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Domain knowledge enhanced deep learning for electrocardiogram arrhythmia classification

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Motivation

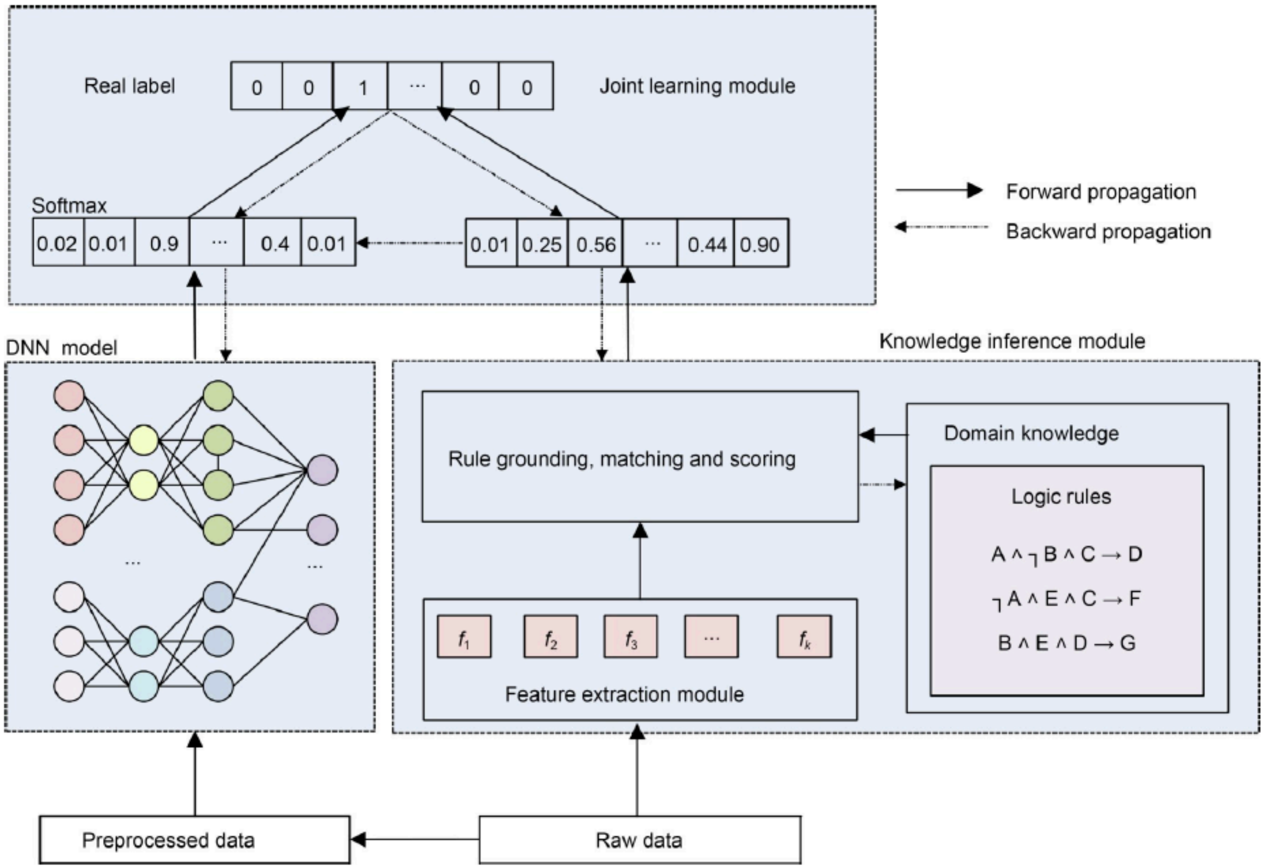
Integrating domain knowledge into the pipeline of neural network raises questions including:

1. How to represent the clinical knowledge so that it can be injected into the deep learning architecture?
2. How can domain knowledge affect the deep neural network (DNN) learning process, when the learning is based on gradient descent and back propagation?
3. Does the integrating really improve or reduce the performance of DNN? And how?

Method

1. The DNN is an arbitrary neural network that takes a preprocessed signal as input and produces the probability of the category to which the input belongs.
2. The knowledge inference module comprises a knowledge base and a rule-grounding, matching, and scoring (GMS) module. The output of the DNN model and the knowledge inference module are n-dimensional vectors, where n is the number of the categories.
3. The joint learning module will train the DNN model and knowledge inference module with backward propagation.

