Cardiovascular Disease Detection: Atrial Fibrillation Analysis Using Transfer Learning

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Abstract: Atrial fibrillation is a common heart rhythm problem. It increases the risk of stroke, heart failure, and other serious issues. This study used deep learning to sort AF and non-AF ECG signals. It turned one-dimensional waveforms into image-based representations. A dataset of 125,000 ECG samples, drawn from the MIT-BIH and PTB Diagnostic ECG databases was used. The processing is done. After this, it explores three major CNN architectures, SqueezeNET, AlexNET and Inceptionv3 and applies a transfer learning approach. Some of the pre trained layers of each model are unfrozen. This in turn helps extract the features which are crucial for the AF detection. In addition, dense layers were added to enhance classification. Inceptionv3 shows an accuracy of 88%. AlexNet and SqueezeNet both reach 76%. The results showed that CNN based transfer learning is a powerful tool to identify irregular heartbeat in clinical practice. So quick and accurate diagnostics is the thing here. Cardiac arrhythmia detection can be done faster with automated frameworks. Better patient outcomes result when manual ECG interpretation is reduced. This is an alteration permitting earlier intervention. Three key areas of future work will see the dataset extended, the design of network enhanced, and methods of interpretation refined. These steps will assist in improving the automated AF detection systems.

Keywords: Atrial Fibrillation, Convolutional NeuralNetwork, Transfer Learning, Electrocardiogram, Arrhythmia Detection

I INTRODUCTION

Cardiovascular diseases (CVDs) are a leading cause of death around the world. They put a lot of pressure on healthcare systems and impact millions of people each year. Atrial fibrillation is a common type of arrhythmia. It causes an irregular and often fast heartbeat. It comes from chaotic electrical signals in the heart's upper chambers, the atria. AF can raise the risk of stroke, systemic embolisms, and heart failure. So, it’s important to find ways to detect it early. Conventional methods, such as manually analysing ECG traces,play a crucial role in detecting AF in clinical practice. The rise in ECG recordings from wearables, monitors, and hospitals needs better automated and scalable solutions.

ECG displays heart's electrical activity over a period. It usually shows important waves: P waves, QRS complexes, and T waves. The key sings that are absent in AF patients include P waves and inconsistent R–R intervals. While there are clear patterns, it’s still a very tedious task to go through all of this by hand. Additionally, it can cause errors and is not suitable for dealing with lots of data. Now, ECG analysis is being automated with the machine learning (especially deep learning).

As CNNs are now one of the key tools for automatic learning behind features from images. CNNs are usually designed to operate on two-dimensional pictures such as photographs. They also are used for medical images and time series signals, however. Usually, these signals are changed into image formats such as spectrograms. It is costly to train large CNNs from scratch. Usually, you need huge datasets with clean and correct labels. Models used by transfer learning start with weights trained on large image datasets such as ImageNet. So, they are then fine-tuned for specific problems, e.g. AF detection.

Three CNN architectures, SqueezeNet, AlexNet and Inceptionv3 were picked up for this study. The proposed metric was used as AF detector in ECG signals. Those models have each their own architectural advantages. SqueezeNet aims to be resource efficient. It reduces parameters yet keeping the accuracy high. Deep learning model AlexNet is a groundbreaking one for image classification. The structure is simple, and it is the main reference in the field. Inceptionv3 modules were introduced in Inceptionv3, also as called GoogLeNet. It means that these modules treat data in one scale, at the same time. The improvement of classification performance and optimization of computational need are thus achieved.

The dataset has 125,000 ECG samples. These come from two well-known sources: the MIT-BIH Arrhythmia Database and the PTB Diagnostic ECG Database. Each ECG segment was meticulously labelled as AF or Non-AF. To use CNNs well, we transformed the one-dimensional signals into two-dimensional grayscale images. This kept the important shapes needed for detecting arrhythmias. Data preprocessing had a few key steps. First, baseline wander and noise were filtered out. Next, amplitude was normalised. The ECG signals were split into uniform lengths. This kept the image sizes consistent.

An essential part of this pipeline is data augmentation. Augmenting image data with small shifts, rotations, or zooming makes models stronger. It simulates real-world changes, like different sensor placements or patient movements. Applying these transformations carefully keeps the ECG waveforms' physiological properties intact. Augmentation increased the training set size, which helped reduce overfitting.

