# An Advanced Two-step DNN-Based Framework for Arrhythmia Detection

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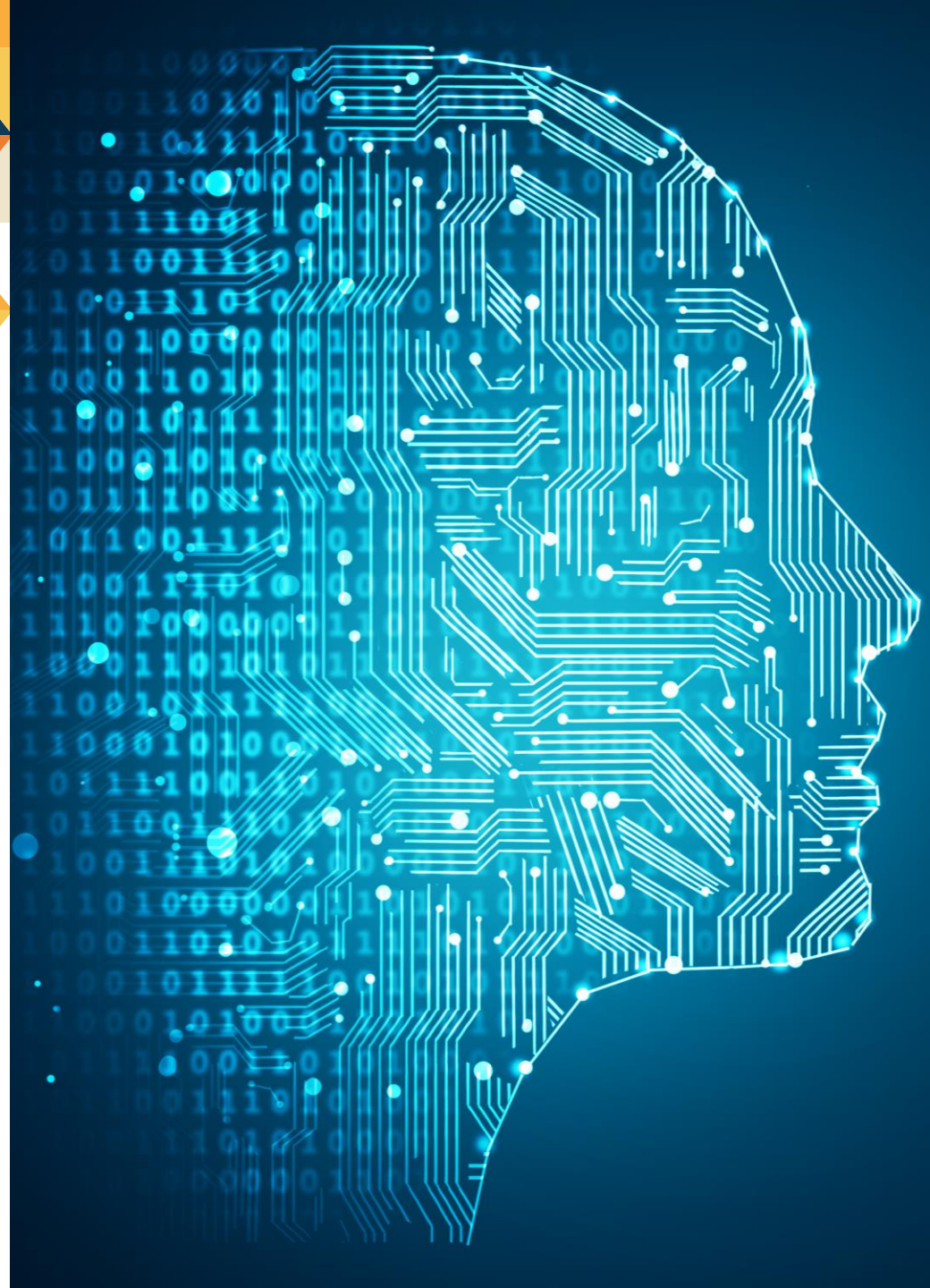
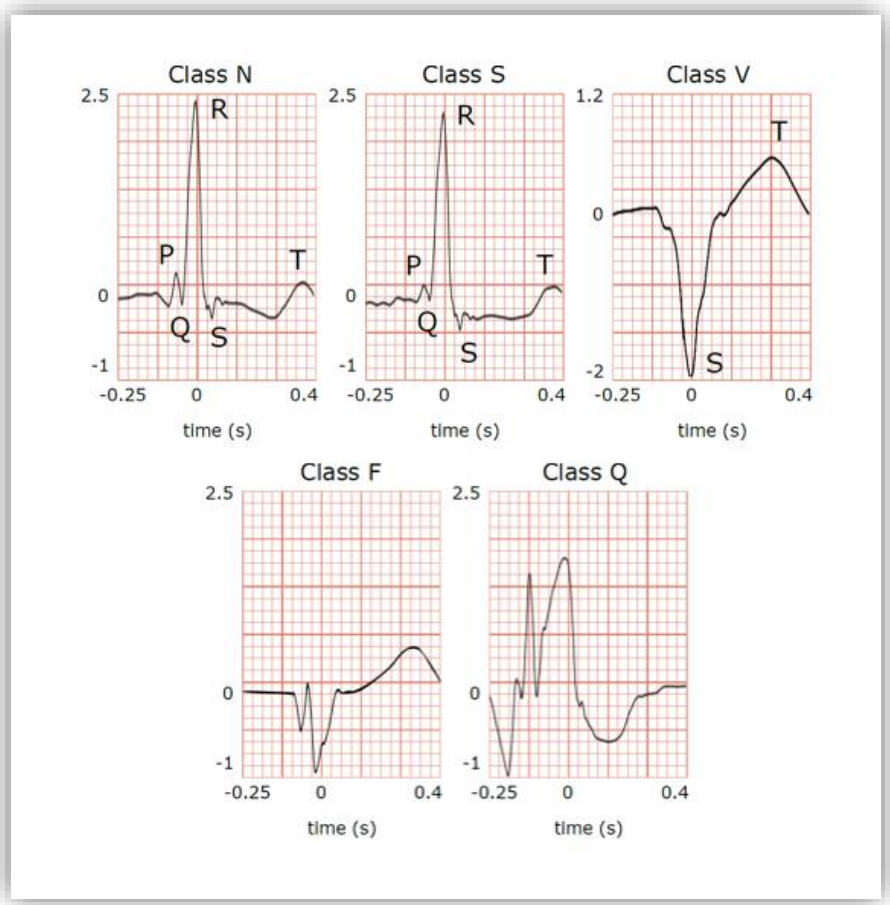


