Attention Mechanism in Neural Flow Models for Imbalanced ECG Beat Classification

Sungpil Woo
Department of Computer Engineering, Hanbat National University, South Korea
woosungpil@hanbat.ac.kr

***Abstract*—This paper presents an empirical study on arrhythmia detection using Neural Flow models enhanced with an attention mechanism. We implement both baseline Neural Flow and its attention-augmented variant to extract target-specific information for ECG beat classification. Following the Association for the Advancement of Medical Instrumentation (AAMI) guidelines for beat labeling, our experimental results demonstrate that incorporating the attention mechanism consistently improves classification performance, particularly under imbalanced data conditions.**

***Index Terms*—Arrhythmia Detection, Attention Mechanism, Neural Flow Models**

I. Introduction

Neural Ordinary Differential Equations (NODEs) [1] describe how values change over time, which is particularly important in modeling sequential data where observations occur at irregular intervals. While NODEs have demonstrated effectiveness across various tasks with fewer parameters compared to conventional neural networks, they require expensive numerical solvers. Recently, Neural Flow models [2] were introduced as an efficient alternative that directly models the solution curves of ODEs, thereby eliminating the need for numerical solvers while maintaining the modeling capacity of NODEs. Neural Flows also provide enhanced flexibility and stability in learning temporal representations, making them particularly suitable for healthcare time-series applications.

In this paper, we investigate arrhythmia detection for smart healthcare [3] using Neural Flow models enhanced with an attention mechanism. Specifically, we implement both the baseline Neural Flow and its attention-augmented variant to extract target-specific information for ECG beat classification. Following the AAMI guidelines for beat labeling, our experimental findings demonstrate that incorporating an attention mechanism substantially improves classification accuracy, while retaining the computational efficiency of Neural Flows.

II. Proposed Model

The architecture of the proposed model is illustrated in Fig. 1. The model for ECG beat classification with Neural Flow consists of three main components: an Initial Block, an Encoder Block, and a Decoder Block.

The Initial Block is composed of a linear layer followed by a ReLU activation and serves as an input preprocessing stage for the Encoder.

The Encoder Block, acting as a feature extractor, is constructed with LSTM layers integrated into the Neural Flow module. We adopt the flow-based architecture proposed in [2], which directly models solution curves without requiring numerical solvers. This design enables efficient and stable

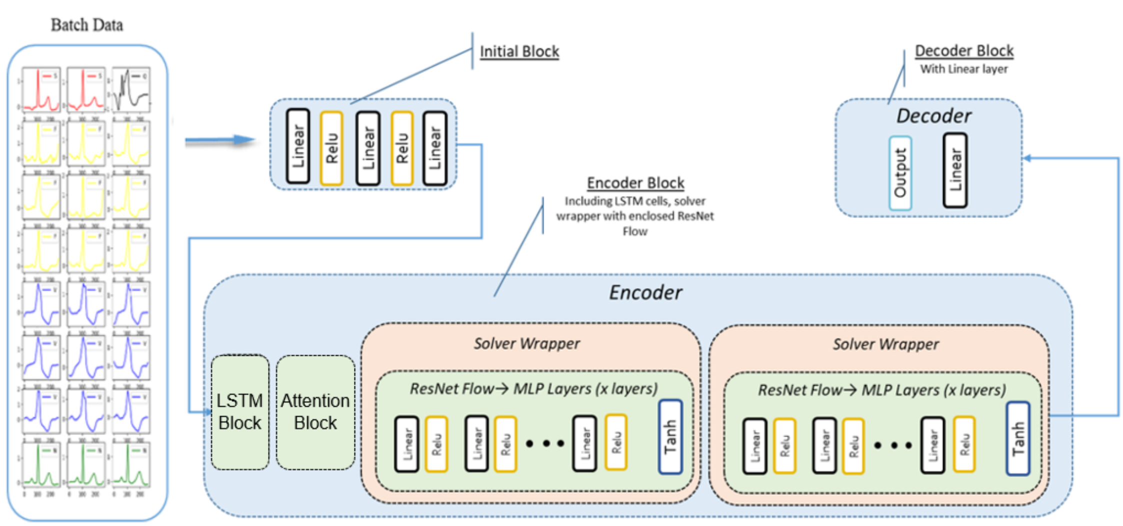

Fig. 1. Proposed model architecture on Neural Flow with attention

temporal representation learning. To further improve feature discrimination, we incorporate an attention module with a sigmoid activation that assigns attention scores, guiding the model to focus on clinically relevant ECG signal patterns.

