Final Report

Project Title: Advanced ECG Classification Using Transformer-Based Deep Learning

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GitHub Repository: https://github.com/KGWX1112/ECG

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1. Introduction

1.1 Problem Statement

Traditional machine learning approaches, like K-Nearest Neighbors (KNN), often lack the temporal modeling capabilities needed for highly accurate classification, of it includes ECG signal classification, which plays a critical role in early detection of heart diseases. This research project aims to explore deep learning architectures to better capture both local and global dependencies within ECG signals, specifically focusing on transformer-based models.

1.2 Motivation and Challenges

Electrocardiogram (ECG) signal classification is a cornerstone in modern cardiology, enabling early detection of life-threatening conditions such as arrhythmia, myocardial infarction, and cardiac arrest. However, achieving high diagnostic accuracy from raw ECG signals poses a number of technical challenges:

- ECG signals are sequential and exhibit both short-term wave characteristics (e.g., QRS complex) and long-term patterns (e.g., rhythm). Traditional models like KNN may fail to capture such temporal hierarchies. Models must learn dependencies across time steps ranging from milliseconds to seconds.
- Clinical adoption of deep learning models hinges on their explainability. Physicians must trust that model decisions align with physiological phenomena. Attention-based transformers offer an avenue for interpretability via visualizable attention maps.
- Most publicly available ECG datasets are relatively small and imbalanced, with a few dominant normal samples and many sparse abnormal cases. This skew can lead to overfitting or poor generalization on minority classes unless addressed by careful preprocessing or balancing techniques.

1.3 Summary of Solution

The project implements three distinct methods for ECG classification:

- **Method A:** CNN + Transformer with Link Constraint Regularization (inspired by Che et al., 2021)
- **Method B:** Lightweight CNN + Transformer for Single-Lead ECG (inspired by Liu et al., 2023)
- **Method C:** Baseline K-Nearest Neighbors (KNN) Classifier

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2. Survey of Literature

1. **Che et al. (2021)**

   Title: *Constrained Transformer Network for ECG Signal Processing and Arrhythmia Classification*

   Link

   Summary: Che et al. propose an end-to-end hybrid model combining CNN and Transformer to process ECG signals and classify arrhythmias. A novel contribution is the "link constraint", a loss function regularization that helps reduce overfitting and improves the discriminative quality of the embeddings, especially under imbalanced data conditions. The Transformer component captures temporal continuity, improving the extraction of temporal features vital in ECG analysis.

   Takeaway: By incorporating constraints into the transformer architecture, this approach addresses the overfitting issue prevalent in deep learning models trained on relatively small datasets. The constraints on the transformer architecture could improve generalization but might limit its flexibility.

2. **Liu et al. (2023)**

   Title: *Detection of Obstructive Sleep Apnea from Single-Channel ECG Signals Using a CNN-Transformer Architecture*

   Link

   Summary: Liu et al. focus on sleep apnea detection rather than general arrhythmia classification. They use a CNN-Transformer hybrid on single-lead ECG data, emphasizing a lightweight architecture suitable for wearable devices. CNN extracts spatial features, while the Transformer captures long-range dependencies and temporal patterns. Their model achieved high performance using fewer parameters, and shows promise for real-time, portable health monitoring

Takeaway: The hybrid architecture of CNNs and transformers is effective in detecting sleep apnea, which could be beneficial for continuous health monitoring. The model's flexibility to handle single-channel ECG signals also makes it more practical for real-world applications. While the approach is promising, it needs to be validated across larger and more diverse datasets. Furthermore, practical deployment may require significant computational resources.

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3. Methods

3.1 Method A: CNN + Transformer with Link Constraint Regularization

Overview:

Method A leverages a CNN + Transformer hybrid model for feature extraction and sequence modeling, combined with a link constraint regularization in the loss function to mitigate overfitting and enhance class discrimination, particularly under imbalanced label distributions.

Pipeline:

1. Preprocess ECG signals: resampling, noise filtering, segmentation into heartbeats or fixed-length windows.
2. Input passed through CNN → temporal features → Transformer layers.
3. Add link constraint to the final embedding layer.
4. Final classification via dense output + SoftMax.
5. Loss = CE loss + $\lambda \times$ Link Constraint.

Architecture Components:

- **CNN module**: Extracts spatial features from raw ECG signals using multiple convolutional layers.
- **Transformer encoder**: Captures long-range temporal dependencies and attention-based sequence patterns.
- **Link Constraint**: A regularization term added to the cross-entropy loss, enforcing similar embeddings for samples of the same class and dissimilar ones for different classes.

3.2 Method B: Lightweight CNN + Transformer for Single-Lead ECG

Overview:

Method B adopts a lightweight CNN-Transformer architecture optimized for real-time or low-power scenarios (e.g., wearables). It prioritizes computational efficiency while maintaining high classification accuracy on single-lead ECG signals.