# HEARTBEAT CLASSIFICATION

Heart arrhythmia is a severe heart problem. It has been a major worldwide health problem for years, accounting for nearly 12% of global deaths every year. Early detection and timely treatment are the keys to survival from arrhythmia. Heartbeat classification on ECG is a core step towards identifying arrhythmia. Generally speaking, heartbeats can be categorized into five super classes: Normal (N), Supraventricular (S) ectopic, Ventricular (V) ectopic, Fusion (F) and Unknown (Q). In particular, problematic arrhythmias are mostly found in S-type and V-type heartbeats.




# CHANLLENGES

1. Morphological similarity between S-type and normal Heartbeats.
2. The inter- and intra-subjects' variations existing in the heart rhythms still impose great challenges to detection tasks.
3. The sporadic occurrence of S-type heartbeats can also be an issue that tends to bias an automated heartbeat classification method.

# EXISTING SOLUTIONS LIMITATIONS

## Feature Engineering

1. Pattern-based classification models often experience difficulties in achieving satisfactory performance on abnormal heartbeat detection, especially when S-type arrhythmia heartbeats are involved.

2. The effectiveness of extracted features, the mutual-influences among features, and the compatibility between the feature distribution and the classifiers are three major factors that lead to a solid upper-bound on model performance.

VS

## Deep Learning

1. Data leakage.

2. Lack of consideration of heartbeat rhythm to assist the classification.

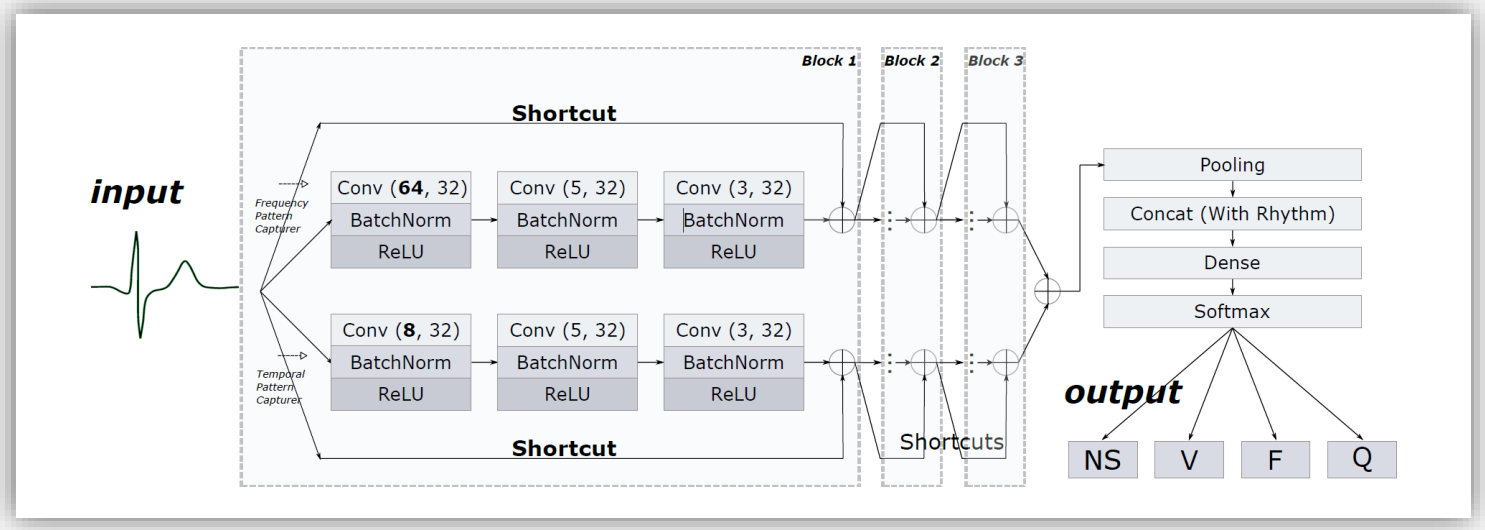
3. Poor performance in identification of S-type heartbeats.

# A Two-step Deep Neural Network-based Heartbeat Classification Framework

Framework = DDCNN + CLSM

# METHODOLOGY STEP 1

## Deep Dual-channel Convolutional Neural Network

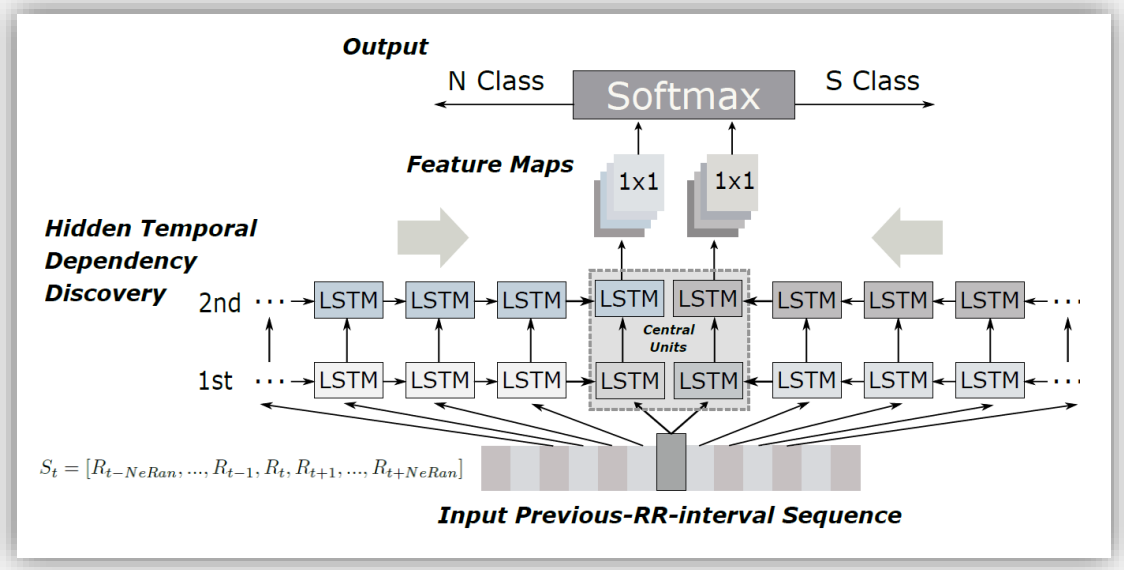



1. DDCNN accepts segmented heartbeats as input and outputs a prediction of probabilities of the N&S-bundle, V, F and Q classes.

2. DDCNN adopts a dual-channel convolution strategy, with the small filter channel capturing subtle fluctuations and the larger filter channel handling wave patterns in ECG heartbeats.

