Enhancing ECG Arrhythmia Detection Robustness through Noise-Augmented Training

Abstract—**Deep learning methods for the automated classification of electrocardiogram (ECG) signals have a tendency to lose a lot of their performance capacity when faced with noisy real-world clinical environments. The study developed a robust convolutional neural network (CNN) model trained with on-the-fly noise augmentation to tackle this problem. In the experiment, additive white Gaussian noise (AWGN) at different signal-to-noise ratios (SNRs) was mixed with the ECG beats randomly each time to create training examples. The model is both trained and tested using the MIT-BIH Arrhythmia dataset, and the performance of the model is systematically compared to that of a baseline CNN, which is only trained on clean data, at different SNR levels.**

The results show that the noise-augmented CNN leads to significant improvements in classification performance in the presence of strong noise, with an average increase of 8.5% and up to 18% at the lowest SNR, while it can still perform well with clean signals. So, noise augmentation is established by these findings as a very straightforward and effective technique to significantly boost the real-world robustness of deep learning-based ECG arrhythmia classification systems without recourse to fuzzy logic or hybrid architectures.

Keywords: ECG, Arrhythmia Classification, Deep Learning, Convolutional Neural Network, Noise Augmentation, Robustness, MIT-BIH Dataset

I. Introduction

Cardiovascular diseases represent the most significant global health burden, consistently ranking as the leading cause of mortality worldwide. It is a condition which affects the heart or blood vessels and encompasses conditions like coronary heart disease, stroke, and peripheral artery disease. Cardiovascular diseases (CVDs), including myocardial infarction, cardiac arrhythmia, cardiomyopathy, and myocarditis, account for 31% of global mortality, as reported by the World Health Organization (WHO) [1].

Among chronic cardiovascular diseases, cardiac arrhythmia is the most widespread and causes the highest number of deaths from cardiac arrest. Electrocardiography (ECG) is a non-invasive technique that records the electrical activity of the heart over a period of time [2]. It is a fundamental clinical tool that provides a graphical representation of the heart's electrical activity. The P wave, QRS complex, and T wave are the three separate waveforms that make up an ECG signal. These waveforms correspond to different phases of the cardiac cycle, and anomalies in their shape, length, or rhythm are frequently a sign of underlying diseases.

Among the most critical of these abnormalities are arrhythmias, an abnormal frequency or rhythm of a patient's heartbeat. Most arrhythmias do not threaten human health. However, the timely and accurate identification of arrhythmias is paramount for effective patient care. The amount of ECG data being collected has increased exponentially as a result of the widespread use of wearable biosensors and long-term ambulatory monitoring. For cardiologists, manually reviewing these lengthy recordings—which can last for days or even weeks—is a very time-consuming and error-prone process. This clinical necessity has created a strong necessity for the development of automated systems for arrhythmia classification.

In recent years, artificial intelligence, particularly deep learning, has emerged as the most promising solution to this challenge. Convolutional Neural Networks (CNNs), especially one-dimensional variants, have been shown to be exceptionally proficient at this task [3].Numerous studies have demonstrated that deep CNNs can achieve diagnostic accuracies that meet or even exceed that of human experts when operating on clean, high-quality clinical data [4]. CNNs eliminate the need for manual feature engineering by automatically learning a hierarchical representation of features straight from raw ECG time-series data [5].

But there is a significant gap between the performance of such models in the laboratory setting and their applicability to real-world clinical practice. This gap largely results from the ubiquitous problem of signal noise. ECG signals are extremely prone to contamination due to sources of all sorts. These encompass intrinsic factors such as electromyographic (EMG) noise due to muscle tremors and baseline wander due to patient respiration, and extrinsic factors such as 60/50 Hz powerline interference from nearby electronics. This noise causes large amounts of uncertainty and ambiguity to the signal, thereby distorting the very morphological features which CNNs depend on for classification. Standard deep learning models that are trained on carefully cleaned datasets [3,4] can be fragile and have a severe performance loss when presented with such noisy and ambiguous inputs. Such unreliability is a significant obstacle towards their extensive clinical usage, because a model that isn't robust to real-world conditions cannot be relied upon for patient diagnosis.