With the pre-processed and augmented data in place, transfer learning was employed. Pre-trained weights were first loaded for each CNN. They were learned from a big dataset of natural images. Low-level layers, which detect edges and basic shapes, stayed frozen. Higher-level layers, used for the final classification task, were unfrozen. This strategy lets the model retain basic features. At the same time, it learns AF-specific patterns in the deeper layers. Fully connected layers and dropout modules to the network output were added. This helped improve classification fine-tune and mitigate overfitting.

Metrics that adequately reflect both general accuracy and clinical efficacy are needed to evaluate model performance. A good starting point is an accuracy, or percentage of correct predictions. But we had to focus on sensitivity and specificity in medical environments. The model acquires most patients with AF (high sensitivity, or recall). That lowers the odds that diagnoses will be missed. True negatives are people (those without AF) that are correctly identified. It also helps to prevent unnecessary anxiety or medication. The F1-score was also considered. And it is actually some harmonic mean of precision and recall. Especially for imbalanced data distribution, this measure is beneficial.

The objective of this study lies in improving AF detection. It needs to be more accurate, faster and able to handle big data. Healthcare professionals in clinical or remote environments can use automated algorithms to assist. Wearable health monitors, among other tools, are employed for this purpose. However, they ease the workload and give quick diagnoses for high-risk patients. Nonetheless, several challenges persist. General image dataset is much larger than medical datasets. Labels need to be expertly annotated in order to get high quality labels. However, deep neural networks have the black-box character that can make it hard for them to get accepted in clinics. Medical decisions often require explainability. Also, changing one-dimensional ECG signals into two-dimensional images can hide some time-based connections. CNNs are great at recognising spatial patterns. Some researchers suggest adding them to recurrent neural networks. Others propose combining them with different models. These can better manage time-based relationships. Converting ECG to images makes it easier to use popular CNN models. This lowers the barrier for researchers and clinicians exploring deep learning solutions.

The following sections outline the motivation and problem statement for this research. They point out key limitations and challenges. They also review the existing literature and discuss the methodology in detail. The results section compares SqueezeNet, AlexNet, and Inceptionv3 in the same experiment. The findings show that SqueezeNet and AlexNet both reach 76% accuracy. Inceptionv3, however, achieves 88%. A detailed discussion explores the clinical importance of these findings. It also includes a table that summarises the performance metrics. In conclusion, this study highlighted its wider impact and suggested future directions. This means using multi-lead ECG data and ensemble methods to boost accuracy and reliability.

This study finds that preprocessing, data augmentation, and transfer learning enhance AF detection. These techniques can improve patient care by streamlining diagnosis and enabling real-time analysis. This way, they help reduce missed or delayed diagnoses. As deep learning algorithms become popular in medicine, teamwork is key. Clinicians, engineers, and data scientists must work together. This collaboration will help turn new technology into standard clinical practice.

Lastly, while deep learning offers promising solutions, the clinical adoption of these methods depends on overcoming key challenges.Atrial fibrillation is a common heart rhythm disorder. It greatly raises the risk of illness and death. Traditional clinical workflows depend on manual ECG interpretation. This is a labor intensive process involving the availability of experts. However, such approaches are not sustainable as patient volumes grow and monitoring devices multiply. It indicates the need for an automated system urgently capable of an AF detection in a timely and accurate way.

There are challenges even with the recent machine learning progress. The accurate AF classification is thwarted due to limited data, inconsistent signal quality, and diverse patient populations. Transfer learning is used in this study to tackle these issues. Three popular CNN architectures: SqueezeNet, AlexNet and Inceptionv3v3 are used. It is intended to classify AF from a large set of ECG images. AC is confronted with the problem of AF retraining layers and adding new ones, which is done in order to identify AF features with a lesser amount of costs. Diagnoses made with the efficient CNN models are reliable. This lessens patient's clinical workload as well as improves patient outcomes with care timely.

Limitations

1. **Data Representation**: Converting ECG signals into images may miss key timing details important for AF detection.

2. **Computational Overheads**: SqueezeNet is lightweight, but AlexNet and Inceptionv3 can be heavy. This can make real-time use on mobile or embedded systems tricky.