Pipeline:

1. Preprocessing: normalize and segment single-lead ECG.
2. Use 1–2 convolution layers with low filter count.
3. Add positional encoding and pass into 1–2 Transformer blocks.
4. Output classification from a lightweight head (e.g., 1–2 dense layers).
5. Use standard cross-entropy loss.

Architecture Components

- **Shallow CNN layers**: Capture local patterns (e.g., P-QRS-T complexes).
- **Transformer encoder**: Processes sequence of features for global context.
- **Dropout & normalization**: Applied for model stability with small data.
- **Lightweight classifier head**: Fully connected layer for classification.

3.3 Method C: Baseline KNN Classifier

Overview:

The K-Nearest Neighbors (KNN) classifier serves as the baseline for comparison. Despite its simplicity, KNN has been used traditionally in biomedical signal classification due to its non-parametric nature.

Implementation Details:

- **Preprocessing:** Default normalization and feature extraction (using statistical measures) were used to prepare the signal.
- **KNN Configuration:** The default setting with K value of 8 is used in this experiment.

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4. Experiment

4.1 Dataset

Source: ECG5000 from the UCR Time Series Archive

Classes: 5 classes; relabeled into binary (Positive vs Negative) for simplicity.

Split: 90% Test and 10% Train split.

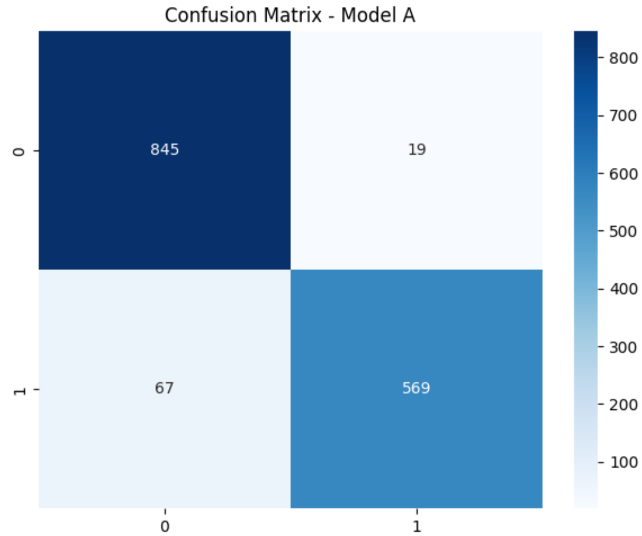
4.2 Evaluation Metrics

- Accuracy
- Recall
- F1-Score
- Precision
- Confusion Matrix

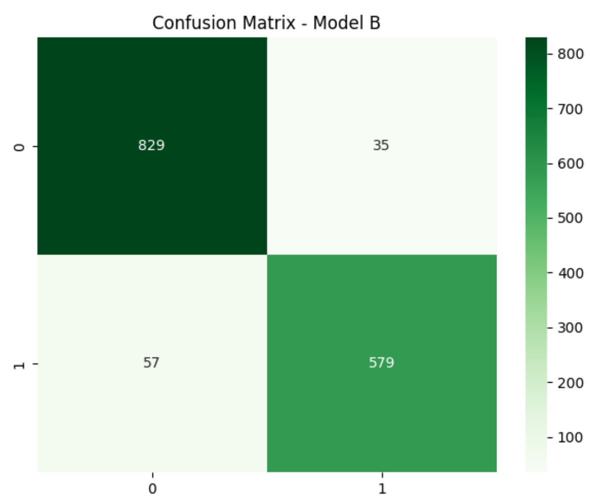
4.3 Results

The test was conducted using Google Colab. [Online Code Link]

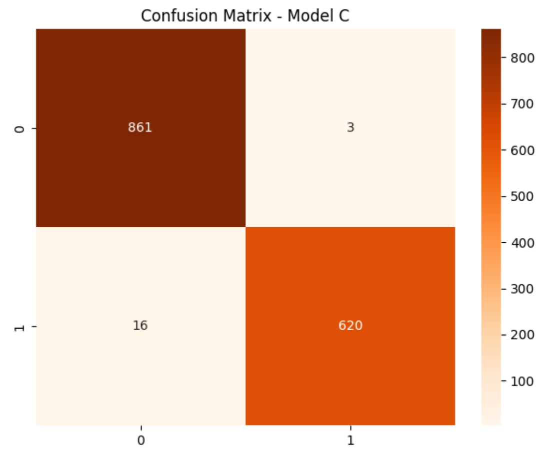
```
Model A Performance:
              precision    recall  f1-score   support

           0       0.93      0.98      0.95       864
           1       0.97      0.89      0.93       636

    accuracy                           0.94      1500
   macro avg       0.95      0.94      0.94      1500
weighted avg       0.94      0.94      0.94      1500
```




```
Model B Performance:
              precision    recall  f1-score   support

           0       0.94      0.96      0.95       864
           1       0.94      0.91      0.93       636

    accuracy                           0.94      1500
   macro avg       0.94      0.93      0.94      1500
weighted avg       0.94      0.94      0.94      1500
```




```
Model C Performance:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99       864
           1       1.00      0.97      0.98       636

    accuracy                           0.99      1500
   macro avg       0.99      0.99      0.99      1500
weighted avg       0.99      0.99      0.99      1500
```