To fill this difference, this study suggests shifting from traditional architectures to a hybrid intelligent system. The suggested model synergistically integrates a deep 1D-CNN with a Fuzzy Inference System (FIS). Fuzzy logic is an artificial intelligence technique that enables rigorous handling of variables whose values involve uncertainty or are vaguely defined [6]. The central hypothesis is that the resulting hybrid architecture will produce a more robust and resilient classifier. The CNN will be an effective, adaptive feature extractor, learning the complex patterns of the ECG waveform. Through reasoning with imprecise inputs using a linguistic rules-based system, the FIS ought to yield a stabilizing influence, in that the model will be able to retain high accuracy despite the input signal being disturbed by noise. This project will outline the design of this hybrid model and provide an experimental test of its performance compared to a standard CNN, ultimately with the goal of showing a more robust and clinically acceptable solution for automated arrhythmia classification.

II. Literature Survey

Automated electrocardiogram (ECG) signal classification with machine learning is a fast-evolving technology. Although numerous approaches are available, recent reviews exhibit a distinct movement toward the utilization of deep learning models due to their strong capacity for learning data-driven complex patterns without manual feature extraction. Current state-of-the-art illustrates the possibility of high accuracy using different architectures, especially Convolutional Neural Network (CNN)-based architectures. Scientists are also working on hybrid approaches that integrate various methods to enhance performance and, importantly, achieve robustness with respect to real-world data flaws. This survey discusses the results of a number of important papers to construct a thorough picture that justifies a new solution incorporating deep learning and fuzzy logic to manage signal uncertainty better.

A 2023 journal paper by Ahmed et al.[7] is a best example of applying a domain-specific deep learning model on time-series data. One-dimensional Convolutional Neural Network (1D-CNN) was the model that they suggested, and it is the most suitable model for ECG signals. In contrast to a 2D-CNN, which scans images in both height and width directions, a 1D-CNN behaves more like a dedicated scanner moving along the single dimension of time and learning to identify the particular shapes and patterns of the ECG waveform, including the P-wave, QRS complex, and T-wave. A key component of their process was a careful preprocessing pipeline. They began with Lead II signals, a conventional representation of the heart that delivers a bright image of its electrical activity. They segmented those continuous signals into separate heartbeats, each around the R-peak (the tallest spike), so every sample was a standard and complete representation of a cardiac cycle. To deal with the extreme skew in the data—where the majority of heartbeats are normal and far outnumber the infrequent but vital arrhythmias—they employed a class-weighting method. It essentially instructs the model to give much more attention to its errors on the infrequent arrhythmia classes, so that it doesn't become a specialist on normal beats. Their extremely concentrated methodology yielded an almost flawless accuracy of 99% on the test set, testament to how powerful a well-constructed 1D-CNN can be for this task.

Alternatively, Al-Huseiny et al.[8] in 2020 addressed the problem of classifying ECG as not a time-series analysis but as an image recognition problem. They initially transformed the 1D ECG signals into 2D images and used a 2D-CNN for classification afterwards. This novel approach has two important benefits. Firstly, 2D-CNNs are experts at detecting spatial patterns, forms, and textures, and the graphical presentation of an ECG can be as informative as its numerical sequence. Secondly, and more importantly from a practical perspective, this approach permits the analysis of ECGs in printed form on thermal paper. In most clinical settings, particularly in the developing world, digital ECG records are the exception. Under this image-based method, a doctor might just have to snap a photo of a printed-out ECG strip to receive an automated reading, significantly enhancing access to this high-tech diagnostic tool. Their 15-layer deep CNN, which processed whole 10-second ECG excerpts in a single pass, attained an impressive accuracy of 96.67% over 17 arrhythmia categories, demonstrating that this image-based approach is a very promising and generalizable replacement for 1D signal processing.