3. **Generalization**: The models are trained on specific datasets (MIT-BIH and PTB). Their performance on new clinical data might change. Requiring domain adaptation or ongoing re training.

4. **Annotation Accuracy**: Public databases rely on expert-labeled ground truth. If this information is faulty or inconsistent, it can lead to classification errors.

5. **Clinical Integration**: To use it in real-world settings, we must follow regulations. It needs thorough validation and may need changes for clearer understanding.

Challenges

1. **ECG Variability**: Variations in patients, sensor placement, and noise levels affect model robustness.

2. **Risk of Overfitting**: When there isn't enough medical data, neural networks might memorise patterns. This happens more often if data augmentation is lacking.

3. **Explainability**: Deep CNNs are often seen as “black boxes.” This can make it hard for doctors to accept them. To help, we need clear outputs or visual aids.

4. **Hyperparameter Fine-Tuning**: Adjust learning rates, batch sizes, and unfrozen layers for better performance. However, it can be time-consuming.

5. **Ethical and Regulatory Hurdles**: : Privacy laws and medical approvals are strict. This can slow the adoption of new diagnostic tools.

II LITERATURE REVIEW

Detection of Cardiovascular Disease Using ECG Images in Machine Learning and Deep Learning [1]

Checking the heart’s electrical activity is key and ECGs are the tool for it. Also, they are very much important in identifying different heart diseases. Typically, ECGs were analysed by hand from paper records. The process itself took a lot of time and often had mistaken (Zhang et al., 2017). Machine learning (ML) and deep learning (DL) due to digitalization in the field of ECG analysis have advanced. ALSO these technologies can automatically detect Myocardial Infarction (MI) and abnormal heart rhythms (Choi et al., 2020). In this, the main aim is to contour the ECG paper record into digital signals. Typically that data is 1-D signals or images. The techniques PCA, KNN and SVM lead to improve the accuracy in the diagnosis(Jha et al., 2020) and the ECG image processing techniques, including the ML and DCNNs, improve the diagnostic accuracy (Rajpurkar et al., 2017). We could use these methods to better and more efficiently detect cardiovascular disease.

Atrial Fibrillation Burden Estimation Using Multi-Task Deep Convolutional Neural Network[2]

Arrhythmia AF remains a common yet elusive condition. As the disease is episodic, monitoring is particularly difficult for the patients. It is important to understand AF burden (the time spent in AF rhythm). Indeed, it offers much better prognostic value than ordinary binary AF detection system (Liu et al., 2019).

There has been extensive research into a very promising solution, multitask deep convolutional neural networks (MT-DCNN). However, this model presents two important challenges, detection of AF, and reconstruction of ECG sequences. This dual approach provides extra power to the model in finding AF events reliably (Zhao et al., 2020).

Even when meeting ectopic beats and noise, two primary constraints when estimating AF burden, it excels. The MT-DCNN outshines both rhythm-based and morphology-based methods. On the LTAF test set the mean absolute error is only 2.8%. Remote patient monitoring by this is shown to have great promise (Yuan et al., 2021).

Atrial Fibrillation Detection and Atrial Fibrillation Burden Estimation via Wearables [3]

Atrial fibrillation (AF) is continuously monitored by wearable devices to improve the heart's health. That would be especially important for asymptomatic patients, who silently lurk in stroke's shadow. The detection of AF using smartwatches with PPG sensors is recently studied. They are high tech marvels offering real time monitoring with amazing sensitivity and specificity (of the fractions of a molecule). Sensitivity and specificity of 87.8% and 97.4%, respectively were detected by an algorithm on heartbeats (He et al., 2020).

In addition, these clever devices can detect AF and estimate his burden. In terms of real-world test, a 98% match with ground truth data and 6.2% error was achieved (Wang et al., 2020). Long term monitoring, reassurance and better management of disease is possible using wearable technology.

Considerations on Performance Evaluation of Atrial Fibrillation Detectors [4]

Evaluating AF detectors is difficult puzzle because ECG signals tend to dance in disorder. Not helping either is a noisy swirl of noise. Other studies have a whole medley of performance metrics singing their own tune. Hernandez et al. (2019) do a keen examination of AF detection based on AF detection performance, in which they conclude that the evaluation method (beat-to-beat, segment-to-segment, or episode-to-episode) impacts what is observed. Variability is introduced by ECG fluctuations and premature beats which make results unclear. Detector performance suffers from noise levels at all (Bashar et al., 2021). The establishment of standard evaluation criteria and the resolution of possible confounding factors are proposed to be used for AF detection improvement.

