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Enhanced ECG Signal Detection using ID-CNN with Attention Mechanism

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ABSTRACT

Hyperkalemia, a potentially life-threatening condition marked by elevated potassium levels in the blood, is often detectable through abnormalities in electrocardiogram (ECG) signals. Despite this, detecting hyperkalemia remains challenging due to the limited sensitivity of existing models in identifying subtle ECG changes associated with varying potassium levels. To address this challenge, we propose an enhanced ECG signal detection model employing a 1D Convolutional Neural Network (CNN) integrated with an attention mechanism. This model architecture features three 1D CNN layers for deep feature extraction, followed by an attention mechanism that dynamically adjusts the weight of these features to improve detection sensitivity. Utilizing the MIMIC-IV dataset, which encompasses diverse ECG recordings, our model demonstrated superior performance in detecting hyperkalemia compared to traditional CNN models. By focusing on the most relevant aspects of ECG signals, our approach significantly enhances detection accuracy and sensitivity. Additionally, comparative analysis of lead performance revealed that even with fewer leads, such as a 2-lead ECG, the model achieved comparable accuracy, making it suitable for deployment in wearable devices.

1. INTRODUCTION

Kidney disease is currently the third fastest-growing cause of death worldwide and stands out as the only non-communicable disease (NCD) with a consistently increasing age-adjusted mortality rate. By 2040, chronic kidney disease (CKD) is expected to become the fifth leading cause of years of life lost (YLL) globally [1]. In India, CKD has reached epidemic proportions, with population-based studies reporting prevalence rates ranging from 4% to 20% [2]. CKD is a widespread health concern that carries numerous complications, one of the most dangerous being hyperkalemia. Hyperkalemia, marked by an excessive concentration of potassium in the blood, significantly heightens the risk of sudden cardiac death among CKD patients. This makes the prompt detection and continuous monitoring of hyperkalemia essential for effective patient management. While blood tests remain the gold standard for diagnosing hyperkalemia, there is an ongoing pursuit for non-invasive, efficient, and accurate diagnostic methods to improve patient diagnosis.

Electrocardiography (ECG) has long been a fundamental tool in diagnosing heart disorders, valued for its non-invasive nature, affordability, and accessibility. This technique provides a graphical representation of the heart's electrical activity, offering crucial insights into various pathological conditions. By analyzing ECG patterns, healthcare professionals can assess cardiac health and identify signs that may have life-saving implications. Hyperkalemia, which is marked by elevated potassium levels (>5.3 mEq/L) in the blood, is one such condition that distinctly alters the ECG waveform [3]. Elevated potassium levels pose a significant risk of sudden cardiac death, particularly in patients with Chronic Kidney Disease (CKD). Early detection of hyperkalemia-induced changes in the ECG can facilitate swift clinical intervention, potentially preventing life-threatening complications. While traditional ECG interpretation relies heavily on the expertise of clinicians, the advent of machine learning and computational techniques is revolutionizing the field by enabling the development of automated ECG analysis systems [4] [5].

Several studies have successfully utilized deep learning models to detect electrolyte abnormalities on ECGs, demonstrating the feasibility of this approach for identifying subtle changes in ECG due to electrolyte imbalance [6] [7] [8] [9] [10]. However, many existing models suffer from low sensitivity which, combined with a high false-positive rate [11], can lead to unnecessary anxiety for patients.

2. METHODS

The dataset used in this work is extracted from MIMICS (Medical Information Mart for Intensive Care) IV ECG: Diagnostic Electrocardiogram Matched Subset [12] [13]. The MIMIC-IV-ECG module comprises approximately 800,000 diagnostic electrocardiograms (ECGs) collected from nearly 160,000 unique patients. Each ECG in this dataset includes 12 leads and spans a duration of 10 seconds, with a sampling frequency of 500 Hz. This subset encompasses all ECGs associated with patients recorded in the MIMIC-IV Clinical Database. For this study, we specifically selected ECG waveforms from the MIMIC-IV ECG matched subset that correspond to patients with either normal or elevated serum potassium levels. To ensure precise correlation between serum potassium levels and ECG characteristics, only recordings were chosen where the time elapsed between the potassium test and the ECG acquisition was under 4 hours. However, not all ECG signals in this dataset met the standards required for thorough analysis. The quality of the signals was affected by factors such as noise, artifacts, and other irregularities. Consequently, pre-processing techniques, including filtering and outlier detection, were applied to enhance data quality for classification purposes. After applying these pre-processing steps, a total of 1503 patient samples were retained for analysis. The distribution of these samples includes 759 cases classified as normal, 744 as hyperkalemia cases. Given that changes in ECG signals due to hyperkalemia are progressive [14], our analysis focused exclusively on moderate and severe cases, defined as serum potassium levels greater than 6 mmol/L.

