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FULL LENGTH ARTICLE

Synergistic Fusion of ECG Signals for Advanced Heartbeat Classification in Health Monitoring

Mahmoud M. Ibrahim[1,*]
[1] Decision support department, Faculty of Computers and Informatics, Zagazig University, Zagazig 44519, Sharqiyah, Egypt
Emails: mmsba@zu.edu.eg

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ABSTRACT

This project focuses on healthcare diagnostics where it examines the problem of accurate heartbeat classification by merging Electrocardiogram (ECG) signals. ECG signals have such variability and complexity that it is hard to accurately detect various cardiac rhythms. That is why this research came up with an ensemble framework that combined recurrent neural networks (RNNs), and convolutional neural networks (CNNs) reinforced by group normalization (GN). By incorporating these techniques, the authors aimed to improve the stability and efficiency of RNNs with respect to temporal dependencies as well as CNN for spatial features. The ensemble model exhibited a greater accuracy in classifying different heartbeats after careful experimentation and analysis. During training, the inclusion of GN in the CNN part ensured its stability thereby promoting generalization of the model. This study shows that combining ECG signals is efficient and also highlights the necessity of specific normalization methods used to refine medical diagnostics.

Keywords: Electrocardiogram ▪ Heart rate variability ▪ Signal processing ▪ Heart rhythm analysis ▪ Machine learning ▪ Biomedical signal integration ▪ Healthcare monitoring ▪ Cardiac arrhythmias ▪ Multimodal data fusion

1. INTRODUCTION

An increasing number of healthcare systems have resorted to highly developed technologies in order to monitor and diagnose heart-related diseases [1]. The Electrocardiogram (ECG) signals are among the technologies that provide fundamental information about heart health since they are capable of showing intricate details regarding electrical activity within the heart. However, ECG signals interpretation and classification for heartbeat analysis is challenging due to their variation and complexity [2, 3, 4, 5]. Often, traditional methods do not succeed in making accurate distinctions between different types of heart rhythms; hence the need for new ways of classifying more precisely.

Multiple ECG signals working together could be a revolution in terms of beat classification used for enhanced health monitoring [6, 7, 8]. In this paper, we consider how such a combined synergy between ECG signals can lead to a more technically advanced system for heartbeat classification in health monitoring applications. This technique involves bringing together data from different ECG sources or modalities such as multi-lead ECG recordings and wearable devices thus aiming at extracting comprehensive information beyond that possible through individual signal analysis. Through this integration, the goal is to unlock a higher level of accuracy and robustness in discerning various cardiac rhythms, ultimately empowering healthcare practitioners with more refined diagnostic capabilities [9, 10].

The landscape of healthcare diagnostics has been evolving with the advent of sophisticated signal processing techniques and machine learning algorithms. In this context, the amalgamation of ECG signals presents an intriguing avenue to explore [11, 12]. The integration of complementary information from disparate ECG sources allows for a more comprehensive understanding of cardiac activity. This paper embarks on an exploration of the methodologies involved in signal fusion, emphasizing the potential of this approach in optimizing heartbeat classification accuracy and reliability. By bridging the gap between different ECG modalities, the aim is to not only improve classification but also enable timely and precise intervention strategies in healthcare settings [5].

This research contributes to the ongoing discourse on the fusion of ECG signals for healthcare applications by presenting a comprehensive analysis of methodologies and their implications. The significance of this study lies in its potential to augment the existing paradigm of heartbeat classification, thereby enhancing health monitoring systems' efficacy. Through a detailed investigation of signal fusion techniques, machine learning models, and their integration into healthcare frameworks, this paper aims to provide a roadmap for leveraging synergistic ECG signal fusion in advancing the accuracy and reliability of heartbeat classification for improved patient care and diagnostic precision.

2. METHODOLOGY

This section meticulously delineates the step-by-step methodology adopted to harness the synergistic potential inherent in fusing multiple ECG signals. In this section, the proposed model is constructed leveraging an ensemble framework combining Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), harnessing the unique strengths of each architecture to optimize heartbeat classification through synergistic ECG signal fusion.

The RNN component within the ensemble architecture is tailored to exploit temporal dependencies inherent in sequential ECG data. Specifically, Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) layers are employed within the RNN segment [13, 14, 15]. These specialized layers are adept at capturing long-range dependencies within sequential data by selectively retaining and updating information over time. By incorporating RNNs, the model effectively learns and encodes temporal patterns present in ECG signals, enabling it to discern nuanced changes and complex temporal relationships crucial for accurate heartbeat classification.