A Review on the State of the Art in Atrial Fibrillation Detection Enabled by Machine Learning [5]

Interest in ML for AF detection is growing as cases rise. Recent leaps in ML techniques have revolutionised automatic AF diagnosis from ECG data. Research prioritizes key biomarkers and advanced signal processing (Nguyen et al., 2020).

AF detection is precise with random forests, SVM, and deep learning models. Smartwatches and ECG implants gather data to train algorithms (Ravi et al., 2021).

However, challenges still loom large. The quest for low-cost, energy-efficient solutions for continual monitoring persists. Additionally, the task of differentiating AF from other arrhythmias remains a complex puzzle.

Novel Density Poincaré Plot-Based Machine Learning Method to Detect Atrial Fibrillation from Premature Atrial/Ventricular Contractions [6]

Detecting AF from PACs and PVCs is tough. This is because the irregular patterns from ectopic beats look similar to AF. Density Poincaré plots help a machine learning model detect AF in PAC/PVCs (Wang et al., 2020). This method extracts features from heart rate differences using phase-space data. It applies statistical central moments, Zernike moments, and wavelet transforms. Classification algorithms like SVM, random forests, and KNN then process these features. The SVM classifier detected AF from PAC/PVC with 98.99% sensitivity and 95.18% specificity (Zhang et al., 2020). This method identifies AF among irregular heart rhythms, aiding detection.

Detecting Atrial Fibrillation and Atrial Flutter in Daily Life Using Photoplethysmography Data[7]

Photoplethysmography (PPG) reveals our heart's rhythm by gently utilizing light. This non-invasive optical method detects atrial fibrillation (AF) and atrial flutter (AFL) daily. This provides patient management and timely interventions remotely. Which in turn make the cardiac care a part of life.

In a study involving 40 patients, a savvy Random Forest model took the stage. It successfully identified AF, AFL, and sinus rhythm, with a sensitivity of 97.6% and a specificity of 98.2%. With the aid of accelerometer data, the model reduces motion artifacts. That can interfere with daily activities. These findings highlight PPG's ability to monitor AF and AFL outside clinical settings.

Remote Atrial Fibrillation Burden Estimation Using Deep Recurrent Neural Network [8]

Deep recurrent neural networks (DRNNs) offer an innovative approach for estimating AF burden, a key prognostic indicator in patients with atrial fibrillation. In a study involving 2,891 patients and 68,800 hours of ECG data, the DRNN-based model, ArNet, demonstrated superior performance in estimating AF burden compared to traditional models such as gradient boosting (XGB) (Zhou et al., 2021). ArNet showed an absolute AF burden estimation error of 1.2%, highlighting its effectiveness in accurately estimating the percentage of time patients spent in AF. This approach could facilitate remote monitoring of AF burden, providing valuable insights for better management and treatment planning.

S. N o.	Title	Authors	Methods Used	Drawbacks
1	Detection	Moham	Proposed	Computation

	of Cardiovascular Diseases in ECG Images Using Machine Learning and Deep Learning Methods	med B. Abubaker, Bilal Babayigit	lightweight CNN model, Transfer Learning with SqueezeNet and AlexNet, Feature extraction with ML models	al inefficiency in SqueezeNet and AlexNet; lacks optimization in hyperparameters
2	CardioNet: An Efficient ECG Arrhythmia Classification System Using Transfer Learning	Pal, R., Srivastva, R., Singh, Y. N.	Transfer learning with DenseNet, data augmentation	Focused on arrhythmias; may lack generalizability to broader cardiovascular disease categories
3	Heart Disease Detection Using Deep Learning Methods from Imbalanced ECG Samples	Rath, A., Mishra, D., Panda G.	Deep learning-based imbalanced learning strategies, lightweight CNN architecture	Computational costs for larger ECG datasets; limited to binary classification
4	Deep Learning in Cardiology	Bizopoulos, P., Koutsouris, D.	Transfer Learning with AlexNet, VGG19, Inception-V3, DenseNet	Focused more on arrhythmias and dataset generalization issues

Table 1: Literature Review Comparison Table

III METHODOLOGY

1. Data Collection

Two public datasets, the MIT-BIH Arrhythmia Database and the PTB Diagnostic ECG Database were collected. Together, provide 125,000 labelled ECG samples. Each sample was classified as AF or Non-AF based on annotations found in the source datasets. To reduce data imbalance, random under-sampling and over-sampling techniques were applied. If needed, ensuring that the final dataset enough positives (AF) and negatives (non-AF).