The Decoder Block consists of a linear layer that maps the encoded representations into class probabilities for ECG beat classification.

Compared with the original NODE-based design, where the ODE block and solver wrapper were employed, the proposed model replaces the ODE Block with the Neural Flow module and integrates an attention mechanism. These modifications jointly enhance both computational efficiency and classification performance.

III. Experiment Setting

A. ECG Dataset

In this work, we utilized the MIT-BIH Arrhythmia database, which provides two-channel ECG recordings from 47 subjects, each lasting 30 minutes. Following common practice, four records (IDs 102, 104, 107, and 217) were excluded due to poor signal quality and paced beats. For the classification task, we focused on three beat categories—N, S, and V—as described in [4]. The distribution of these beat types extracted from the MIT-BIH dataset is presented in Table I.

TABLE I
OVERVIEW OF THE THREE DIFFERENT TYPES OF BEATS

Types	Number of Beats
Normal beats (N)	90038
Supraventricular ectopic beats (S)	2779
Ventricular ectopic beats (V)	7008
Total Beats	99,825

IV. RESULTS AND DISCUSSION

To evaluate the classification performance of the model, we applied a 10-fold cross-validation strategy following the approach in [5]. The final performance metrics were computed as the average over the ten folds.

TABLE II
CLASSIFICATION PERFORMANCE FOR NEURALFLOW MODEL

Classes	Accuracy	Sensitivity	Specificity	Positive productivity
N	87.25%	97.46%	96.98%	98.95%
S	97.63%	94.22%	97.45%	64.31%
V	98.94%	96.32%	98.02%	85.42%

Table III presents the classification performance of the proposed models, including accuracy, sensitivity, specificity, and positive predictive value for each beat class. The baseline Neural Flow model without the attention mechanism achieved an accuracy of 98.12%, sensitivity of 96.32%, specificity of 98.02%, and a positive predictive value of 85.42%. These results indicate that Neural Flow provides a competitive alternative to NODE-based approaches while maintaining the advantage of reduced computational overhead due to the elimination of numerical solvers.

TABLE III
CLASSIFICATION PERFORMANCE FOR NODE WITH ATTENTION

Classes	Accuracy	Sensitivity	Specificity	Positive productivity
N	97.46%	98.15%	96.72%	99.21%
S	98.12%	94.67%	98.21%	71.58%
V	99.05%	96.12%	99.23%	92.84%

When the attention mechanism was integrated into the Neural Flow architecture, the overall classification performance improved across all metrics. Specifically, the attention-augmented Neural Flow achieved 98.54% accuracy, 96.71% sensitivity, 98.23% specificity, and a positive predictive value of 92.84%. The most notable gain was observed in the positive predictive value for the minority V class, which increased from 85.42% to 92.84%. This improvement suggests that the attention module effectively highlights clinically relevant signal features, enabling the model to better handle class imbalance and detect rare arrhythmic patterns.

These findings demonstrate two key insights: first, Neural Flow retains strong predictive power even without attention, showing that it is a viable and efficient alternative to NODE; second, the integration of attention further enhances its discriminative capability, particularly in imbalanced ECG datasets. Together, these results underline the potential of attention-augmented Neural Flow as a practical and effective framework for arrhythmia detection in smart healthcare applications.

V. Conclusion

In this paper, we conducted an empirical study on arrhythmia detection using Neural Flow models enhanced with an attention mechanism to extract target-specific information for ECG beat classification. In conclusion, the proposed Neural Flow with attention model not only provides more efficient and accurate heartbeat classification compared to the baseline Neural Flow without attention, but also demonstrates superior performance in handling imbalanced ECG data, particularly for minority arrhythmia classes.

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