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ARRHYTHMIA CLASSIFICATION USING 2D CNN

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Abstract - This project focuses on developing and evaluating an arrhythmia classification system using CNNs, emphasizing smaller input sizes for computational efficiency. It transforms ECG signals from the MIT-BIH Arrhythmia database into images for CNN-based classification. The simplified CNN classifier prioritizes practicality and efficiency, exploring trade-offs between performance and resources. It investigates optimal input sizes balancing computational efficiency and accuracy. Anticipated outcomes include advancing arrhythmia detection with insights into CNNs' efficacy with smaller inputs and offering practical recommendations for efficient classification models. A refined 2D CNN, integrating MobileNet models, is tailored for specific arrhythmia classes, optimizing efficiency and interpretability for accurate categorization. Classes include Atrial Fibrillation, Murmur, Ventricular Tachycardia, PVC, Supraventricular Tachycardia, and Normal rhythms.

***Key Words*: Convolutional Neural Network, CNN, CNN 2D, Mobile Net Image Classifier, Electrocardiogram (ECG), Arrhythmia**

1.INTRODUCTION

This project aims to develop an efficient arrhythmia classification system using Convolutional Neural Networks (CNNs), particularly focusing on exploring smaller input sizes to enhance computational efficiency. By simplifying the image classifier and grouping classes based on transformed ECG signals from the MIT-BIH and PTB Arrhythmia databases, the objective is to achieve high accuracy in classifying arrhythmia while minimizing computational resources. The initiative addresses the challenge of accurately classifying arrhythmia, a critical cardiac abnormality, by investigating the feasibility of a simplified CNN 2D classifier with smaller input sizes. The ultimate goal is to contribute to more effective arrhythmia diagnosis by leveraging advanced computational methods. The project is driven by a commitment to improving healthcare practices and advancing precise and accessible arrhythmia detection. By transforming ECG signals into image data and implementing a simplified CNN 2D image classifier, the research aims to provide practical insights into the efficacy of CNNs with smaller input sizes and offer recommendations for efficient arrhythmia classification models. The use of CNN 2D and MobileNet architectures underscores the focus on capturing spatial dependencies within ECG signals while optimizing computational efficiency, thus bridging the gap between technological advancements and cardiac health diagnosis.

1.1 Classification of Arrhythmias:

Annotated Codes	Arrhythmia Beat type annotated in MIT-BIH	Corresponding arrhythmia class in AAMI
1	N (Normal beat)	N
2	L (Left bundle branch block beat)	
3	R (Right bundle branch block beat)	
11	j (Nodal (junctional) escape beat)	
34	e (Atrial escape beat)	
4	a (Aberrated atrial premature beat)	S
7	J (Nodal [junctional] premature beat)	
8	A (Atrial premature beat)	
9	S (Premature or ectopic supraventricular beat)	
5	V (Premature ventricular)	V
10	E (Ventricular escape beat)	
6	F (Fusion of ventricular and normal beat)	F
12	Paced beat	Q
13	Unclassifiable beat	
38	Fusion of paced and normal beat	

2. Literature Review:

Machine learning is a powerful tool used in various aspects of our lives, from analysing images and predicting future trends to improving recommendations and enhancing healthcare, banking, defense, education, and robotics.

Researchers across different fields rely on machine learning algorithms to make tasks smarter and more efficient. In this research, we employed different machine learning techniques like - Fractional Fourier Transform, KNN Algorithm, Logistic Regression, Dual-Channel 1D-CNN.

[1]. In this model, the authors have introduced a Three-Heartbeat multilead ECG Recognition method for Arrhythmia Classification with the utilization of 1D-CNN

algorithm. They have used methods like Multi-Lead Coupling, Dual-Channel 1D-CNN with Residual block and Priority Model Integrated Voting method, for leveraging information from various data resources, Enhanced feature learning, model selection and integration and several benefits. This model mainly concentrates on the utilization of 1D CNN and the dataset is taken from MIT-BIH arrhythmia dataset for classification of arrhythmia. The disadvantage of this model is, the THML ECG data relies on QRS wave detection which could result in several consequences like performance degradation, misclassification, loss of information.