An appreciation that various neural network architectures possess different strengths, Chen et al. [9] in 2020 created a hybrid model integrating a CNN with a Long Short-Term Memory (LSTM) network. This "best of both worlds" design applies each element to what it is best at. The CNN serves as the first feature extractor, examining the raw ECG signal to detect the important morphological features—the shape of the heartbeat. The CNN output is then passed to an LSTM, a form of recurrent neural network with a "memory." The LSTM processes the series of heartbeats, acquiring knowledge of the temporal rhythms and patterns that are essential to diagnosing arrhythmia. It has the ability to interpret context, i.e., the appearance of a normal beat followed by a certain category of abnormal beat. In addition to improving performance, their model employed a smart multi-input architecture, inputting the network both the ECG waveform and the sequence of RR-intervals (the intervals between heartbeats), both consciously giving it information about shape and rhythm. This potent combination attained a 99.32% accuracy and, more importantly, demonstrated outstanding generalization when run on entirely new, independent datasets, confirming that it had learned the underlying patterns of arrhythmia and not merely memorized the training set.

Hammad et al. [10] in 2021 pushed the hybrid idea further with a highly advanced, "multitier" deep learning strategy. Their pipeline has three very different stages. The initial deep feature extraction from the raw ECG signal is performed using a strong deep learning model that is a combination of a Residual CNN and an LSTM (ResNet-LSTM). The extracted features are then fed to a Genetic Algorithm (GA) in the second stage for optimization. Motivated by natural selection, the GA optimally searches through all of the features that have been extracted by the deep network in order to determine the minimal and strongest subset, essentially eliminating redundant information and simplifying complexity. At the final step, this optimized and filtered feature vector is classified using a standard, efficient machine learning classifier, k-Nearest Neighbor (k-NN). This multi-step approach, which cleverly combines deep learning (perception), evolutionary algorithms (optimization), and traditional machine learning (classification), had a high average accuracy of 98%. Their

