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TRANSFORMING STROKE PREVENTION IN CAMEROON: AN AI-BASED METHOD FOR DETECTING ATRIAL FIBRILLATION

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Abstract

Complex human diseases, particularly cardiovascular diseases, have a significant impact globally and in Cameroon. Among these diseases, stroke stands out due to its high mortality rate, exacerbated by the lack of medical infrastructure and appropriate technical resources for early diagnosis and effective management. In this context, prevention, especially through the identification of risk factors, is of crucial importance. Atrial fibrillation, an independent risk factor for stroke, increases the likelihood of being affected by this condition fivefold. However, its diagnosis currently relies on the manual classification of cardiac arrhythmias, a tedious, time-consuming method, prone to errors, and difficult to access in a country like Cameroon, where the doctor-to-population ratio is extremely low (1.1 doctors per 10,000 inhabitants).

Faced with these challenges, this research proposes an innovative method for the automatic recognition of atrial fibrillation, and normal heart rhythm using wavelet transform and a convolutional neural network (CNN) based on transfer learning with the AlexNet architecture. Experimental results obtained by testing the approach demonstrates interesting accuracy across three international databases (the MIT-BIH, Chapman ECG Database, and The 2017 PhysioNet/CinC Challenge databases) while being computationally efficient for Cameroonian healthcare infrastructure. This automated solution could revolutionize the

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diagnosis of cardiac arrhythmias by reducing errors, speeding up the process, and addressing the lack of medical resources.

In conclusion, this research offers a promising perspective for improving stroke prevention and management in Cameroon and other resource-limited regions. It also paves the way for future applications in other cardiovascular diseases, thereby strengthening healthcare systems in developing countries.

Keywords: ECG, CNN, Stroke, atrial fibrillation, cardiac arrhythmias

1. General Introduction

1.1. Introduction

Stroke is the second leading cause of death worldwide and in sub-Saharan Africa, accounting for 10% of global mortality [1]. In Cameroon, the situation is even more concerning, with a mortality rate of 25% within one month after the onset of stroke [1] [2]. Cardiovascular diseases, particularly stroke, are a major public health burden, and atrial fibrillation (AFIB) is a significant independent risk factor, increasing stroke risk fivefold. Early diagnosis of AFIB is critical, yet manual classification from ECG signals remains labour-intensive and reliant on expert interpretation. This challenge is exacerbated in resource-limited settings like Cameroon (especially remote areas), where the doctor-to-patient ratio is critically low (1.1 doctors per 10,000 inhabitants) [3].

To address this gap, automated ECG analysis systems—particularly those leveraging deep learning—have shown promise in improving diagnostic accuracy and efficiency. This study proposes a simple, robust, and accurate system for automatically classifying AFIB and normal sinus rhythm (NSR) using a CNN-based approach with transfer learning. The method includes a comprehensive construction guide and employs Continuous Wavelet Transform (CWT) to convert 1D time-series ECG signals of varying sampling rates into 2D images. This transformation enables the extraction of temporal and spectral features, which are then classified using the AlexNet architecture.

1.2. Literature review

In the past decade, researchers have made significant strides in developing machine-learning algorithms to diagnose arrhythmic diseases from ECG data. Algorithms like Adaptive Backpropagation Neural Networks [4], Logistic Regression [5], Random Forests

[6], Principal Component Analysis [7], Support Vector Machines (SVM) [8], and k-Nearest Neighbours [9] have demonstrated promising results.

Traditional methods for ECG signal classification rely heavily on feature engineering and conventional machine learning algorithms. However, these approaches have their limitations, particularly in managing the nonlinearities of heavy loads and automatically extracting features. Manual feature extraction in traditional methods can be prone to subjective factors and may not capture subtle changes in ECG signals, leading to potential misdiagnoses.

Deep learning techniques have increasingly been employed for ECG signal classification to address these challenges, as they can automatically extract meaningful features from raw data and handle complex nonlinear relationships. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRUs), and Residual Neural Networks have all been explored for this purpose. CNN, in particular, excels in capturing spatial and temporal features, robustness to noise, scalability, and generalization, and flexibility in input representations [10].

Several authors have explored the use of Convolutional Neural Networks (CNNs) for classifying cardiac arrhythmias from ECG signals. Below in Table 1 is a summary of some works in the literature:

Table 1: Summary of some works in the literature

Author	Approach	Database	Results
Xiaolong Z. et al. [11]	▪ Segmentation of single-channel ECG signals based on heartbeats and heart rate evolution. ▪ Transformation of heartbeats into two-beat coupling matrices, used as 2D inputs for a CNN classifier. ▪ Simultaneous capture of rhythm morphology and beat-to-beat correlation in the ECG.	MIT-BIH Arrhythmia	▪ Detection of supraventricular ectopic beats (SVEB) and ventricular ectopic beats (VEB). ▪ Performance for VEB detection: all metrics exceed 90%. ▪ Performance for SVEB detection: all metrics exceed 70%.