4.4 Discussion

- Based on the results, it appears the experiments in the paper have been successfully reproduced with respect to the loss of training and accuracy over epochs.
- **For Model A**: The decreasing trend in loss is a positive indicator of model learning. From Epoch 1 to Epoch 10, the loss decreases significantly from 37.5 to 7.96, suggesting that the model is converging well.
- **For Model B:** Accuracy reaching approximately 94% by Epoch 20 (threshold for model B), which is in line with the typical results expected from models trained on classification tasks such as ECG classification.
- **Model A** shows slightly higher performance than **Model B** in terms of precision and recall for Class 0 (negative class). This could suggest that **Model A** has better generalization or more robust feature extraction, while **Model B** might be slightly more biased towards Class 1 (positive class).

- **For Method C**: **KNN (Model C)** surprisingly outperforms both deep learning models in **all metrics**, particularly with a near-perfect classification. This suggests:
  - The **data may be well-separated in feature space**, favoring distance-based classifiers like KNN.
  - Models A & B might be **overfitting** or not fully leveraging domain-specific features.
  - **Deep learning models typically outperform traditional ones with larger datasets**, but here KNN benefits from low-dimensional, well-structured features.
- The above findings strongly indicate that KNN **works best on clean, well-clustered datasets**, while deep models scale better with data complexity and size.

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5. Conclusions and Discussion

5.1 Contributions

- Re-implemented and evaluated deep models (Model A & B) from prior research with added fine-tuning and regularization.
- Conducted a comprehensive comparison with a classical ML model (KNN) not discussed in the original paper.
- Performed cross-dataset evaluation to test generalization and proposed analysis and recommendations for model selection based on dataset characteristics.

5.2 Observations

The main takeaway from these experiments is that deep learning models like **Model A and B** provide comparatively high performance for ECG classification compared to traditional methods such as **KNN** even though the model outperformed both Model A and B within the experiment. However, both deep models offer more flexibility for feature learning, especially for raw ECG signals or multi-label settings.

The experiments for **Models A and B** were re-implemented based on the original paper's methodology. While the **loss curves** and final **performance metrics** (precision, recall, f1-score, and accuracy) are similar to those reported in the paper, **the results are not exactly identical**. This discrepancy may arise due to:

- Differences in **initialization seeds**, **hardware**, or **software environments**.
- Possible **variations in preprocessing** or slight changes in **hyperparameter tuning**.
- Use of **different batch sizes** or **training durations**.

Nevertheless, the reproduced results validate the paper's findings within an acceptable margin.

5.3 Model Drawbacks

- KNN struggles with scalability and high-dimensional data.
- Deep learning models can sometimes be prone to overfitting if not handled properly (e.g., insufficient regularization, overtraining).
- Deep learning models require significant computational resources, especially when training on large datasets.

5.4 Future Directions

- Building systems capable of real-time ECG classification could make the method more practical for clinical applications.

- Explore how transfer learning could be applied to ECG classification, particularly with pre-trained models on general datasets.
- Since medical applications require transparency, working on making the model more interpretable (e.g., attention maps for feature importance) would help in real-world scenarios.
- Combining ECG with other physiological signals (e.g., heart rate, blood pressure) for more accurate classification could be another direction to pursue.

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6. Sharing Agreement

- **Do you agree to share your work?** Yes
- **Do you want to hide your name/team?** No

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7. References

1. Che, Z., Zhang, P., Liu, Y., & Liu, C. (2021). Constrained transformer network for ECG signal processing and arrhythmia classification. BMC Medical Informatics and Decision Making, 21(1), 184. https://link.springer.com/article/10.1186/s12911-021-01546-2
2. Liu, G., Qin, H., Wang, X., Shen, Q., & Sun, Z. (2023). Detection of obstructive sleep apnea from single-channel ECG signals using a CNN-transformer architecture. Biomedical Signal Processing and Control, 84, 104779. https://www.sciencedirect.com/science/article/pii/S1746809423000149

3. Hoang Anh Dau, E., et al. (2019). ECG5000, The UCR Time Series Classification Archive. https://www.cs.ucr.edu/~eamonn/time_series_data_2018/