[2]. In this model, the authors have introduced a Differential Beat Accuracy for ECG Family Classification Using Machine Learning, which mainly concentrates on Electrocardiogram Stress test and Echocardiogram of a patient for disease detection and classification. The algorithm used in this model is KNN algorithm and it also uses methods like Signal processing, balancing and normalization for feature extraction, noise reduction and scaling features. The dis advantage of this model are, the ECGs can only detect electrical abnormalities within the heart itself and ECG only provides a snapshot of the heart's activity at the time of the test. Which may result in limited predictive capability, incomplete diagnostic picture.

[3]. In this model, the authors have introduced a Machine Algorithm for Heartbeat Monitoring and Arrhythmia Detection Based on ECG Systems with the help of Two-Event-Related Moving Averages (TERMA) and Fractional Fourier Transform (FrFT) for event related signal processing, time-frequency analysis. This model mainly concentrates on cross-database training and testing with improved characteristics. This overcomes the issues that are occurred due to noise and artifacts including physical movements, electrode motions and external interferences. The drawback of this model is that, in both training and testing, illness features were normalized and the normal patient characteristics were not normalized. When applying normalization to all the testing and training data, the classifier's exactness suffers even further.

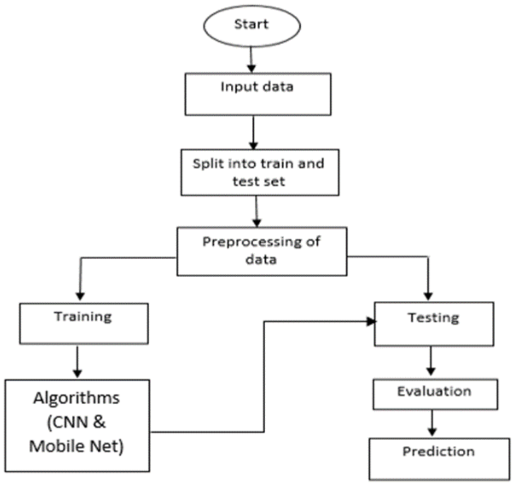
[4]. In this model, the authors have introduced a Global ECG Classification by Self-Operational Neural Networks With Feature Injection with the utilization of Neural Network Architecture which helps in increasing flexibility, nonlinearity of the model. The ECG database contains 48ECG recordings, each recording time is 30 min, the sampling frequency is 360Hz, and each ECG record is composed of two leads. But this model results in False negative which is probably the biggest concern with ECG. For some heart patients, the ECG may be entirely normal and yet their conditions should be reflected in the ECG.

[5]. In this model, the authors have introduced Prediction of Cardiac Arrhythmia using Machine Learning with the utilization of methods like- KNN classifier, Support vector Machine, Logistic Regression and Naïve Bayes' classification. The methods result in simple implementation, effective high-dimensional spaces, efficiency, and robustness. The drawback of this model is Feature Selection and poor Classification Performance on large datasets which result in insufficient feature selection, overfitting and underfitting, and quality related issues of the model.

3.Proposed System:

In the proposed arrhythmia classification system, a refined 2D CNN, integrating MobileNet models, is tailored for specific classes - Atrial Fibrillation (F), Murmur (M), Ventricular Tachycardia (V), PVC (Premature Ventricular Contraction - Q), Supraventricular Tachycardia (S), and Normal (N). This approach optimizes computational efficiency, accommodates diverse ECG signal patterns, and enhances interpretability for accurate categorization within these specified classes.

Project Flow:



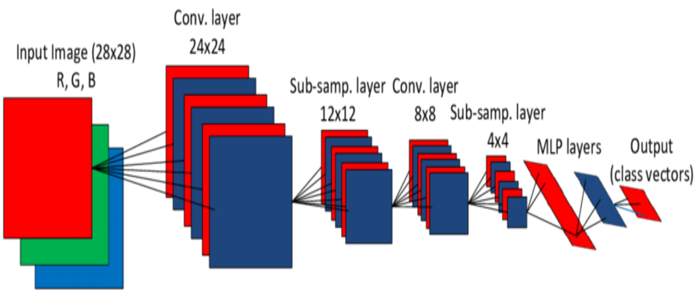
3.1Methodologies:

3.1.1 2D-CNN:

Convolutional Neural Network 2D (CNN2D) is a pivotal architecture in deep learning designed specifically for image processing tasks. It excels in capturing intricate spatial hierarchies and patterns within two-dimensional data, making it highly effective for image classification, object detection, and feature extraction. The architecture addresses a fundamental challenge in visual data analysis by employing convolutional layers that enable the model to detect local features and spatial relationships within images.