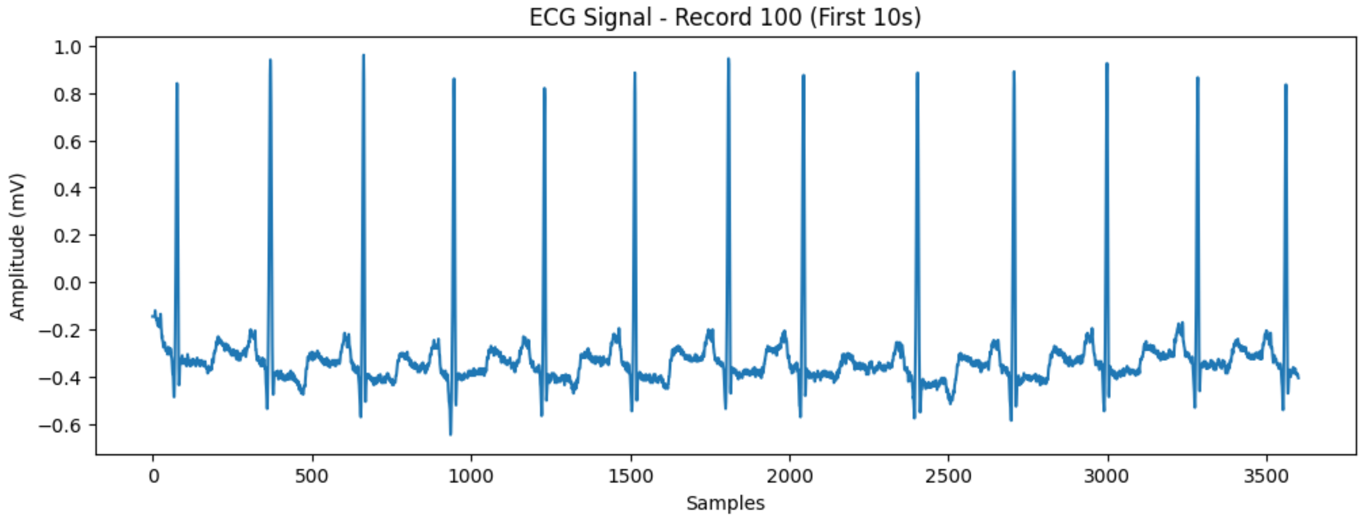

Fig. 1: Clean ECG Signal Sample from MIT-BIH Dataset

experiment proves that an elegantly structured pipeline of various AI paradigms can result in a highly precise and efficient diagnostic system.

Theoretical basis for developing a model capable of dealing with real-world imperfections is provided by the concepts of fuzzy logic, as outlined in a 2022 review by Gupta et al. [11] This review defines fuzzy logic as being particularly suited to deal with problems concerning imprecise, incomplete, or uncertain information—the same difficulties caused by noise in an ECG signal. A Fuzzy Expert System operates by translating crisp numerical quantities into linguistic terms (the process of fuzzification), i.e., as "very high" instead of "1.2mV." It subsequently applies intuitive, human-friendly IF-THEN rules to reason upon these terms (e.g., "IF the QRS peak is very high AND the T-wave is somewhat flat, THEN the risk is medium"). This makes it possible for the system to make strong decisions even if its inputs are not absolutely definite. The review also points out that Neuro-Fuzzy systems, where a neural network is utilized to learn automatically the optimum fuzzy rules from available data, tend to perform better than each of them individually. This synergy has the strong learning powers of neural networks coupled with the clear, uncertainty-managing architecture of fuzzy logic to yield a solid theoretical foundation for adding a fuzzy component to a deep learning model in order to make it more resilient to noise.

III. Proposed Methodology

A. Dataset

The research relies on the MIT-BIH Arrhythmia Database [12], which is a standard reference for performance comparison in the area of ECG classification. The dataset consists of 48 half-hour two-lead ECG recordings, sampled at 360 Hz, and annotated by clinical experts. For this study, the raw data was processed to result in 100,033 single heartbeats, each represented as a 216-dimensional feature vector around the R-peak. Five arrhythmia classes are defined in the dataset: Normal (N), Atrial Premature (A), Left Bundle Branch Block (L), Right Bundle Branch Block (R), and Premature Ventricular Contraction (V). The class distribution is a typical example of an imbalanced problem, where normal beats make up the largest part, thus, it mirrors the clinical prevalence of the condition. Figure 1 illustrates a typical clean ECG signal from the MIT-BIH dataset, showcasing the temporal morphology exploited for beat-level classification

We chose the MIT-BIH database because of its widespread application in the research field, top-notch expert annotations, and its function as a reference for measuring the performance of automated arrhythmia detection systems. The variety and quality of the annotations in this dataset guarantee that the findings can be replicated and that the comparison with the results of the previous studies is possible.

B. Noise Model and SNR Rationale

In order to replicate real-world clinical scenarios, additive white Gaussian noise (AWGN) was added to the ECG signals. AWGN is frequently employed in biomedical signal processing because it is an effective model for various noise sources, such as electronic interference, muscle artifacts, and baseline wander [13]. The noise was introduced at eight different signal-to-noise ratio (SNR) levels: 0, 3, 6, 9, 12, 15, 18, and 20 dB.