The raw ECG signals extracted from the MIMIC-IV database were initially contaminated with power line interference, muscle noise, and baseline wander. To address these issues, we applied a third-order Butterworth filter to effectively remove high-frequency noise. Furthermore, another Butterworth filter was used to eliminate baseline wander from the signals. To ensure consistency and enable precise feature extraction, the signals were normalized using z-score normalization prior to the training process.

The initial dataset comprised ECG signals with dimensions 1512x5000x12, where 1512 represents the number of samples, 5000 the number of time steps, and 12 the number of leads. Following data pre-processing, which involved removing NaN values, the dataset was reduced to 1503x5000x12. Additionally, to address the issue of ambiguous signal regions at the start and end of the recordings—where signal integrity could not be guaranteed—500 samples from both the beginning and end of each signal were excluded. This adjustment resulted in a final dataset size of 1503x4000x12. This pre-processing ensures that the data used for model training and evaluation is of consistent quality and suitable for accurate analysis.

3. DEEP LEARNING MODEL

Deep learning, a branch of machine learning, focuses on training neural networks with multiple layers to identify complex patterns within data. These deep neural networks excel at automatic feature extraction and can learn hierarchical representations directly from raw data. Owing to its ability to capture intricate relationships, deep learning has achieved significant success across various fields, including computer vision, natural language processing, and signal processing.

Figure 1 shows the proposed model architecture. The proposed model for classifying ECG signals integrates a one-dimensional Convolutional Neural Network (1D CNN) with an attention mechanism [15] to enhance the detection of normal versus hyperkalemic conditions. The architecture begins with an input layer designed to accommodate 12 lead ECG data. It features multiple convolutional layers, each with its own set of filters, kernel sizes, and the LeakyReLU [16] activation function, which helps address the issue of dying neurons by allowing a small, non-zero gradient when the unit is not active. This activation function, combined with Batch Normalization [17], which normalizes activations to stabilize and accelerate training, maxpooling layer and dropout layer [18], contributes to improved learning and model performance. The convolutional layers are followed by a simple self-attention mechanism that enables the model to focus on the most relevant portions of the ECG signal by computing and applying attention scores, thus enhancing sensitivity to critical features. A global average pooling layer then consolidates the extracted features into a fixed-size representation. The network concludes with fully connected dense layers, including an output layer that produces probabilities for binary classification. The model is trained using the Adam optimizer, which adapts learning rates for efficiency, and is evaluated using binary cross-entropy loss and accuracy metrics. The network processes a 12-lead ECG signal as input and produces a probability value. This probability reflects the likelihood of the ECG signal being classified as hyperkalemic or normal. This architecture effectively combines convolutional and attention-based approaches to differentiate between normal and hyperkalemic ECG signals.

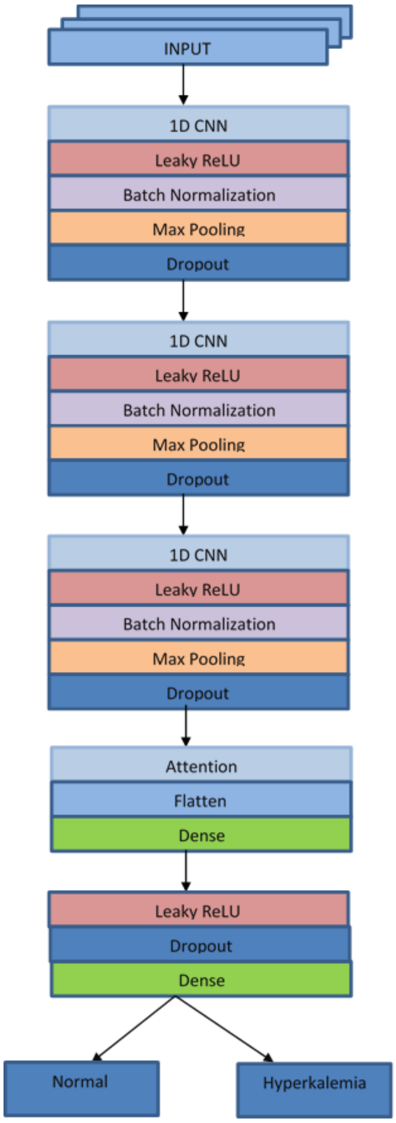

Figure 1: Proposed Model Architecture

4. IMPLEMENTATION

All experiments in this study were conducted using Google Colab. The dataset, sourced from the MIMIC-IV ECG: Diagnostic Electrocardiogram Matched Subset, comprised recordings from 1,512 unique patients. Each ECG signal was 10 seconds in duration and sampled at 500 Hz, with data available for all 12 leads for every patient. The data was split into 80% for training and validation, with 20% of this training set reserved specifically for validation. The remaining 20% of the data was set aside for testing. 5 fold cross validation was used. After thorough preprocessing, including filtering, outlier detection, and data selection, a dataset of 1503 12-lead ECG recordings (comprising 759 normal and 744 hyperkalemic samples) was prepared for further analysis, resulting in an input matrix of size