At the core of CNN2D is its ability to learn hierarchical representations through convolutional operations, allowing it to discern complex patterns and dependencies within images. The architecture is well-suited for tasks where understanding the spatial arrangement of features is crucial, such as recognizing objects in images or identifying patterns within medical scans.

2D-CNN Architecture:

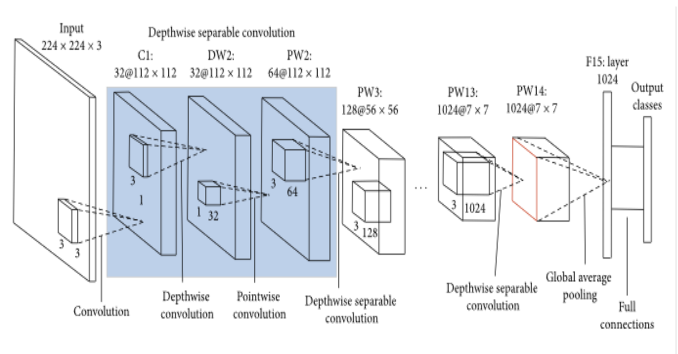


3.1.2 MobileNet:

MobileNet is a specialized architecture in deep learning designed to address the computational constraints of mobile and edge devices while maintaining high accuracy in image processing tasks. Introduced to cater to real-time applications on resource-constrained platforms, MobileNet introduces innovative techniques to significantly reduce the number of parameters and computations.

At the core of MobileNet is the concept of depthwise separable convolutions, a key innovation that enhances computational efficiency. Unlike traditional convolutional layers, depthwise separable convolutions decouple spatial and depth-wise convolutions, substantially reducing the computational load. This makes MobileNet particularly suitable for deployment on devices with limited computational resources, ensuring efficient image processing in real-time scenarios.

MobileNet Architecture:



4. Implementation:

4.1 Preprocessing:

The loaded image data is crucial, involving tasks such as addressing potential image artifacts, handling missing or corrupted images, encoding categorical labels if necessary, and normalizing pixel values. The overarching goal is to meticulously prepare the image data, ensuring it is in an optimal state for utilization in the subsequent machine learning model.

4.2 Data Splitting:

After preprocessing your data, it's customary to divide it into training and testing sets. The training set is utilized for model training, while the testing set assesses its performance. While splitting can be random, maintaining class distribution is crucial, particularly in classification tasks.

4.3 Model Training:

Now that the data is split, you can proceed to train your machine learning model. This entails feeding the training data into the model to learn patterns and relationships. The model selection hinges on your problem's nature (classification, regression, etc.) and data characteristics. Training might involve hyperparameter tuning to optimize performance.

4.4 DATASET DESCRIPTION:

The ECG arrhythmia database is the image version of this dataset (https://www.kaggle.com/shayanfazeli/heartbeat). This dataset is composed of two collections of heartbeat signals derived from two famous datasets in heartbeat classification, The MIT-BIH (Massachusetts Institute of Technology - Beth Israel Hospital) Arrhythmia Dataset and The PTB(Pulmonary Tuberculosis) Diagnostic ECG Database.

The dataset consists of 6 different classes and each class represent each type of arrhythmia. They are-
N-Normal: This class of arrhythmia refers to a normal rhythm of the heart and it indicates that the heart is healthy.

Training: 75700 images
Testing: 18900 images
S-Supraventricular Tachycardia: This class refers to a condition, where the heart beats in a premature contraction that originates above the ventricles, before the next expected normal heartbeat.

Training: 2223 images
Testing: 556 images

V-Ventricular Tachycardia: This class refers to a condition, where the premature contractions are originating from the lower chambers of the heart occurring before the next normal heartbeat.

Training: 5789 images

Testing: 1447 images

F-Atrial fibrillation: This class refers to a condition of a heartbeat, that is a fusion of a premature ventricular contraction and a normal beat.