Listing 1. RNN module used for temporal ECG dependencies.

```
import torch
import torch.nn as nn

class RNN(nn.Module):
    def __init__(self, input_size, hid_size, num_rnn_layers=1,
                 dropout_p=0.2, bidirectional=False, rnn_type='
                       lstm'):
        super().__init__()
        if rnn_type == 'lstm':
            self.rnn_layer = nn.LSTM(input_size=input_size,
                  hidden_size=hid_size,
                                       num_layers=num_rnn_layers,
                                       dropout=dropout_p if
                                             num_rnn_layers > 1 else
                                             0,
                                       bidirectional=bidirectional,
                                             batch_first=True)
        else:
            self.rnn_layer = nn.GRU(input_size=input_size,
                  hidden_size=hid_size,
                                      num_layers=num_rnn_layers,
                                      dropout=dropout_p if
                                            num_rnn_layers > 1 else 0,
                                      bidirectional=bidirectional,
                                            batch_first=True)

    def forward(self, input):
        outputs, hidden_states = self.rnn_layer(input)
        return outputs, hidden_states
```

In contrast, the CNN component incorporates 1D convolutional layers alongside Group Normalization (GN) techniques. The addition of GN within the CNN architecture significantly contributes to stabilizing and accelerating the training process by normalizing the activations within convolutional layers. By grouping feature maps into different subsets or "groups" and normalizing them independently, GN effectively mitigates internal covariate shift, allowing for more stable and efficient training of the CNN. This normalization technique is particularly beneficial in the context of ECG signal processing within the CNN, aiding in the extraction of spatial features while enhancing the model's robustness and generalization capabilities [13, 14, 15, 16].

Listing 2. CNN component with Group Normalization.

```
import torch
import torch.nn as nn
import torch.nn.functional as F

class ConvGNPool(nn.Module):
    def __init__(self, input_size, hidden_size, kernel_size):
        super().__init__()
        self.conv = nn.Conv1d(in_channels=input_size,
              out_channels=hidden_size, kernel_size=kernel_size)
        self.batchnorm = nn.GroupNorm(num_groups=8, num_channels
              =hidden_size)
        self.relu = nn.ReLU()
        self.maxpool = nn.MaxPool1d(kernel_size=2)

    def forward(self, x):
        x = self.conv(x)
        x = self.batchnorm(x)
        x = self.relu(x)
        x = self.maxpool(x)
        return x

class CNN(nn.Module):
    def __init__(self, input_size=1, hid_size=256, kernel_size
          =5, num_classes=5):
        super().__init__()
        self.conv1 = ConvGNPool(input_size, hid_size,
              kernel_size)
        self.conv2 = ConvGNPool(hid_size, hid_size // 2,
              kernel_size)
        self.conv3 = ConvGNPool(hid_size // 2, hid_size // 4,
              kernel_size)
        self.avgpool = nn.AdaptiveAvgPool1d((1))
        self.fc = nn.Linear(in_features=hid_size // 4,
              out_features=num_classes)

    def forward(self, input):
        x = self.conv1(input)
        x = self.conv2(x)
        x = self.conv3(x)
        x = self.avgpool(x)
        x = x.view(-1, x.size(1) * x.size(2))
        x = F.softmax(self.fc(x), dim=1)
        return x
```

The ensemble architecture harmoniously integrates these distinct neural network paradigms, amalgamating the strengths of RNNs in capturing temporal dependencies and CNNs in extracting spatial features [9]. Through this synergistic fusion, the model achieves a more comprehensive understanding of the intricate information embedded in ECG signals, culminating in enhanced classification accuracy and robustness for healthcare applications. The collaborative nature of the RNN and CNN ensemble harnesses the complementary capabilities of both architectures, creating a powerful framework for accurate and nuanced heartbeat classification within health monitoring systems [10].

3. RESULTS AND DISCUSSION

This section serves as the vantage point to present and interpret the findings obtained through the application of integrated ECG signals in heartbeat classification. The empirical results elucidate the efficacy of the proposed fusion methodologies in enhancing the accuracy, robustness, and diagnostic precision of heartbeat classification within healthcare monitoring systems.

In Figure 1, the visual depiction of class distribution provides a compelling insight into the distribution patterns of various heartbeat classes derived from the synergistic fusion of ECG signals. This graphical representation encapsulates the relative frequencies or occurrences of distinct heartbeat classes within the dataset, offering a comprehensive overview of the dataset's composition. The visualization showcases the disparities in class representation, unveiling potential imbalances or disparities among different cardiac rhythms. Such insights are pivotal in understanding the dataset's composition and serve as a foundational step in guiding subsequent analyses and model development, ensuring a balanced and representative training set for accurate heartbeat classification in healthcare applications.