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Acharya et al. [12]	R-wave amplitude processing.	PhysioBank MIT-BIH Arrhythmia	Classification accuracy: Achieved 94.03% accuracy in diagnosing heartbeats from original ECGs and 93.47% accuracy from noise-free ECGs, respectively.
Zubair et al. [13]	Wavelet transform	MIT-BIH Arrhythmia	Classification accuracy: 92.7%.
Baloglu et al. [14]	Wavelet transform	MIT-BIH Arrhythmia	Classification accuracy: 99.8%.

The work of Baloglu et al. [14] stands out with an accuracy of 99.8%, demonstrating the effectiveness of their wavelet transform-based approach.

Other authors, such as Acharya et al. [12] and Xiaolong Z. et al. [11], also achieved impressive results, with accuracies above 90%.

These studies, associated with the study of Fatma et al. [10] and Rahul et al. [15] confirms that CNNs, combined with appropriate preprocessing techniques (such as segmentation, wavelet transform, or R-wave amplitude processing), can effectively classify cardiac arrhythmias without requiring manual parameter extraction.

1.3. How an Automatic cardiac arrhythmia diagnostic system operates

A system for automatic diagnosis of arrhythmias is generally divided into two main parts (The input model and the classifier) and it's composed of a typical operational chain (as shown in Figure 1) that should include the steps: ECG signal acquisition, Signal preprocessing, Detection of QRS complexes, Extraction of relevant features, and Final classification of cardiac arrhythmias.

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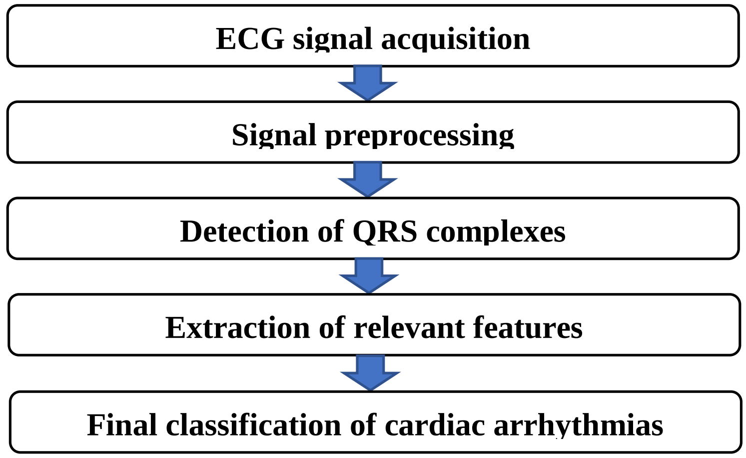

Figure 1: Schematic representation of an automatic arrhythmia diagnosis system

- The acquisition of ECG signals and their transformation into a format that can be used for automatic processing. The acquisition is later used to build up the databases.
- Pre-processing: During the acquisition of ECG signals, various sources of distortion can affect the data. The pre-processing stage aims to reduce the impact of these disturbances while ensuring that the essential components of the signal remain intact. Common sources of interference include electrical grid noise (often referred to as "50 Hz" interference), baseline fluctuations (caused by breathing or patient movement), and electromyographic noise (EMG) resulting from muscle activity. Although effective techniques have been developed to address the first two types of noise, EMG interference remains particularly challenging due to the overlap of its frequency spectrum with that of the useful ECG signal.
- The detection of QRS complexes and segmentation of the cardiac cycle: This stage in automatic processing is both crucial and sensitive, involving the segmentation of the signal into consecutive homogeneous frames. This process effectively separates the clinically significant waveforms: the P and T waves, along with the QRS complex.
- Parameter extraction: The goal is to identify the (vector of characteristics) derived from the elementary waves generated during the segmentation phase, focusing on the parameters that most effectively predict the patient's condition. This parameter extraction can be performed either in the time domain or the frequency domain.
- Classification: By utilizing the appropriate parameters, the classification system should be capable of "providing the diagnosis," effectively assisting or taking over the role of the doctor.

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1.4. Performance evaluation parameters of an Automatic cardiac arrhythmia diagnostic system

The performance of the detection algorithm is assessed based on four standard metrics, typically measured for each record:

- **True Positive (TP):** The algorithm predicts an example as part of set C, and it is indeed part of set C.
- **True Negative (TN):** The algorithm predicts an example as not part of set C, and it is truly not part of set C.
- **False Positive (FP):** The algorithm predicts an example as part of set C, but it is not part of set C.
- **False Negative (FN):** The algorithm predicts an example as not part of set C, but it is part of set C.

Performance is evaluated based on sensitivity, specificity, and classification accuracy (precision). Sensitivity refers to the algorithm's ability to correctly identify an element belonging to class C as part of class C, while specificity measures its ability to correctly classify an element not in C as outside of C. These metrics are calculated as follows:

$$\text{Sensitivity (Recall)} = \frac{\text{TP}}{\text{TP+FN}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Equation 1}$$

$$\text{specificity (}= \frac{TN}{TN+FP} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Equation 2}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Equation 3}$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Equation 4}$$

These metrics are used to evaluate the accuracy and reliability of classification systems.