# METHODOLOGY STEP 2

## Central-towards LSTM Supportive Model




Update equations:

Given an input sequence $S_t$, update equations of a unit in the proposed central-toward LSTM layer depend on the unit's position $n$ at the layer, where $n \in [0, 2 * NeRan + 1]$.

Let $g_{f,n}$, $g_{i,n}$, $g_{o,n}$, $h_n$ denotes the \textit{forget} gate, \textit{input} gate, \textit{output} gate, and the output of the $n^{th}$ unit, respectively.

$$g_{q,n} = \begin{cases} \sigma(W_q S_t[n] + U_q h_{n-1} + b_q), n < NeRan + 1 \\ \sigma(W_q S_t[n] + U_q h_{n+1} + b_q), n \geq NeRan + 1 \end{cases}, q \in f, i, o$$

where $W$ and $U$ are the weight matrix of inputs and recurrent connections, respectively, and $b$ denotes the bias.

We define the change of the memory as:

$$\widetilde{c}_n = \begin{cases} tanh(W_c S_t[n] + U_c h_{n-1} + b_c), n < NeRan + 1 \\ tanh(W_c S_t[n] + U_c h_{n+1} + b_c), n \geq NeRan + 1 \end{cases}$$

Then the cell state is determined by the following equation:

$$c_n = \begin{cases} g_{f,n} \circ c_{n-1} + g_{i,n} \circ \widetilde{c}_n, & n < NeRan + 1 \\ g_{f,n} \circ c_{n+1} + g_{i,n} \circ \widetilde{c}_n, & n \geq NeRan + 1 \end{cases}$$

The output of the unit depends on the cell state, which is given by:

$$h_n = g_{o,n} \circ tanh(c_n)$$

# RULE-BASED DATA AUGMENTATION

## Important Medical Facts

1. S-type heartbeats normally have shorter previous-RR-intervals than the normal ones.
Q1: what is the valid range of distance between previous-RR-intervals of S-type and normal heartbeats?

2. Heartbeats of the same type exhibit a limited variation in the previous-RR- intervals within a short period.
Q2: how much the variation is?

3. Some normal heartbeats can be found within the neighborhood scope of a S-type beat.
Q3: how many normal heartbeats can be found?

**Algorithm 1:** Rule-based Data Augmentation

**Input:** $gap$, $varPct$, $nAmt$, $nVals$ and $sVals$;
**Output:** $synSeq$;
$synSeq \leftarrow new(list)$;
$centralS \leftarrow$ a random pick from $sVals$;
$amount \leftarrow$ a random pick from $nAmt$;
$candidate \leftarrow$ a random pick from $nVals$;
**while** $candidate < centralS + gap$ **do**
    $candidate \leftarrow$ a random pick from $nVals$;
**for** $i$ *in range(amount)* **do**
    $var \leftarrow$ a random float in $[1 - varPct, 1 + varPct]$;
    $synSeq.add(candidate * var)$;
**for** $i$ *in range*$(2 * NeRan - amount - 2)$ **do**
    $var \leftarrow$ a random float in $[1 - varPct, 1 + varPct]$;
    $synSeq.add(centralS * var)$;
shuffle($synSeq$);
insert $centralS$ into the central position of $synSeq$;
return $synSeq$;

# EVALUATION DATABASES

## MIT-BIH-AR

The database contains 48 two-lead ambulatory ECG recordings from 47 patients. The recordings were digitized at 360 Hz per second per channel with 11-bit resolution over a 10-mV range. For most of them, the  first lead is modi ed limb lead II (except for the recording 114). The second lead is a pericardial lead. In this study, only the modified limb lead II is used.

## MIT-BIH-SUP

The database consists of 78 two-leads recordings, with each of them approximately 30 minutes in length. The recordings are sampled at 128 Hz. They were chosen to supplement the examples of supraventricular arrhythmias in the MIT-BIH-AR database.

## INCART

This database consists of 75 ECG recordings sampled at 257 Hz. Each recording contains 12 standard leads. Similarly, only the modied limb lead II is used in this study. Most of the recordings have ventricular ectopic heartbeats.

PhysioBank

# EXPERIMENTS

## E1: Overall heartbeat classification

The proposed framework outperforms the listed works in majority of evaluation metrics. In particular, the proposed framework introduces significant improvements in the S-type heartbeat detection, which is one of the most problematic task for the existing methods.

## E2: Generalization

The trained framework is applied to MIT-BIH-SUP and INCART to demonstrate its generalizability.

## E3: Data augmentation

We investigate the effectiveness of our rule-based data augmentation method and compare it to the SMOTE algorithm.