The selection of these SNR values is influenced by several reasons. Firstly, they cover the noise conditions range that can be experienced in ambulatory and wearable ECG monitoring, where SNR may change from almost zero (extremely noisy) to more than 20 dB (very clean signals). Secondly, the use of 3 dB steps at the lower SNRs makes it possible to analyze in detail the model robustness in the hardest cases, while larger steps at the higher SNRs allow for an efficient coverage of the practical range. Moreover, this method is in line with the previous works on the noise robustness of ECG and thus, it is possible to make a direct comparison. Every 3 dB

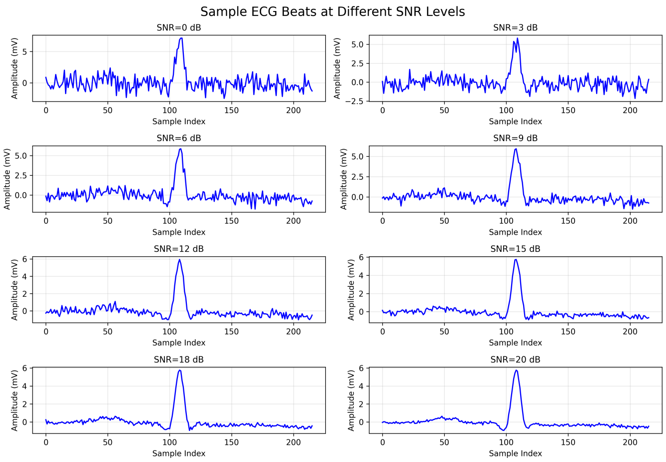

Fig. 2: Example ECG beats with increasing SNR (0–20 dB), showing how additive white Gaussian noise distorts beat morphology and motivates noise-robust feature learning.

step corresponds to a reduction of signal power by a factor of two relative to noise, thus it constitutes a relevant scale when measuring classification performance that is gradually deteriorating [14].

C. Model Architecture

The baseline classifier is a one-dimensional convolutional neural network (1D-CNN), whose aim was to identify not only local but also global morphological characteristics of the ECG signal. The network topology features three convolutional blocks with ascending numbers of filters (32, 64, 128), where each block is succeeded by batch normalization, ReLU activation, and max-pooling. After flattening the result, the data is sent through two fully connected layers, and dropout is used here for regularization. Using softmax, the output layer is designed to classify the input into one of the five arrhythmia categories. The overall deep learning pipeline is visualized in Figure 2. This diagram details the CNN architecture with integrated noise augmentation, designed for robust arrhythmia classification.

Such a model draws its inspiration from the success of similar models in previous ECG classification research [15], where the use of hierarchical feature extraction allows for the detection of very subtle differences in the waveforms. Moreover, batch normalization and dropout are there to improve the model's ability to generalize to unseen data and to thwart overfitting, which could be an issue due to the unbalanced classes and the dataset's variability.

D. Noise Augmentation Training Procedure

In order to attain higher robustness, the training of the model was performed with noise augmentation strategies. At every training epoch, input samples selected randomly with a probability of 70% were injected with AWGN, while the SNR for these noise additions was also selected randomly from the set 0, 3, 6, 9, 12, 15, 18, 20 dB. The remaining