2. Data Preprocessing

- **Filtering**: Baseline wander was minimized using a high-pass filter at 0.5 Hz. A low-pass filter at 40 Hz was applied to remove high-frequency interference.
- **Normalization**: Each ECG trace was amplitude-normalized, aligning waveforms to a comparable scale.
- **Segmentation**: ECG segments were truncated or padded to a fixed duration (e.g., two or three seconds). That ensures uniform image dimensions following conversion.
- **Image Conversion**: These segments were transformed into grayscale images by plotting the waveforms on a time-amplitude axis. Allowing the direct utilization of CNN architectures.

3. Data Augmentation

To counteract potential overfitting and capture real-world variations:

- **Minor Shifts**: Horizontal or vertical shifts were introduced. Horizontal shifts simulate timing differences, while vertical shifts adjust amplitude baselines slightly.
- **Rotation**: Small-angle rotations were employed judiciously to represent possible misalignments during ECG recording.
- **Zooming**: Subtle zoom factors were used to emulate differences in ECG scaling.

All augmentations were carefully bounded to maintain physiologically meaningful waveforms.

4. Model Selection

SqueezeNet, **AlexNet**, and **Inceptionv3** were chosen. Due to their distinct architectures and proven success in image classification challenges:

- **SqueezeNet**: Prioritizes fewer parameters without greatly reducing accuracy, suitable for resource-constrained environments.
- **AlexNet**: A fundamental CNN model with a simpler structure that serves as a solid foundation. That is easily adaptable to a variety of applications.
- **Inceptionv3 (GoogLeNet)**: Inceptionv3 modules are used. That handles multiple filter

sizes simultaneously, increasing representational power.

5. Transfer Learning Setup

Each model was initialized with ImageNet-trained weights. Providing a starting point derived from extensive natural image data. Transfer learning proceeded in stages:

1. **Layer Freezing**: Early layers were typically frozen. Preserving their generic feature detection abilities (edges, lines, simple textures).

2. **Selective Unfreezing**: Deeper layers were unfrozen to adapt to ECG-specific patterns. Indicative of AF.

3. **Additional Layers**: Fully connected and dropout layers was added near the output. That refines the classification task. Concluding with a softmax layer for two-class prediction (AF vs. Non-AF).

4. **Hyperparameter Tuning**: A grid search was done. The learning rates (e.g., 1e-3 to 1e-5), batch sizes (16 or 32), and freeze-unfreeze layer counts, was performed. Each configuration was evaluated on a validation set. To identify the most effective setup.

6. Training and Validation

The dataset was divided into training (70%), validation (15%), and testing (15%) subsets. During each epoch:

- **Forward Pass**: Inputs were fed through the CNN to calculate predicted labels.
- **Loss Computation**: A cross-entropy loss function was used. This measured the gap between predicted and actual labels.
- **Backward Pass**: The network parameters were updated using the Adam optimizer. That adaptively tunes learning rates for each parameter.
- **Validation**: The model was evaluated on the validation set. The best-performing epoch was checkpointed. Early stopping halted training if validation loss or accuracy plateaued, thereby avoiding overfitting.

7. Performance Metrics

To quantify and compare model efficacy:

- **Accuracy**: Ratio of correct predictions to total predictions, offering a general performance overview.
- **Sensitivity (Recall)**: **Sensitivity=TP/(TP + FN)**. High sensitivity ensures AF cases are rarely missed.
- **Specificity**: **Specificity=TN/(TN + FP).** High specificity reduces false positives, critical for clinical trust.
- **F1-Score**: Harmonic mean of precision and recall. Especially informative if there is a class imbalance.