1503x4000x12. To enhance the dataset, data augmentation techniques were employed to duplicate samples from both classes. The evaluation metrics used for this study were Accuracy, Sensitivity, Specificity and Reciever Operating Characteristics Area Under Curve (ROC-AUC)

5. RESULTS

In our experiments, we systematically tuned several hyperparameters to optimize the performance of the proposed model. Specifically, we evaluated the effects of different optimizers, batch sizes, L2 regularization values, and dropout rates on model performance. For each configuration, we assessed the model using standard metrics, including accuracy, sensitivity, and specificity. To ensure that our model did not overfit, we closely monitored the loss curves during training. The training and validation loss were plotted to visually inspect for signs of overfitting, such as a divergence between the training and validation loss. We adjusted hyperparameters accordingly to maintain a balance between model complexity and generalization. Table 1 presents the results of the 5 fold cross validation. All 12 leads of data was used for training.
Figure 2 shows the training and validation loss curves.

Table 1: Results of 5 Fold Cross Validation

Folds	Accuracy	Sensitivity	Specificity
1	0.89	0.83	0.948
2	0.91	0.84	0.96
3	0.94	0.89	0.99
4	0.95	0.90	0.99
5	0.94	0.92	0.96
Avg	**0.92**	**0.88**	**0.97**

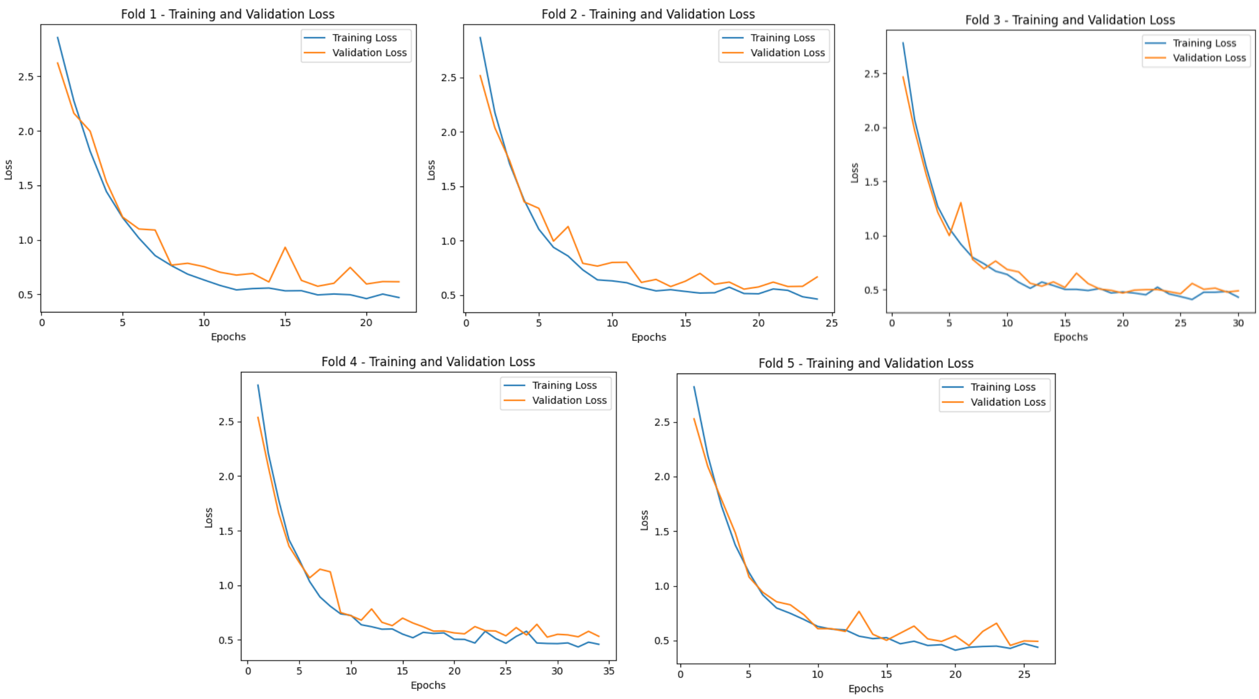

Figure 2: Training & Validation Loss

In addition to evaluating the full set of 12 leads, we examined the performance of individual leads and various combinations of leads to understand their contributions to hyperkalemia detection. The analysis included:

- **Individual Leads:** Each lead was assessed independently. Notably, Lead 2 demonstrated a high classification performance, achieving an AUC of 94%, with excellent specificity and sensitivity. This suggests that Lead 2 alone can provide robust diagnostic information.
- **Lead Combinations:** Various combinations of leads were tested to evaluate their collective impact on classification performance. Specifically, combinations of 2 leads and 6 leads were analyzed to determine if multiple leads provide complementary information that improves diagnostic accuracy.