2. Materials and Methods

2.1. Materials

2.1.1. Hardware

We used a HP Z-Book computer with the following features:

- **Processor**: Intel(R) Core (TM) i7-4710MQ CPU @ 2.50GHz 2.50 GHz
- **Installed RAM:** 32.0 GB (31.7 GB usable)

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- **Storage**: 932 GB HDD TOSHIBA MQ04ABF100V -63, 233 GB SSD Samsung SSD 850 EVO 250GB
- **Graphics Card:** NVIDIA Quadro K3100M (4 GB), Intel(R) HD Graphics 4600 (113 MB)
- **System Type:** 64-bit operating system, x64-based processor

2.1.2. Software

Operating System

- **Edition:** Windows 10 Pro
- **Version:** 2009

MATLAB

- **Version:** R2020a
- WFDB tool V 0.10.0
- Statistics and Machine Learning Toolbox V 11.7
- Deep Learning Toolbox Model for AlexNet Network V 20.1.0
- Deep Learning Toolbox V 14.0
- DSP System Toolbox V 9.10
- Wavelet Toolbox V 5.4

2.2. Methods

2.2.1. Dataset

The study utilised three publicly available datasets: the MIT-BIH Atrial Fibrillation Database (AFDB) [16] [17], the Chapman ECG Database [18] [19], and the 2017 PhysioNet/CinC Challenge Database [20] [21]. The AFDB contains 25 long-term ECG recordings of patients with AFIB, The PhysioNet/CinC Challenge Database includes a diverse set of ECG signals, including normal rhythms, AFIB, and other arrhythmias. In contrast, the Chapman ECG Database comprises 45,152 patient ECGs, covering a range of cardiac conditions, including atrial fibrillation (AFIB), normal sinus rhythm (NSR), and various other arrhythmias.

2.2.2. Preprocessing

The ECG signals were pre-processed to ensure uniformity in sampling rates. Signals from the MIT-BIH database were resampled to 300 Hz and 500 Hz, those from the PhysioNet/CinC Challenge were resampled to 250 Hz and 500 Hz, and those from the Chapman ECG Database were resampled to 250 Hz and 300 Hz. The ECG signals were resampled to 250 Hz, 300 Hz, and 500 Hz to match native rates of source datasetswhile ensuring compatibility across datasets. These frequencies were selected based on the following considerations:

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- **250 Hz (>200)**: Adequate for capturing key ECG features [22] and aligns with clinical standards.
- **300 Hz**: Aligns with common preprocessing standards for MIT-BIH data
- **500 Hz**: Preserve high-frequency features such as P/T waves.
- **Computational Efficiency:** reduce memory/processing demands

Resampling was performed using MATLAB's resample function with anti-aliasing (40% cutoff for downscaling) to avoid spectral distortion. The signals are segmented into 10-second episodes, resulting in 1800 segments for training and 612 segments for validation, making a total of 2412 segments.

No additional filtering was made on the 1D time series signals to increase robustness and generalization.

2.2.3. Feature Extraction

The Continuous Wavelet Transform (CWT) was applied to convert the ECG signals into 2D scalogram images. This transformation allows the CNN to capture both temporal and spectral features, enhancing the model's ability to distinguish between AFIB and NSR.

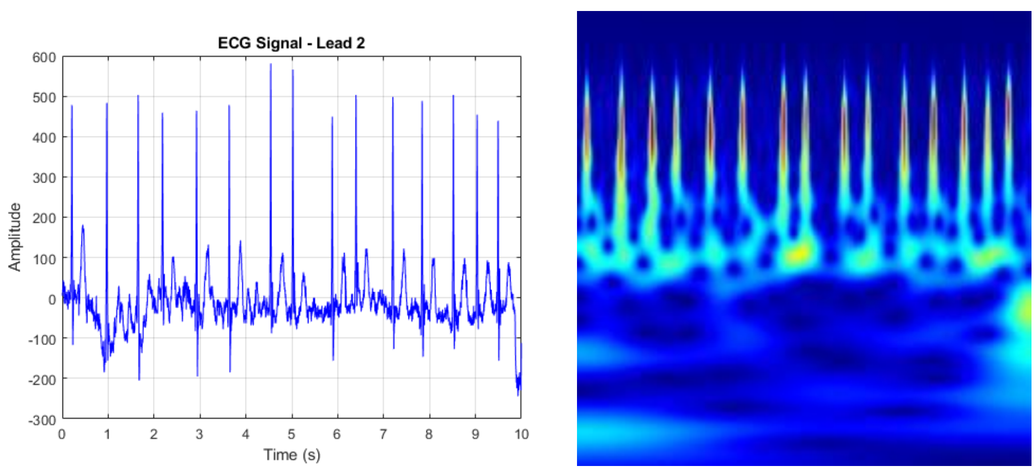

Figure 2: AFIB (JS00036.mat) 10 seconds 1D time series signal and scalogram - Chapmann AFIB

See supporting file 2 : MATLAB code for CWT conversion

2.2.4. Model Architecture

The AlexNet architecture, a renowned convolutional neural network (CNN), was utilised for classification as it shows outstanding performance compared to other CNN architectures [23].

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Compatible with transfer learning, AlexNet also has a balance of accuracy and is compatible with low-power hardware.