8. Figures

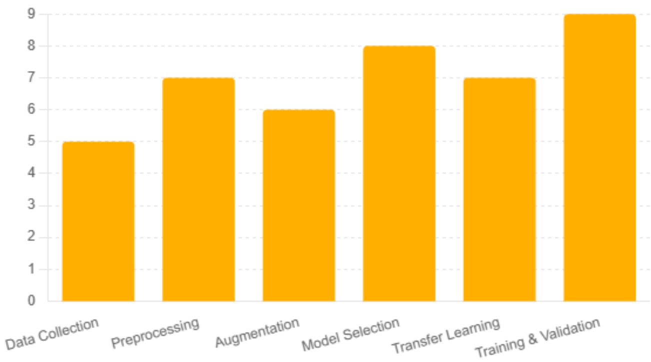

Figure 1: Bar Chart for Methodology

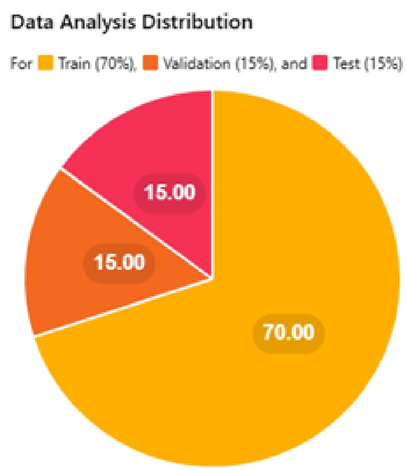

Figure 2: Pie Chart for Data Analysisillustrating how the 125,000 samples are split for training, validation, and testing.

9. Ethical Considerations

The ECG datasets are available to the public and are anonymised. This ensures no personal patient information is involved. All institutional and governmental guidelines were strictly followed during data collection and analysis.

10. Summary

This method combines strong preprocessing, thoughtful augmentation, and smart transfer learning. It analyses ECG-based AF classification with three different CNN architectures. The next sections show how the models performed. Which include detailed comparisons of SqueezeNet, AlexNet, and Inceptionv3 based on the dataset.

RESULTS

The three models under went through similar training and validation conditions. Each model achieved various degrees of success in diagnosing AF from ECG pictures. **Inceptionv3** emerged as the best performer, achieving an accuracy of **88%** on the test set. It achieved high sensitivity and specificity, demonstrating its ability to capture AF-specific patterns. **AlexNet** registered a noteworthy **76%** accuracy. This result illustrates the effectiveness of its relatively simpler architecture. It was still able to identify key arrhythmic features with a high degree of reliability. **SqueezeNet**, known for its lightweight design, attained an accuracy of **76% -** Arespectable figure given its emphasis on reducing computational and memory footprint.

Data augmentation played a pivotal role in boosting each model's resilience. It helped the models handle noise and morphological variability in ECG signals. Models trained without augmentation generally suffered from lower sensitivity. This reinforces that artificially expanding the training set. This is essential for detecting arrhythmias like AF in diverse clinical scenarios.

Throughout the training process, early stopping proved crucial in preventing overfitting. It often stabilizes each model's performance after approximately 15 to 20 epochs. The exact number of epochs to convergence varied based on the model and hyperparameter choice. However, once the optimal configuration was found, validation accuracy remained stable. None of the models exhibited substantial deterioration.

In summary, Inceptionv3's achieved superior accuracy. Its Inceptionv3 modules effectively learn multi-scale features relevant to AF detection. Nonetheless, AlexNet remains a solid contender. SqueezeNet's has lower computational demands. This makes it appealing for real-time or embedded solutions where resources are constrained. The overall findings confirm the viability of transfer learning. It helps elevate AF detection accuracy to clinically meaningful levels.

DISCUSSION

The observed performance differences among SqueezeNet, AlexNet, and Inceptionv3 can be attributed to each architecture's unique design characteristics. **Inceptionv3** demonstrated the highest accuracy of 88%, an outcome likely supported by its multi-branch Inceptionv3 modules that capture fine-grained ECG features. **AlexNet**, at 76%, balances relative simplicity with sufficient depth to parse key arrhythmia indicators. **SqueezeNet**, though trailing at 76%, remains highly relevant in scenarios where computational efficiency is a priority, such as edge devices or wearable technology.