System model



- DNN model: F_c: $X \rightarrow \boldsymbol{Y}$
- Knowledge inference module: F_k: $\hat{X} \times \boldsymbol{Y} \rightarrow C$, $C \in \mathbb{R}^+$

Domain knowledge representation

- Fuzzy logic rules representing the domain knowledge

$$\eta_r:\ P_1 \land P_2\ \cdots \land P_m\ \rightarrow\ H_r$$

- Soft truth computation based on Łukasiewicz's *t*-norm

Clause	Soft truth value
$\bigwedge_i p_i$	$\max\left(\sum_i p_i - \lvert P \rvert + 1, 0\right)$
$\bigvee_i p_i$	$\min\left(\sum_i p_i, 1\right)$
$\neg p$	$1 - p$

Rule-grounding, matching, and scoring

- Atom translation: When the training data is input, the features are extracted and the corresponding predicates are grounded.
- Predicate translation: Given set P of base predicates, the predicates are defined as $p(x_1, x_2, \ldots, x_\mathrm{m})$. The predicates are grounded as p or its negation $\neg p$.
- Proposition translation: Combination of predicates with logical operator conjunction ($\wedge$) and disjunction ($\vee$).
- Rule translation: For a rule $r_\mathrm{body} \rightarrow r_\mathrm{head}$, computed the distance under interpretation I to satisfy the rule is defined as $d_r(I) = \max(I(r_\mathrm{body}) - I(r_\mathrm{head}), 0)$.

Joint learning method

The objective of the framework is to train the neural network while minimize the mismatch between the classification and knowledge inference.

$$\mathcal{L} = \mathcal{L}_{\mathrm{C}} + \lambda\, \mathcal{L}_{\mathrm{K}}.$$

$$\mathcal{L}_{\mathrm{C}} = \frac{1}{N} \sum_{i=1}^{N} \left(l\left(y_i, p_\theta (y_i | x_i)\right)\right),$$

$$\begin{aligned}
\frac{\partial \mathcal{L}_{\mathrm{K}}}{\partial \theta} &= \frac{\partial \left(\mathrm{KL}\left(p_{\mathrm{k}}(\hat{x}_i) \| p_\theta (y_i | x_i)\right)\right)}{\partial \theta} \\
&= \sum_{i=1}^{N} \frac{\partial \left(p_{\mathrm{k}}(\hat{x}_i) \ln \frac{p_{\mathrm{k}}(\hat{x}_i)}{p_\theta (y_i | x_i)} \right)}{\partial \theta} \\
&= - \sum_{i=1}^{N} \left(p_{\mathrm{k}}(\hat{x}_i) \frac{\partial \ln p_\theta (y_i | x_i)}{\partial \theta} \right),
\end{aligned}$$

$$\frac{\partial \mathcal{L}}{\partial \theta} = - \sum_{i=1}^{N} \left(\left(y_i + p_{\mathrm{k}}(\hat{x}_i) \right) \nabla p_\theta (y_i | x_i) \right),$$

Major results

1. Test results of our model for 8 arrhythmias against normal records from 12-lead ECG signals.

Table 4 Performance of the proposed model

Class	Sen	Spe	Pre	Acc	F_1
NSR	0.873	0.983	0.894	0.968	0.883
AF	0.928	0.989	0.946	0.979	0.936
I-AVB	0.850	0.997	0.970	0.981	0.906
LBBB	0.911	0.995	0.863	0.992	0.886
RBBB	0.985	0.983	0.954	0.983	0.899
PAC	0.900	0.990	0.900	0.982	0.900
PVC	0.950	0.990	0.914	0.986	0.902
STD	0.915	0.988	0.920	0.979	0.891
STE	0.826	0.993	0.789	0.988	0.887

Major results (Cont’d)

2. Performance comparation with state-of-the-art methods

Table 9 Performance comparison between the proposed method and the state-of-the-art methods

Class	Average F_1 score							
	CNN			RNN	CRNN			Proposed
	INCE	ResNet	VGGNet	LSTM	CNN+LSTM	CNN+GRU	CNN+RNN+Attention	
NSR	0.717	**0.893**	0.783	0.738	0.806	0.795	0.790	0.883
AF	0.889	0.900	0.890	0.768	0.918	0.897	0.930	**0.936**
I-AVB	0.872	0.850	0.841	0.741	0.881	0.865	0.850	**0.901**
LBBB	0.841	0.874	0.872	0.705	**0.900**	0.821	0.860	0.886
RBBB	0.854	0.922	0.901	0.821	0.925	0.911	**0.930**	0.894
PAC	0.798	0.849	0.703	0.590	0.845	0.734	0.750	**0.901**
PVC	0.786	0.776	0.738	0.807	0.727	0.852	0.850	**0.902**
STD	0.783	0.762	0.721	0.658	0.782	0.788	0.800	**0.918**
STE	0.704	0.797	0.549	0.294	0.615	0.509	0.560	**0.889**
Average	0.805	0.847	0.771	0.680	0.809	0.797	0.813	**0.893**

Best performances are in bold

Conclusions

1. Domain knowledge is represented by fuzzy logic rules, which can map a proposition into a real value in the range [0,1], making the truth degree comparable to the probability vector.

2. Logic rules are indifferentiable but can be relaxed using the *t*-norm, so the derivation can be computed and the gradient descent method can be applied to train the model jointly.

3. The performance is improved because the knowledge inference module reduces the influence of lost input data information, similarity between classes, and features of different importance.

Jie SUN received the BS and MS degrees in computer science from Lanzhou University, China in 1998 and 2003 respectively, and the PhD degree in computer science from Zhejiang University, China, in 2009. She is currently a lecturer in Ningbo University of Technology, Zhejiang, China. Her research interests include the application of artificial intelligence in physiological signals analysis and diagnosis. Dr. Sun was a member of China Computer Federation.