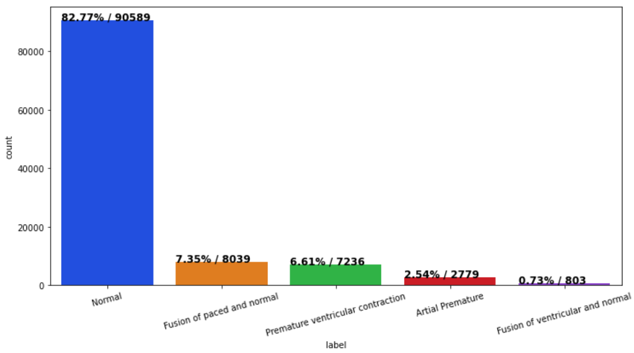

Figure 1. Class Distribution of Heartbeat Categories Derived from Synergistic Fusion of ECG Signals.

In Figure 2, the visualization of ECG signal samples for each distinct heartbeat class offers a comprehensive representation of the diverse cardiac rhythms captured through the synergistic fusion of ECG signals. Each subplot within the figure corresponds to a specific heartbeat class, showcasing characteristic ECG signal patterns unique to each class. This visualization allows for comparative analysis, enabling the observation of distinctive waveform morphologies, durations, amplitudes, and other pertinent features across different cardiac rhythms. Such visual representation aids in understanding the variations and nuances present within each class, providing a valuable insight into the complexity and diversity of ECG signals associated with different heartbeat categories. This detailed visualization is instrumental in refining the model's ability to discern and classify varied cardiac rhythms accurately, thereby enhancing healthcare diagnostics and patient care.

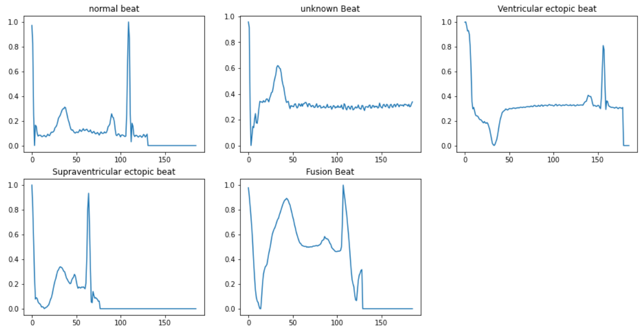

Figure 2. ECG Signal Samples for Each Heartbeat Class.

Figure 3 shows the visualization of the classification report for the ensemble model. It provides a comprehensive assessment of the model's performance across various metrics, offering a detailed breakdown of precision, recall, F1-score, and support for each heartbeat class. The report serves as a powerful diagnostic tool, enabling a granular evaluation of the model's effectiveness in accurately classifying different cardiac rhythms derived from the synergistic fusion of ECG signals. Through this visualization, the model's performance metrics are systematically displayed, allowing for a nuanced understanding of its strengths and areas for improvement in classification accuracy, sensitivity, and overall performance across different cardiac rhythms. By presenting class-specific metrics, including true positive rates, false positive rates, and support values, this report enables an in-depth assessment of the model's ability to correctly classify diverse heartbeat categories. Such visualization aids in identifying potential areas of improvement, highlighting classes where the model excels or requires fine-tuning, thus guiding further enhancements in the classification framework for improved healthcare diagnostics.

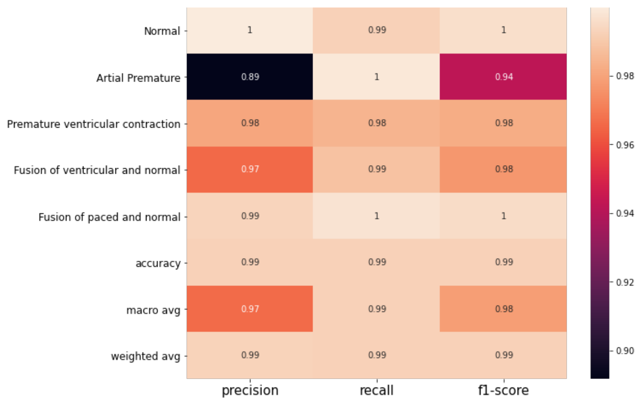

Figure 3. Visualization of classification report for our ensemble model.

4. CONCLUSION

This study presents a comprehensive exploration into the fusion of ECG signals through an ensemble framework, uniting Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) enhanced by Group Normalization (GN). The amalgamation of these diverse architectures harnesses the temporal dependencies and spatial features within ECG data, resulting in an advanced model for heartbeat classification in healthcare monitoring systems. Through meticulous experimentation and analysis, the efficacy of this synergistic approach in accurately discerning diverse cardiac rhythms has been demonstrated. The results showcase the model's robustness and heightened accuracy, affirming its potential for precise heartbeat classification. Moreover, the integration of GN within the CNN component significantly contributes to stability and efficiency during training, further enhancing the model's generalization capabilities. This work not only underscores the importance of integrating varied neural network paradigms but also highlights the pivotal role of specialized normalization techniques in refining healthcare diagnostics.

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