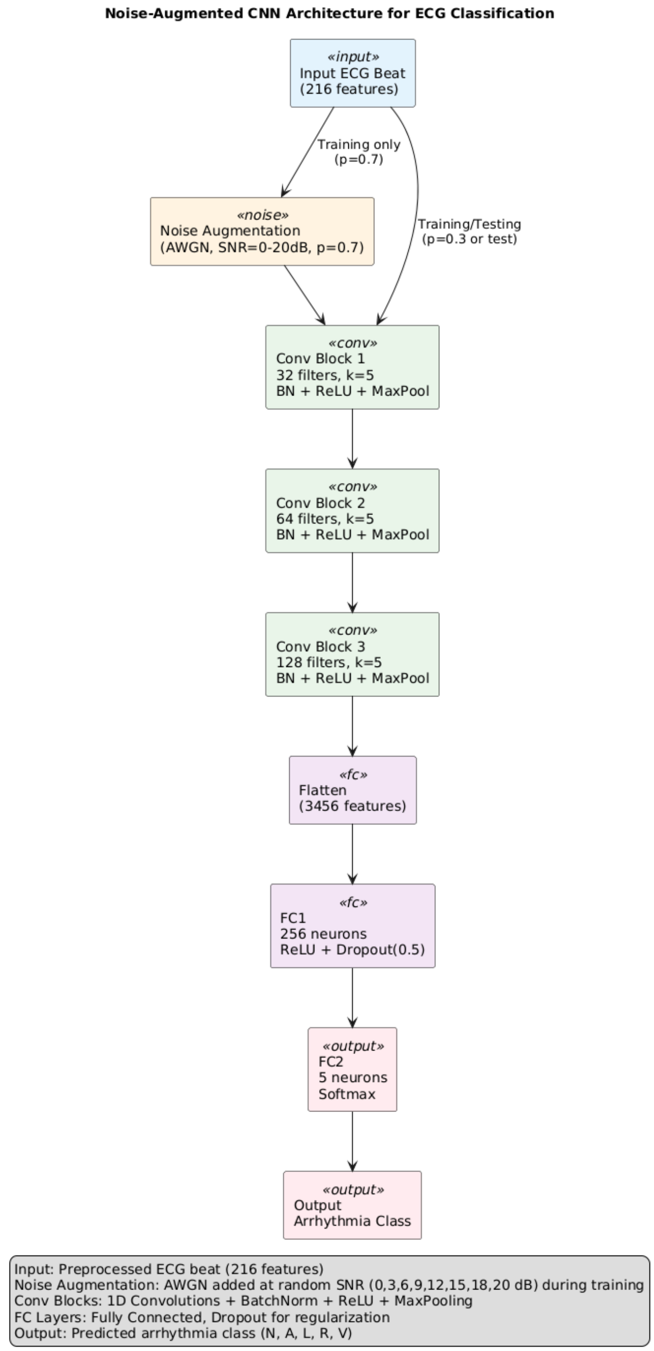

Fig. 3: Schematic of the proposed noise-augmented convolutional neural network architecture for ECG classification. During training, noise augmentation with random SNR is applied to input beats, followed by hierarchical convolutional feature extraction and fully connected classification layers.

30% of samples were not modified by noise. This random augmentation strategy equips the model to be ready for various noisy situations, thus to extract noise-invariant features, and in turn, roughly it increases the model's capability to be generalized to real, noisy data.