Transfer learning was applied by fine-tuning the pre-trained AlexNet model to adapt it to the task. To customise the network for binary classification (AFIB vs. NSR), the final three layers were replaced with new, task-specific layers. The model's training process employed stochastic gradient descent with momentum (SGDM) for efficient optimisation, and its performance was rigorously evaluated on an independent test dataset.

3. Results and Discussions

3.1. Results

The AlexNet model proved highly effective in classifying ECG signals into AFIB (Atrial Fibrillation) and NSR (Normal Sinus Rhythm) when tested on a combined dataset comprising the MIT-BIH AFIB Database, Chapman Database, and the PhysioNet/CinC Challenge. To optimize performance, we fine-tuned the model using a random search approach, exploring key hyperparameters such as learning rates (0.001 to 0.0001), batch sizes (16, 32, 64, and 128), and training durations (10 and 20 epochs). This systematic optimization ensured robust classification accuracy while preventing overfitting. The results after testing our approach on the different dataset are shown in Table 2, 3, 4 and 5 below.

Table 2 : Training AlexNet across our general database (consisting of the three databases) with various hyperparameter configurations and a range of learning rates.

Epoch	**MB**	**Learning rate**	**Performance**	**F1 Score**
10	128	0.001	Accuracy: 59.97% Sensitivity: 54.25% Specificity: 65.69%	0.58
10	16	0.0001	Accuracy: 84.48% Sensitivity: 87.91% Specificity: 81.05%	0.85

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10	32		Accuracy: 83.82% Sensitivity: 91.83% Specificity: 75.82%	0.85
10	64		Accuracy: 83.17% Sensitivity: 94.12% Specificity: 72.22%	0.85
10	128		Accuracy: 85.95% Sensitivity: 92.48% Specificity: 79.41%	0.87
20	16		Accuracy: 82.68% Sensitivity: 88.56% Specificity: 76.80%	0.84
20	32		Accuracy: 81.21% Sensitivity: 93.46% Specificity: 68.95%	0.83
20	64		Accuracy: 85.29% Sensitivity: 88.24% Specificity: 82.35%	0.86
20	128		Accuracy: 83.82% Sensitivity: 94.77% Specificity: 72.88%	0.85
10	16	0.00001	Accuracy: 83.17% Sensitivity: 91.50% Specificity: 74.84%	0.84
10	32		Accuracy: 83.17% Sensitivity: 90.85% Specificity: 75.49%	0.84
10	64		Accuracy: 83.66% Sensitivity: 88.24% Specificity: 79.08%	0.84
10	128		Accuracy: 84.80% Sensitivity: 87.58% Specificity: 82.03%	0.85
20	**16**		**Accuracy: 86.27% Sensitivity: 89.22% Specificity: 83.33%**	**0.87**
20	32		Accuracy: 83.50% Sensitivity: 92.16% Specificity: 74.84%	0.85
20	64		Accuracy: 84.31% Sensitivity: 85.95% Specificity: 82.68%	0.85
20	128		Accuracy: 84.80% Sensitivity: 91.83% Specificity: 77.78%	0.86

See supporting image 1 for the confusion matrix of the parameters with the highest accuracy.

See supporting image 2 for the ROC curve of the parameters with the highest accuracy.

Table 3 : Training AlexNet across the 250Hz Database with various hyperparameter configurations and a range of learning rates.

Epoch	MB	Learning rate	Performance
10	16	0.0001	Accuracy: 83.82% Sensitivity: 90.20% Specificity: 77.45%
10	32		Accuracy: 87.25% Sensitivity: 88.24% Specificity: 86.27%
10	**16**	**0.00001**	**Accuracy: 88.24% Sensitivity: 91.18% Specificity: 85.29%**
10	32		Accuracy: 87.75% Sensitivity: 84.31% Specificity: 91.18%
10	64		Accuracy: 84.80% Sensitivity: 85.29% Specificity: 84.31%
10	128		Accuracy: 84.31% Sensitivity: 83.33% Specificity: 85.29%
20	16		Accuracy: 87.75% Sensitivity: 90.20% Specificity: 85.29%

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Table 4 : Training AlexNet across the 300Hz Database with various hyperparameter configurations and a range of learning rates.

Epoch	MB	Learning rate	Performance
10	16	0.0001	Accuracy: 86.76% Sensitivity: 85.29% Specificity: 88.24%
10	64		Accuracy: 89.22% Sensitivity: 91.18% Specificity: 87.25%
20	16		Accuracy: 86.76% Sensitivity: 88.24% Specificity: 85.29%
20	64		Accuracy: 88.73% Sensitivity: 92.16% Specificity: 85.29%

Table 5 : Training AlexNet across the 500Hz Database with various hyperparameter configurations and a range of learning rates.