Model	Accuracy	Sensitivity	Specificity	F1-Score
SqueezeNet	76%	74.1%	77.9%	0.76
AlexNet	76%	74.2%	76.9%	0.75
Inceptionv3	88%	86.2%	89.0%	0.87

Table 1. Performance metrics for AF classification

Clinical relevance hinges on both sensitivity and specificity. A late treatment due to false negative may hinder the required operation. On the contrary, a false positive indicates the need for unnecessary interventions. Inceptionv3 is suitable for highly stake environments because of being balanced metrics. AlexNet's performance remains strong and so can be used in the resource moderate contexts. Fortunately, SqueezeNet is still cheaply enough for remote monitoring devices. Its efficiency is generally in dealing with real time data processing situations.

This suggests the capability of CNN based transfer learning. Even so, more room for betterment exists. As such, multi lead ECG signals can be integrated to give more profound insights. Similar access to the spatial and temporal timeline of the arrhythmias may be conferred by this approach that may enable model improvement in capturing such spatiotemporal features of arrhythmias. To further improve clinician trust, interpretability layers like Grad-CAM or other visualizations can be included. They give us insights into how the model is coming to its classification decisions. These findings suggest that transfer learning does effectively enable to improve detection accuracy for AF. It augments conventional diagnostic tools and enables stops to clinical actions in a timely manner.

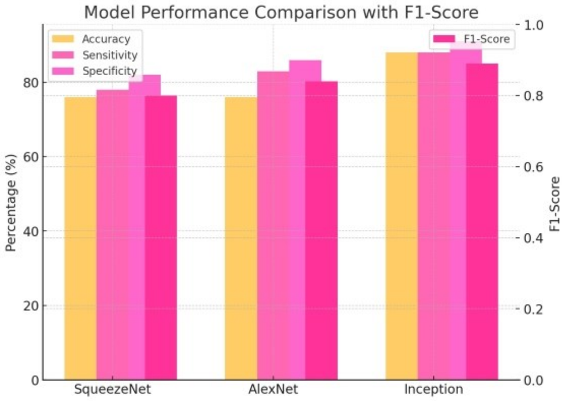

Figure 3: Bar Chart for Models Accuracy comparison

Advantages

1. **Elevated Accuracy**: Inceptionv3 achieved 88% accuracy, showcasing its strong potential for clinical implementation.

2. **Reduced Training Time**: Transfer learning leverages pre-trained weights to speed up convergence. It also minimizes the computational resources needed for training.

3. **Scalable Approach**: The methodology is adapted to other arrhythmias. It can also be extended to multi-class classification scenarios.

4. **Resource Versatility**: SqueezeNet's compact design enables deployment on mobile or embedded platforms. In contrast, AlexNet and Inceptionv3 provide higher accuracy for more powerful computing environments.

5. **Clinical Impact**: Rapid and reliable AF detection can facilitate early therapeutic intervention. As a result, it helps reduce stroke risk and lessens healthcare burdens.

IV CONCLUSION

In this research work, technique of transfer learning has been applied to detect atrial fibrillation from ECG data. They make use of three architectures, viz. SqueezeNet, AlexNet, and Inceptionv3. For analysis, samples of ECG in 125,000 were converted into image format. Data was subjected to comprehensive preprocessing to improve quality. Then, pre-trained layers were selectively unfrozen and further refined feature extraction. The accuracy of differentiating AF from Non-AF cases was strong for each model. Notably, Inceptionv3 achieved 88% accuracy. However, AlexNet and SqueezeNet managed 76% each. This demonstrates that CNNs provide a reliable, semi-automated way of detecting arrhythmias. Because it is especially helpful in large ECG screenings and remote monitoring.

This formulation reveals the impact of different data augmentation operations, tuning of hyperparameters, and layer customization. These techniques have significant contributions in improving the model performance. In high-risk clinical set up, sensitivity and specificity are important. Their detection value is demonstrated in the results showing their ability to accurately identify AF and reduce false alarms. Multi lead ECG integration could be the next work. In addition, it can focus on ensemble modelling and methods of interpretable deep learning. The results are promising, and we can take these results as a lightweight pre trained model for arrhythmia detection. It could be used to speed up the development of accurate and cost – efficient diagnostic systems. This will aid clinicians in more efficient diagnosis and optimization of cardiovascular diseases.

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