The results of the comparative performance of various leads are presented in table 2.

Table 2: Comparative performance of individual leads in classificatio

Metrics	**2L**	**3L**	**6L**	**12 L**	**L1**	**L2**	**L3**	**aVR**	**aVL**	**aVF**	**V1**	**V2**	**V3**	**V4**	**V5**	**V6**
Accuracy	**0.91**	**0.90**	**0.90**	**0.92**	0.89	0.87	0.86	0.88	0.87	0.88	0.90	0.90	0.88	0.86	0.87	0.89
Sensitivity	**0.90**	**0.88**	**0.90**	**0.88**	0.85	0.84	0.83	0.85	0.86	0.93	0.86	0.87	0.88	0.81	0.89	0.89
Specificity	**0.91**	**0.93**	**0.91**	**0.96**	0.93	0.90	0.89	0.91	0.87	0.83	0.94	0.93	0.88	0.92	0.84	0.89
AUC	**0.95**	**0.95**	**0.95**	**0.97**	0.93	0.94	0.92	0.93	0.93	0.94	0.94	0.94	0.94	0.93	0.93	0.95

The combination of all 12 leads achieved the highest performance metrics with an accuracy of 0.92 and an AUC of 0.97. 2L(Lead 1,2) shows robust performance with an accuracy of 0.91 and an AUC of 0.95. Lead 2, in particular, demonstrates strong sensitivity and specificity, suggesting that even a limited lead configuration can achieve high diagnostic value. The performance of 6L(leads V1-V6) The performance with these leads is notable, achieving an accuracy of 0.90 and an AUC of 0.95. This combination of precordial leads effectively captures the necessary information for accurate classification. Overall, while the 12-lead configuration provides the best diagnostic accuracy, specific lead combinations, such as the two-lead and six-lead configurations, also offer significant diagnostic capability. Notably, Lead 2 stands out for its strong individual performance, making it a viable option for scenarios where fewer leads are preferred, such as in wearable devices.

6. DISCUSSION & CONCLUSION

The classification of ECGs for detecting hyperkalemia has evolved through various approaches, each with its strengths and limitations. Traditional methods utilizing statistical features [19] have shown good accuracy but fall short in representing the complexities of hyperkalemia. These methods, while straightforward, lack the depth required to capture the nuanced differences in ECG signals that are indicative of hyperkalemia. In contrast, morphological features offer a more direct representation of the physiological changes associated with hyperkalemia. However, accurately extracting these morphological features is challenging due to noise and other interfering factors, which can significantly affect the reliability of the results.

Recent advancements in deep learning have shown promising results in ECG classification, largely due to the ability of these algorithms to model non-linear data relationships. For instance, Galloway et al. [9] utilized a deep convolutional neural network (DNN) with 11 layers to detect hyperkalemia in patients with Chronic Kidney Disease (CKD), achieving high performance with an AUC ranging from 0.853 to 0.901 and a negative predictive value exceeding 99% at a high-sensitivity operating point. This underscores the model's potential as a screening tool, especially for ECGs from devices with fewer leads. Lin et al. [8] introduced ECG12Net, an 82-layer deep convolutional neural network, which outperformed experts in detecting dyskalemias. Despite its complexity, the model demonstrated approximately 50% sensitivity for both hypokalemia and hyperkalemia, highlighting the need for improved sensitivity. Kwon et al. [7] presented an ensemble deep learning model for multiple electrolyte imbalances, including hyperkalemia, achieving ROC-AUC values of 0.839. This approach's effectiveness in handling complex conditions underscores the value of ensemble methods. Urtnasan et al. [6] developed a 5-layer CNN for noninvasive hyperkalemia screening, achieving high F1 scores and demonstrating the robustness of CNNs combined with attention mechanisms. In contrast to traditional statistical and morphological methods, deep learning models that integrate feature extraction with attention mechanisms offer a more robust and interpretable solution for hyperkalemia detection. The comparative analysis of individual and combined ECG leads indicated that even with fewer leads, such as a 2-lead ECG, the model achieved good specificity and sensitivity, with an AUC of 0.95. This finding suggests that the model can be effectively deployed in wearable devices, offering a practical solution for continuous hyperkalemia monitoring in real-time..

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