Epoch	MB	Learning rate	Performance
10	16	0.0001	Accuracy: 76.47% Sensitivity: 87.25% Specificity: 65.69%
10	64		Accuracy: 77.45% Sensitivity: 96.08% Specificity: 58.82%
20	16		Accuracy: 77.45% Sensitivity: 94.12% Specificity: 60.78%
20	64		Accuracy: 77.45% Sensitivity: 93.14% Specificity: 61.76%

3.2. Discussions

The results indicate that the combination of CWT and CNN-based transfer learning is highly effective for the automatic classification of AFIB and NSR across multiple Datasets. The use of CWT for feature extraction allows the model to capture both temporal and spectral information, which is crucial for accurate classification. The high accuracy (86.27%) achieved by the proposed system suggests that it can be a valuable tool for early AFIB detection, particularly in resource-limited settings where expert interpretation of ECG signals is scarce.

Compared to other methods, the proposed approach offers several advantages, including robustness to noise and the ability to generalise across different datasets as it was trained based on 3 databases with different frequencies. This can be illustrated on Table 6 below.

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Table 6: Comparing our approach with other in the literature

Author	Database	Results
Xiaolong Z. et al. [11]	MIT-BIH Arrhythmia	Overall performance of 80 %
Acharya et al. [12]	PhysioBank MIT-BIH Arrhythmia	Classification accuracy: Achieved 94.03% accuracy in diagnosing heartbeats from original ECGs and 93.47% accuracy from noise-free ECGs, respectively.
Zubair et al. [13]	MIT-BIH Arrhythmia	Classification accuracy: 92.7%.
Baloglu et al. [14]	MIT-BIH Arrhythmia	Classification accuracy: 99.8%.
T. Mahmud et al. [24]	MIT-BIH Arrhythmia	Classification accuracy: 99.45%.
Proposed Methode	• MIT-BIH AFDB • Chapman ECG Database • The 2017 PhysioNet/CinC Challenge Database	Classification accuracy: 86.27%.

While Baloglu et al. achieved 99.8% accuracy and T. Mahmud et al achieved 99.45% accuracy on MIT-BIH alone, our system maintains 86.27% accuracy across three heterogeneous datasets, demonstrating superior generalizability for real-world deployment.

This study was limited to retrospective data from existing databases. Future validation with prospective Cameroonian patient data is needed to assess clinical utility

4. Conclusion

This study presents a novel approach for the automatic classification of atrial fibrillation (AFIB) and normal sinus rhythm (NSR) using a CNN-based model with transfer learning. The proposed system achieved a classification accuracy of 86.27% across cross ECG datasets (MIT-BIH database, the 2017 PhysioNet/CinC Challenge, and the Chapman ECG Database), demonstrating its potential for accurate and efficient AFIB detection. By leveraging CWT for

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feature extraction and AlexNet for classification, the system offers a robust solution for accurate diagnosis of AFIB, particularly in regions like Cameroon, where limited medical resources and a shortage of specialists pose significant challenges in stroke prevention.

4.1. Implications of the Study

The proposed system can significantly improve healthcare delivery in low-resource settings by; **Reducing diagnostic delays** (Automated AFIB detection eliminates the need for time consuming manual ECG analysis), **Lowering misdiagnosis rates** (AI-based classification minimizes human error, ensuring more accurate diagnosis) and **Enhancing accessibility** (The method is computationally efficient, making it feasible for hospitals and clinics with limited infrastructure).

4.2. Contribution to Science

This research advances the field of AI in cardiology particularly in regions with limited medical resources and shortage of specialists by:

- Validating the effectiveness of CWT, CNN and transfer learning for ECG classification, even with varying signal sampling rates, thus reducing the need for large datasets.
- Providing a reproducible framework for future studies on arrhythmia detection in resource-constrained environments.

4.3. Recommendations and suggestions for future studies.

To maximize the impact of this work, we recommend, the model should be tested with real-time ECG data from Cameroonian hospitals to assess its practical performance, a mobile compatible version should be developed to support remote diagnostics and the economic feasibility of deploying the model should be evaluated.

Future work should focus on real-world implementation, ensuring that this technology reaches the patients who need it most. With continued refinement and collaboration, AI-powered ECG analysis could become a cornerstone of cardiovascular care in developing nations.

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ISSN 2709-3409 (Online)

6. References

B.-D. A. Kemnang, L. B. Bita'a, S. H. S. Yomi, B. T. Djidjou, R. M. Mboumo, C. D. Douanla, V. Wouafack-Kenfack, F.-C. N. Tsakeng and O. T. H. M. , "Distribution et itinéraire thérapeutique des patients reçus pour accident vasculaire cérébral à l'Hôpital Régional de Bafoussam, Cameroun," *Pan African Medical Journal,* 2019.

N. A, "Cameroun: comment comprendre et prévenir les AVC dans notre contexte actuel," *Google Scholar,* 2016.

W. H. Organisation, "Health Analytical Profile Cameroon," World Health Organisation, Yaounde, 2016.

B. M. Asl, A. R. Sharafat and S. K. Setarehdan, "An adaptive backpropagation neural network for arrhythmia classification using R-R interval signal," *Neural Network World,* 2012.

M. T. Ai, S. Sumiati and V. Rosalina, "A Predictive Model for Heart Disease Diagnosis Based on Multinomial Logistic Regression," *Information Technology,* 2021.

C. ZOU, A. MÜLLER, U. WOLFGANG, D. RÜCKERT, P. MÜLLER, M. BECKER, A. STEGER and E. M. , "Heartbeat Classification by Random Forest With a Novel Context Feature: A Segment Label," *IEEE Journal of Translational Engineering in Health and Medicine,* vol. 10, pp. 1-8, 2022.