## Others

We have also implemented experiments to investigate how the hyper-parameters influence the proposed model.

**Table 3.** Performance comparison on DS2 of MIT-BIH-AR

| Method | ACC | N | | | S | | | V | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | REC | PRE | F1 | REC | PRE | F1 | REC | PRE | F1 |
| **DDCNN + CLSM** | **95.1** | 97.5 | 97.6 | **97.6** | **83.8** | **59.4** | **69.5** | 80.4 | 90.2 | 85.0 |
| **DDCNN Only** | 93.4 | 97.9 | 95.7 | 96.7 | 13.2 | 20.7 | 16.1 | 87.2 | 87.7 | 87.5 |
| **DDCNN Only (without Concat)** | 85.9 | 90.2 | 95.9 | 93.0 | 3.9 | 3.5 | 3.7 | 82.4 | 46.3 | 59.2 |
| Acharya, U.R [1] | 71.3 | 73.3 | 95.0 | 82.6 | 6.3 | 2.3 | 3.4 | 90.8 | 28.2 | 43.5 |
| De Chazal [6] | 81.9 | 86.9 | 99.2 | 92.6 | 75.9 | 38.5 | 51.1 | 77.7 | 81.9 | 80.0 |
| Ye C [14] | 86.4 | 88.5 | 97.5 | 92.8 | 60.8 | 52.3 | 56.3 | 81.5 | 63.1 | 71.2 |
| Zhang Z [17] | 86.7 | 88.9 | 99.0 | 93.7 | 79.1 | 36.0 | 49.5 | 85.5 | **92.8** | **89.0** |
| Shan C [4] | 93.1 | **98.4** | 95.4 | 96.9 | 29.5 | 38.4 | 33.4 | 70.8 | 85.1 | 77.3 |
| Mariano L [10] | 78.0 | 78.0 | **99.1** | 87.3 | 76.0 | 41.0 | 53.3 | 83.0 | 88.0 | 85.4 |

* Results in this table are presented in percentage (%), which are obtained on DS2 of MIT-BIH-AR following the same evaluation procedures.

**Table 4.** Generalization performances (%) on MIT-BIH-SUP and INCART

| Method | Dataset | ACC | N | | S | | V | |
|---|---|---|---|---|---|---|---|---|
| | | | REC | PRE | REC | PRE | REC | PRE |
| **Proposed** | MIT-BIH-SUP | 88.2 | 90.6 | 97.8 | 72.6 | 53.5 | 70.0 | 43.0 |
| **Proposed** | INCART | **91.6** | **92.0** | **99.6** | 81.0 | **14.4** | **91.0** | 81.9 |
| Mariano L [10] | INCART | 91.0 | 92.0 | 99.0 | 85.0 | 11.0 | 82.0 | 88.0 |

**Table 5.** The impact of data augmentation method on CLSM's performance

| Method | ACC(%) | N | | S | |
|---|---|---|---|---|---|
| | | REC(%) | PRE(%) | REC(%) | PRE(%) |
| **CLSM + Rule-based Method** | **97.7** | **98.2** | **99.4** | **85.6** | **65.7** |
| CLSM + SMOTE | 94.7 | 97.7 | 96.8 | 19.6 | 25.5 |

# DISCUSSION

Experimental results achieved on the three real-world ECG databases have proven the effectiveness and the robustness of the proposed framework and indicated that the proposed framework has the potential to make a substantial clinical impact. In particular, the proposed CLSM structure distinguishes our framework from the others. It provides a promising solution for separating S-type heartbeats from normal heartbeats which is one of the most problematic tasks for existing arrhythmia detection methods. Although CLSM is initially designed as the second-step structure in the proposed framework, it is a general and flexible binary classifier. For those works suffering from the confusion of S-type and normal heartbeats, CLSM can be easily integrated as a complement without changing their original structures. This is why we define CLSM as a supportive model.

# CONCLUSION

This work presents a two-step DNN-based classification framework to identify arrhythmia-related heartbeats from ECG recordings. The framework consists of a deep dual-channel convolutional neural network (DDCNN) and a central-towards LSTM supportive model (CLSM). In step-1, DDCNN incorporates both temporal and frequent patterns to identify V, F and Q-type heartbeats. In step-2, CLSM distinguishes S-type heartbeats from normal ones by taking advantage of the central-towards LSTMs to learn and abstract hidden temporal information of each heartbeat. The experimental results obtained on three real-world databases show that the proposed framework has the potential to make a substantial clinical impact.

# THANK YOU