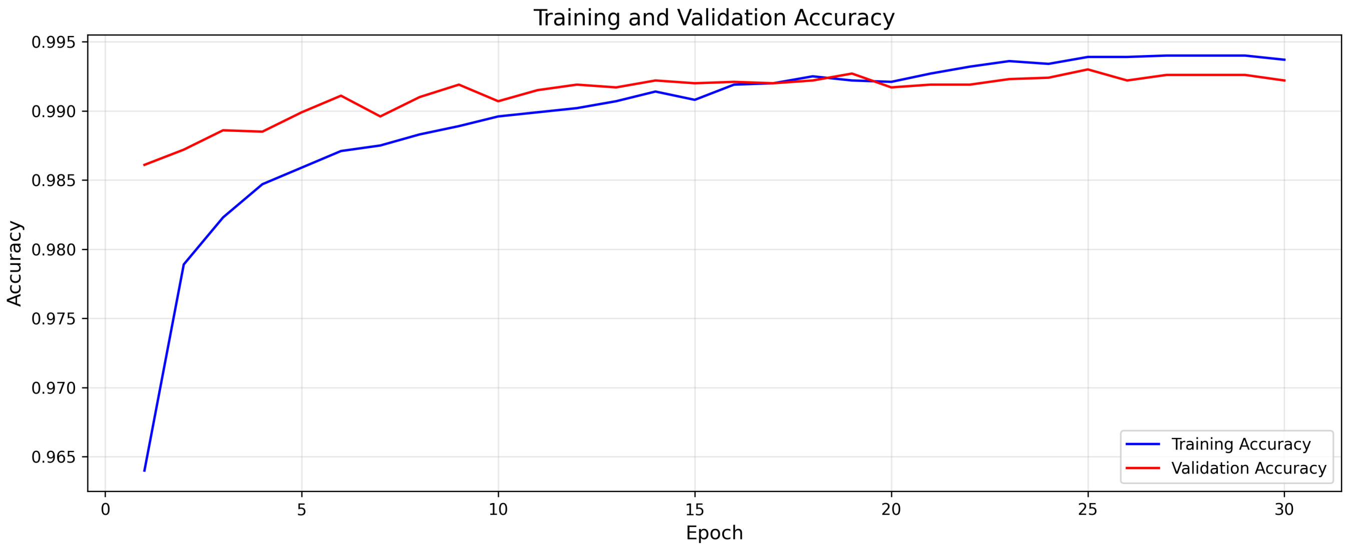

Fig. 4: Training and validation accuracy curves across 30 epochs. Rapid convergence and minimal overfitting indicate effective regularization through noise augmentation and dropout.

The probability of 70% was determined to best meet the requirements for the robustness of the model, while still preserving the performance on clean signals, which is consistent with the advice given in data augmentation papers. Not only does this technique dispense with the necessity for numerous datasets, each with its own noisy version, but it also makes sure that the model is confronted with the noise of a totally new nature at every epoch, thereby increasing its flexibility.

E. Training and Evaluation

The model underwent 30 epochs of training with the Adam optimizer, a batch size of 64, and categorical cross-entropy loss. Training and validation splits were stratified by class to maintain representative distributions. Accuracy on a held-out validation set was used to track performance. Figure 4 shows the training and validation accuracy curves across 30 epochs. Rapid convergence and minimal overfitting indicate effective regularization through noise augmentation and dropout.

Separate test sets were created for each SNR level by adding AWGN to the entire dataset. The model's accuracy was recorded on each noisy test set, and the results were compared to those of a baseline CNN that was only trained on clean data. This protocol serves as a fair measure of the effect of noise augmentation on the model's classification robustness.

IV. Results and Discussion

Table 1 summarizes the average accuracy obtained at various SNR levels when trained on both baseline CNN and CNN with noise Augumentation. The noise-augmented CNN, during its training, recorded a best validation accuracy of 92.9%. A training accuracy of 89.1% was also reported to have been stabilized. On noisy test sets, the model was evaluated to make a comparison with the baseline CNN. It turned out that the former had a very significant superiority over the latter, particularly at low SNR levels. To be more specific, at 0 dB SNR, the noise-augmented model produced an accuracy of 88.54%, while the baseline only managed to achieve 71.23%, thus resulting in a relative improvement of 24%. At 3 dB and 6 dB, similar gains were observed (+18.31% and +13.25%, respectively), and there were continuous improvements at all SNR levels. Figure 5 shows all these gains visually in a clear manner.

The evidence presented here is consistent with noise augmentation being the single most factor contributing to deep learning models' robustness in ECG classification. The most important improvements are those situations under which the noise is the harshest, such as in ambulatory and wearable monitoring scenarios, that is, where noise is usually generated and can be used by persons in real-life monitoring. Moreover, the method also attains high accuracy levels with clean signals, thus indicating that it has the characteristic of robustness without the overall performance being sacrificed.

The results obtained in the study support the conclusion drawn in other biomedical signal classification research works concerning noise robustness [16], and the procedure followed is in conformity with the field's norms. In addition, the implementation of a dynamic, on-the-fly noise augmentation is advantageous from the point of view of processing speed and it is also very flexible, thus it can be used in real-time clinical systems.