V.-S. Pham, A. Nguyen, H. B. Dang, H.-C. Le and M. T. Nguyen, "Diagnosis of sudden cardiac arrest using principal component analysis in automated external defibrillators," *Scientific Reports,* 2023.

V. C, T. T, R. M, S. A and M. M, "ECG Signal Feature Extraction and SVM Classifier Based Cardiac Arrhythmia Detection," in *2023 Second International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT)*, Trichirappalli, India, 2023.

D. F. S. Losada, J. J. S. Gómez and J. A. Z. Vela, "Classification of ECG Signals Using Machine Learning Techniques," *Academic Journal of Interdisciplinary Studies,* vol. 13, 2024.

Journal of Tertiary and Industrial Sciences *Vol. 5, No. 2, 2025*
ISSN 2709-3409 (Online)

F. Murat, F. Sadak, O. Yildirim, M. Talo, E. Murat, M. Karabatak, Y. Demir, R.-S. Tan and U. R. Acharya, "Review of Deep Learning-Based Atrial Fibrillation Detection Studies," *International Journal of Environmental Research and Public Health,* vol. 18, 2021.

X. ZHAI and D. C. TIN, "Automated ECG Classification Using Dual Heartbeat Coupling Based on Convolutional Neural Network," *IEEE Access,* 2018.

U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, M. Adam, A. Gertych and T. R. San, "A deep convolutional neural network model to classify heartbeats," *Computers in Biology and Medicine,* 2017.

M. Zubair, J. Kim and C. Yoon, "An Automated ECG Beat Classification System Using Convolutional Neural Networks," in *2016 6th International Conference on IT Convergence and Security (ICITCS)*, Prague, Czech Republic, 2016.

U. B. Baloglu, M. Talo, O. Yildirim, R. S. Tan and U. R. Acharya, "Classification of myocardial infarction with multi-lead ECG signals and deep CNN," *Pattern Recognition Letters,* vol. 122, pp. 23-30, 2019.

J. Rahul and L. D. Sharma, "Advancements in AI for cardiac arrhythmia detection: A comprehensive overview," *Computer Science Review,* vol. 56, 2025.

A. Goldberger, L. Amaral, L. Glass, J. Hausdorff, P. Ivanov, R. Mark, J. Mietus, G. Moody, C. Peng and H. Stanley, PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals, 2020. [Online]. Available: https://physionet.org/content/afdb/1.0.0/.

A. Goldberger, L. Amaral, L. Glass, J. Hausdorff, P. Ivanov, R. Mark, J. Mietus, G. Moody, C. Peng and H. Stanley, "A new method for detecting atrial fibrillation using R-R intervals.," *Computers in Cardiology,* 1983.

J. Zheng, H. Guo and H. Chu, "A large scale 12-lead electrocardiogram database for arrhythmia study (version 1.0.0)," *PhysioNet,* 2022.

J. Zheng, H. Chu, D. Struppa, J. Zhang, S. Yacoub, H. El-Askary, A. Chang, L. Ehwerhemuepha, I. Abudayyeh, A. Barrett, G. Fu, H. Yao, D. Li, H. Guo and C. Rakovski, "Optimal Multi-Stage Arrhythmia Classification Approach," *Scientific Reports,* vol. 10, 2020.

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G. D. Clifford, C. Liu, B. Moody, L.-w. H. Lehman, I. Silva, Q. Li, A. E. Johnson and d. R. G. Mark, "AF Classification from a Short Single Lead ECG Recording: the PhysioNet/Computing in Cardiology Challenge 2017," *Computing in Cardiology,* vol. 44, 2017.

G. D. Clifford, C. Liu, B. Moody, L.-w. H. Lehman, I. Silva, Q. Li, A. E. Johnson and d. R. G. Mark, PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals., 2020. [Online]. Available: https://physionet.org/content/challenge-2017/1.0.0/. [Accessed 2024].

O. Kwon, J. Jeong, H. B. Kim, I. H. Kwon, S. Y. Park, J. E. Kim and Y. Choi, "Electrocardiogram Sampling Frequency Range Acceptable for Heart Rate Variability Analysis," *Healthcare Informatics Research,* vol. 3, no. 24, 2018.

N. Rahuja and S. K.Valluru, "A Comparative Analysis of Deep Neural Network Models using Transfer Learning for Electrocardiogram Signal Classification," in *6th International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT)*, 2021.

T. Mahmud, S. A. Fattah and M. Saquib, "DeepArrNet: An Efficient Deep CNN Architecture for Automatic Arrhythmia Detection and Classification From Denoised ECG Beats," *IEEE Access,* vol. 8, 2020.

