table S2. Classification results of four rhythm types by the DCNN model on the test set.

|                | Value, % (95% CI) |           |           |         |
|----------------|-------------------|-----------|-----------|---------|
|                | Sensitivity       | Specificity| PPV       | NPV     |
| SR             | 95.7 (95.2 to 96.2)| 98.8 (98.6 to 98.9) | 97.0 (96.6 to 97.4) | 98.2 (97.9 to 98.5) |
| PVC and PAC    | 75.4 (74.0 to 76.8)| 97.0 (96.8 to 97.3) | 82.7 (81.4 to 84.0) | 95.4 (94.9 to 96.0) |
| VT and SVT     | 87.5 (86.5 to 88.5)| 97.6 (97.4 to 97.9) | 89.3 (88.4 to 90.3) | 97.2 (96.7 to 97.7) |
| AF             | 94.4 (93.9 to 94.9)| 93.4 (93.0 to 93.8) | 89.1 (88.4 to 89.7) | 96.7 (96.2 to 97.2) |
| Average        | 88.2 (87.4 to 89.1)| 96.7 (96.4 to 97.0) | 89.5 (88.7 to 90.3) | 96.9 (96.4 to 97.3) |

Overall accuracy 90.4 (90.1 to 90.9)

DCNN, deep convolutional neural network; SR, sinus rhythm; PVC, premature ventricular contraction; PAC, premature atrial contraction; VT, ventricular tachycardia; SVT, supraventricular tachycardia; AF, atrial fibrillation; PPV, positive predictive value; NPV, negative predictive value.
**Table S3. Classification results of two rhythm types by the DCNN model on the test set.**

| Value, % (95% CI) | Sensitivity | Specificity | PPV | NPV |
|-------------------|-------------|-------------|-----|-----|
| **SR**            | 95.7 (95.2 to 96.2) | 98.8 (98.6 to 98.9) | 97.0 (96.6 to 97.4) | 98.2 (97.9 to 98.5) |
| non-SR (PVC, PAC, VT, SVT, and AF) | 98.8 (98.6 to 98.9) | 95.7 (95.2 to 96.2) | 98.2 (98.0 to 98.4) | 97.0 (96.6 to 97.3) |
| **Average**       | 97.2 (96.9 to 97.5) | 97.2 (96.9 to 97.5) | 97.6 (97.3 to 97.9) | 97.6 (97.3 to 97.9) |
| **Overall accuracy** | 97.8 (97.7 to 98.0) |

DCNN, deep convolutional neural network; SR, sinus rhythm; PVC, premature ventricular contraction; PAC, premature atrial contraction; VT, ventricular tachycardia; SVT, supraventricular tachycardia; AF, atrial fibrillation; PPV, positive predictive value; NPV, negative predictive value.
Table S4. Machine learning-based models for 6 rhythm types classification.

|       | SR           | PVC          | PAC           | VT           | SVT          | AF           | Average       | Sensitivity | Specificity | PPV          | NPV          |
|-------|--------------|--------------|---------------|--------------|--------------|--------------|---------------|-------------|-------------|--------------|--------------|
| **ANN** |              |              |               |              |              |              |                | (%) (95% CI) | (%) (95% CI) | (%) (95% CI) | (%) (95% CI) |
| SR    | 82.1 (81.2 to 83.0) | 21.6 (19.8 to 23.4) | 14.6 (13.0 to 16.3) | 58.4 (55.2 to 61.6) | 57.8 (56.2 to 59.5) | 87.5 (86.8 to 88.2) | **53.7 (52.0 to 55.3)** | 93.1 (92.8 to 93.4) | 93.1 (92.8 to 94.6) |              |              |
| PVC   | 84.1 (83.2 to 84.9) | 19.7 (17.9 to 21.5) | 17.2 (15.4 to 19.0) | 51.7 (48.5 to 54.9) | 54.7 (53.1 to 56.4) | 83.5 (82.7 to 84.3) | **51.8 (50.1 to 53.5)** | 92.8 (92.4 to 93.1) | 93.3 (92.4 to 94.2) |              |              |
| PAC   | 91.8 (91.4 to 92.2) | 97.0 (96.8 to 97.2) | 96.8 (96.5 to 97.0) | 95.8 (95.6 to 96.1) | 96.4 (96.1 to 96.6) | 78.9 (78.2 to 79.5) | **85.1 (83.0 to 86.3)** | 68.9 (67.9 to 69.9) | 93.0 (92.0 to 94.1) |              |              |
| VT    | 84.3 (83.7 to 84.9) | 98.9 (98.7 to 99.0) | 98.4 (98.2 to 98.5) | 97.1 (96.9 to 97.3) | 97.3 (97.1 to 97.6) | 71.5 (70.8 to 72.2) | **61.7 (60.0 to 63.4)** | 68.9 (67.9 to 69.9) | 93.0 (92.0 to 94.1) |              |              |
| SVT   | 84.3 (83.7 to 84.9) | 98.9 (98.7 to 99.0) | 98.4 (98.2 to 98.5) | 97.1 (96.9 to 97.3) | 97.3 (97.1 to 97.6) | 71.5 (70.8 to 72.2) | **61.7 (60.0 to 63.4)** | 68.9 (67.9 to 69.9) | 93.0 (92.0 to 94.1) |              |              |
| AF    | 71.9 (70.2 to 73.6) | 71.9 (70.2 to 73.6) | 71.9 (70.2 to 73.6) | 71.9 (70.2 to 73.6) | 71.9 (70.2 to 73.6) | 71.9 (70.2 to 73.6) | **71.9 (70.2 to 73.6)** | 68.2 (65.9 to 70.4) | 89.7 (88.9 to 90.4) |              |              |
| **Average** |              |              |               |              |              |              | **53.7 (52.0 to 55.3)** | 93.1 (92.8 to 93.4) | 93.7 (92.8 to 94.6) |              |              |

SR, sinus rhythm; PVC, premature ventricular contraction; PAC, premature atrial contraction; VT, ventricular tachycardia; SVT, supraventricular tachycardia; AF, atrial fibrillation; ANN, artificial neural network; RF, random forest; KNN, k- nearest neighbors; SVM, support vector machine; PPV, positive predictive value; NPV, negative predictive value.
Figure S1. Processes for machine learning-based arrhythmia detection models’ development.

(A) peaks detection and IPI series extraction. (B) PPG waveform features and IPI series features calculation. (C) models development with different machine learning algorithms. PPG, photoplethysmography; IPI, inter-beat intervals; STD, standard deviation; SampEn, sample entropy; ShEn, Shannon entropy; SPI, spectral purity index; CoV, coefficient of variation; nRMSSD, normalized root mean square of successive differences; COSEn, coefficient of sample entropy.
Figure S2. Flowchart of study participants.

ECG and PPG indicate electrocardiogram and photoplethysmography.
Figure S3. Examples of synchronous ECG and PPG signals in sinus rhythm (A), premature ventricular contraction (B), premature atrial contraction (C), ventricular tachycardia (D), supraventricular tachycardia (E), and atrial fibrillation (F).

ECG, electrocardiogram; PPG, photoplethysmography.