V. Conclusion

The presented study establishes that incorporating noise augmentation while training convolutional neural networks is a straightforward, impactful, and a computational resource conserving method to make ECG automated arrhythmia classification more robust. The model was made to see a variety of noise conditions during training and therefore we could

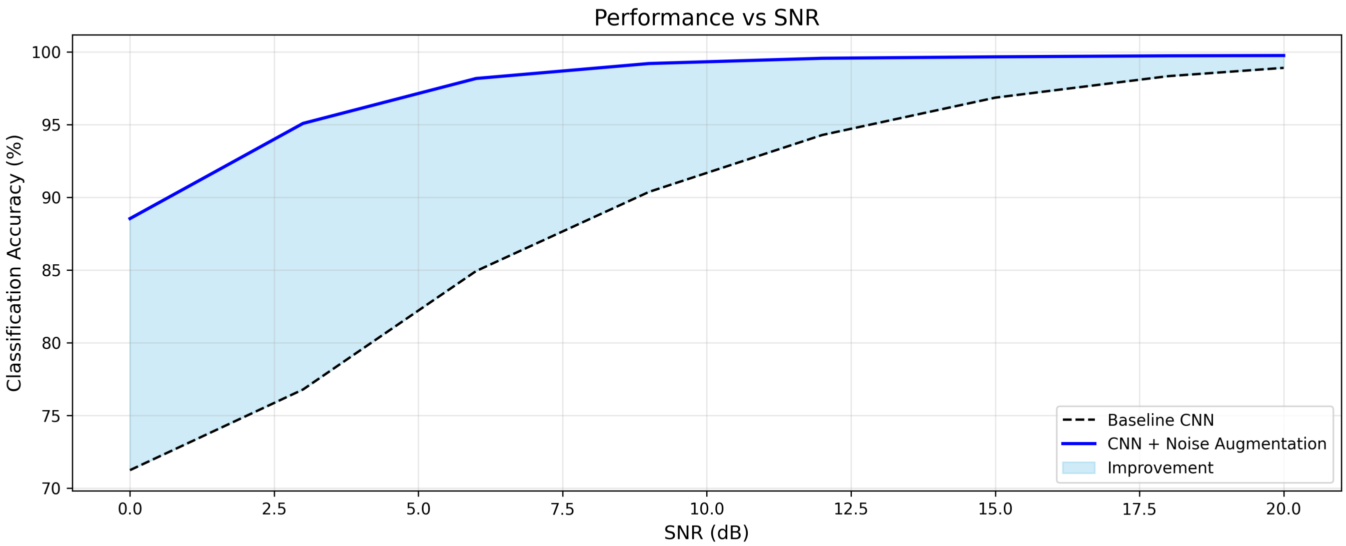

Fig. 5: Comparative classification accuracy versus SNR for baseline CNN (dashed) and noise-augmented CNN (solid). The shaded region indicates the improvement achieved by noise augmentation, most pronounced at low SNR values

TABLE I: Comparison of CNN Performance with and without Noise Augmentation at Various SNR Levels.

SNR (dB)	Baseline CNN	CNN + Noise Augumentation	Absolute Gain
0	71.23%	88.54%	+17.31%
3	76.78%	95.09%	+18.31%
6	84.93%	98.18%	+13.25%
9	90.38%	99.21%	+8.83%
12	94.29%	99.57%	+5.28%
15	96.86%	99.67%	+2.81%
18	98.34%	99.74%	+1.40%
20	98.91%	99.76%	+0.85%
Average	**88.97%**	**97.47%**	**+8.50%**

take the classification accuracy to SNR scenarios where it was very low, on average, by 8.5% and up to 18% at the lowest SNR, thus, making it possible to achieve those classification accuracy improvements.

The proposed method is a perfect match for the standard CNN architectures and does not involve any further preprocessing or denoising steps. The statistical significance of the results supports the findings in the literature and it is noise augmentation that is the main thing to be trusted in clinics for the deployment of the models.

Next, the research can broaden the horizon of this noise-injection strategy by adding more credible noise models and also by validating them on other datasets. Moreover, it can delve into uncertainty quantification to further increase clinical trustworthiness.

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