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7. Supporting files

7.1. Supporting file 1: MATLAB code for classification

```
%% ECG Signal Classification using Transfer Learning with AlexNet
% Classifies ECG signals as AFIB (Atrial Fibrillation) or NSR (Normal Sinus Rhythm)
% Includes clinical performance metrics: Sensitivity, Specificity, PPV, NPV and F1 score

clear; close all; clc;

%% 1. Data Preparation
trainDataPath = 'C:\Users\MARC\Documents\MATLAB\AfNET\Trainning';
valDataPath = 'C:\Users\MARC\Documents\MATLAB\AfNET\Validation\Validation only 250Hz';

trainImgs = imageDatastore(trainDataPath, ...
   'IncludeSubfolders', true, ...
   'LabelSource', 'foldernames');

valImgs = imageDatastore(valDataPath, ...
   'IncludeSubfolders', true, ...
   'LabelSource', 'foldernames');

% Verify class distribution
labelCount = countEachLabel(trainImgs);
disp('Training set class distribution:');
disp(labelCount);

%% 2. Network Architecture Setup
net = alexnet;
numClasses = 2; % AFIB (Positive), NSR (Negative)

layers = [
   net.Layers(1:end-3)
   fullyConnectedLayer(numClasses, ...
      'WeightLearnRateFactor', 20, ...
      'BiasLearnRateFactor', 20)
```

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```
    softmaxLayer
    classificationLayer
];

%% 3. Training Configuration
options = trainingOptions('sgdm', ...
    'MiniBatchSize', 16, ...
    'MaxEpochs', 10, ...
    'InitialLearnRate', 1e-5, ...
    'ValidationData', valImgs, ...
    'Plots', 'training-progress');

%% 4. Network Training
[netTransfer, trainInfo] = trainNetwork(trainImgs, layers, options);

%% 5. Model Evaluation (Enhanced Clinical Metrics)
[predLabels, scores] = classify(netTransfer, valImgs);
trueLabels = valImgs.Labels;

% Confusion matrix
cm = confusionmat(trueLabels, predLabels);
disp('Confusion Matrix:');
disp(cm);

% Calculate metrics
TP = cm(1,1); % True AFIB (Positives)
FP = cm(2,1); % False AFIB
TN = cm(2,2); % True NSR (Negatives)
FN = cm(1,2); % False NSR
accuracy = (TP + TN) / sum(cm(:));
sensitivity = TP / (TP + FN); % Recall/True Positive Rate
specificity = TN / (TN + FP); % True Negative Rate
PPV = TP / (TP + FP); % Positive Predictive Value (Precision)
NPV = TN / (TN + FN); % Negative Predictive Value
F1_score = 2*(PPV*sensitivity)/(PPV + sensitivity); % Harmonic mean

% Display metrics
```

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```
fprintf('\n--- Clinical Performance Metrics ---\n');
fprintf('Accuracy:    %.2f%%\n', accuracy*100);
fprintf('Sensitivity: %.2f%% (True Positive Rate)\n', sensitivity*100);
fprintf('Specificity: %.2f%% (True Negative Rate)\n', specificity*100);
fprintf('PPV:         %.2f%% (Precision)\n', PPV*100);
fprintf('NPV:         %.2f%%\n', NPV*100);
fprintf('F1 Score:    %.2f\n', F1_score);

% Enhanced confusion matrix with metrics
figure
confusionchart(trueLabels, predLabels, ...
   'Title', sprintf('AFIB vs NSR Classification (Accuracy: %.1f%%)', accuracy*100), ...
   'RowSummary', 'row-normalized', ...
   'ColumnSummary', 'column-normalized');

% ROC Curve
figure
[fpr, tpr, ~, auc] = perfcurve(trueLabels, scores(:,1), 'AFIB');
plot(fpr, tpr, 'LineWidth', 2)
hold on
plot([0 1], [0 1], 'k--') % Random classifier line
xlabel('False Positive Rate (1-Specificity)')
ylabel('True Positive Rate (Sensitivity)')
title(sprintf('ROC Curve (AUC = %.3f)', auc))
legend(sprintf('AlexNet (AUC=%.3f)', auc), 'Random', 'Location', 'southeast')
grid on

%% 6. Save Results
save('ECG_AlexNet_Model.mat', 'netTransfer', 'trainInfo', 'cm', ...
   'accuracy', 'sensitivity', 'specificity', 'PPV', 'NPV', 'F1_score', 'auc');
```

7.2. Supporting file 2: MATLAB code for CWT conversion

```
function convertSignalsToImages(ECG_signal_data_file, database_name, segment_length, fs)
%CONVERTSIGNALSTOIMAGES Converts ECG signals to CWT scalogram images
%   Converts ECG segments to time-frequency images using Continuous Wavelet Transform
```

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```
%   and saves them as JPEG files in label-specific folders

    % Load ECG data
    try
        data = load(ECG_signal_data_file);
        ecgDatabase = data.ecgDatabase; % Assuming structure array with 'signal' and 'label'
    catch
        error('Failed to load ECG data file');
    end

    % Verify required fields
    if ~isfield(ecgDatabase, 'signal') || ~isfield(ecgDatabase, 'label')
        error('Input file must contain ecgDatabase with signal and label fields');
    end

    % Create CWT filter bank
    cwt_filter = cwtfilterbank(...
        'SignalLength', segment_length, ...
        'Wavelet', 'amor', ...
        'VoicesPerOctave', 12, ...
        'SamplingFrequency', fs);

    % Create main output folder
    main_folder = 'ECG_Images';
    if ~exist(main_folder, 'dir')
        mkdir(main_folder);
    end

    % Process each ECG record
    for record_idx = 1:length(ecgDatabase)
        try
            current_label = ecgDatabase(record_idx).label;
            ecg_signal = ecgDatabase(record_idx).signal;

            % Create label-specific folder (remove invalid filename characters)
            safe_label = regexprep(current_label, '[^a-zA-Z0-9]', '');
            output_folder = fullfile(main_folder, sprintf('%s_%dHz', safe_label, fs));
```

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```
        if ~exist(output_folder, 'dir')
          mkdir(output_folder);
        end

          % Compute CWT
          cfs = abs(cwt_filter.wt(ecg_signal));

          % Normalize and convert to image
          normalized_cfs = rescale(cfs); % Scale to [0, 1]
          uint8_cfs = uint8(255 * normalized_cfs); % Convert to 8-bit
          im = ind2rgb(uint8_cfs, jet(256));

          % Resize and save
          im_resized = imresize(im, [227 227]);
          img_name = sprintf('%s_%s_%d_%03d.jpg', database_name,safe_label,fs,
record_idx);
          imwrite(im_resized, fullfile(output_folder, img_name));

      catch ME
        warning('Error processing record %d: %s', record_idx, ME.message);
        continue;
      end
  end

  fprintf('Conversion complete. Images saved in %s folder.\n', main_folder);
end
```

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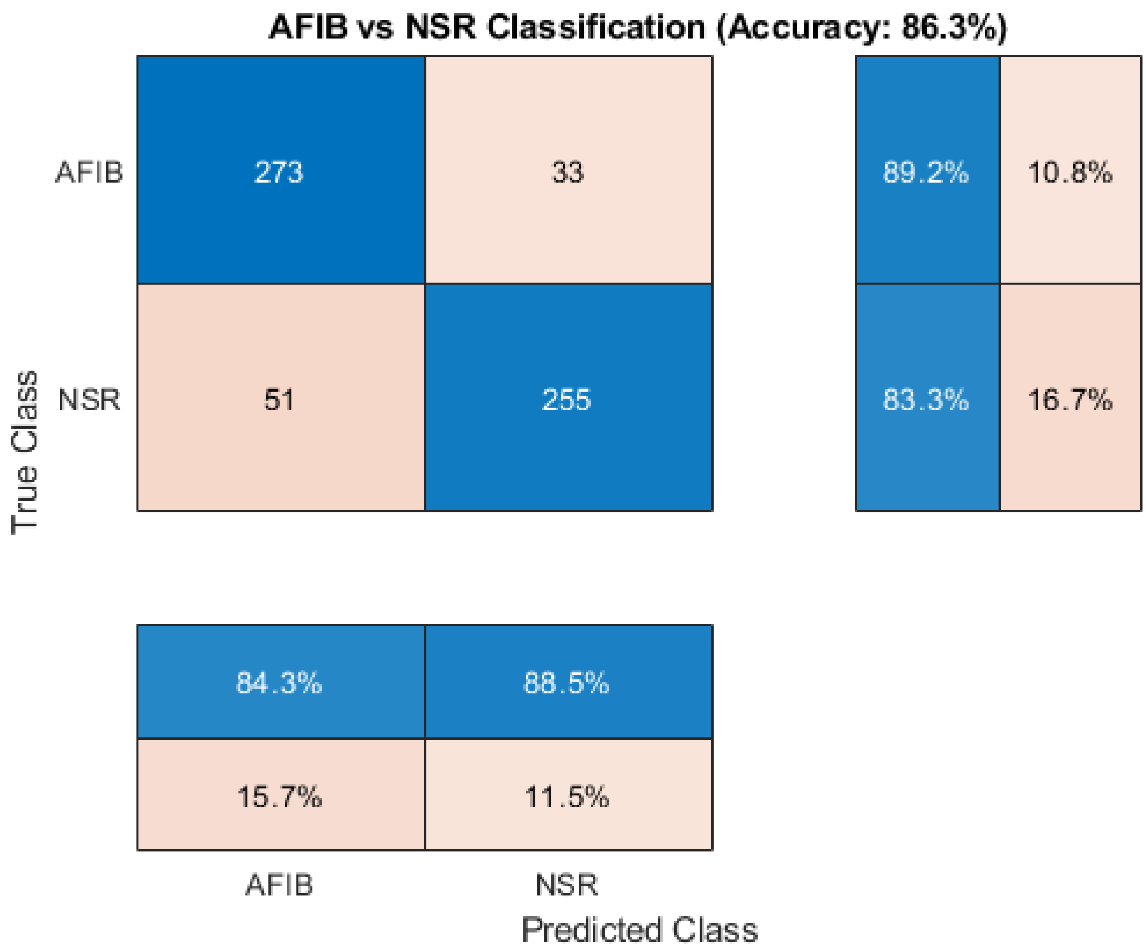
7.3. Supporting image 1: Confusion matrix of our approach



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7.4. Supporting file 2: ROC curve of the parameters with the highest accuracy.