Training: 642 images

Testing: 161 images

Q-Premature Ventricular Contraction: This class refers to a condition of extra heartbeats that begin in one of the heart's two lower pumping chambers thus causing a sensation of a fluttering in the chest.

Training: 6431 images

Testing: 1608 images

M-Murmur: This class refers to a condition where the heart makes a whooshing or swishing sound when blood flows abnormally over heart valves. When we come across this type of classification, it indicates that further investigation needs to be done. Because this murmur can be present in both healthy people who do not have heart problems and also people who have heart related issues.

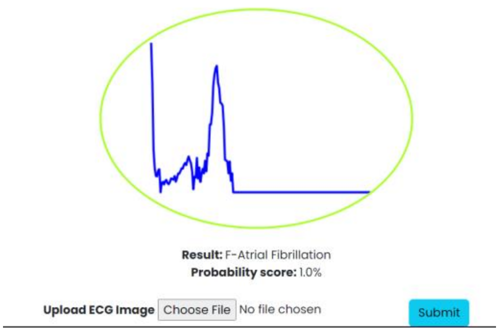
Training: 8405 images

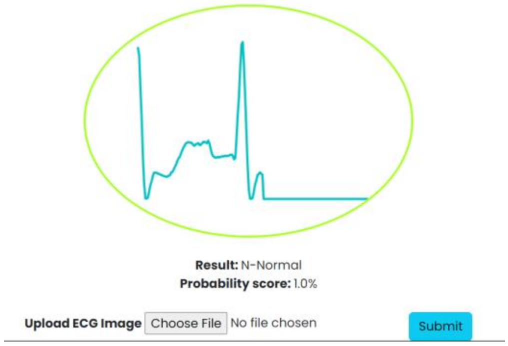
Testing: 2101 images

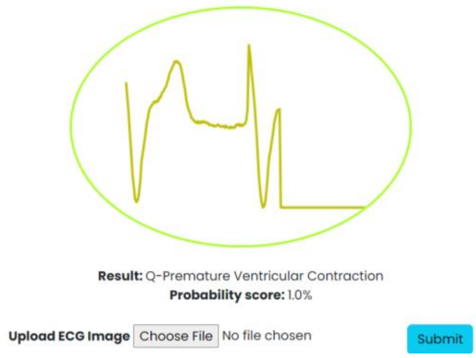
4.Generating Results:

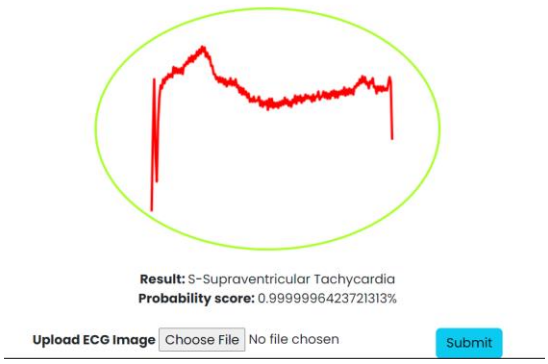
Leverage the trained model to predict outcomes on new, unseen data using the predict method.

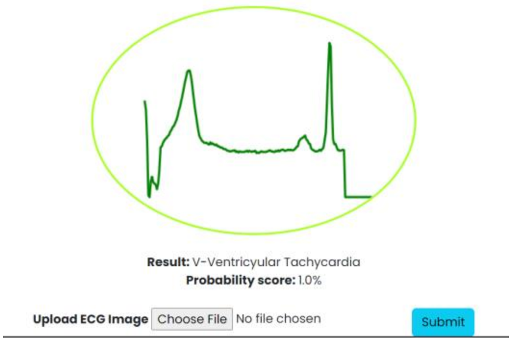
The quantitative results demonstrate that 2-D CNN outperformed MobileNet across all performance metrics. This suggests that 2-D CNN is more suitable for the task of image classification in this context. The qualitative analysis further supports this conclusion, as 2-D CNN exhibited a higher degree of accuracy in identifying intricate features within the images.











5. CONCLUSIONS

In conclusion, the results of this project indicate that 2-D CNN outperforms MobileNet in the task of image classification based on the metrics evaluated. These findings provide valuable insights for researchers and practitioners in the field of machine learning, highlighting the importance of algorithm selection in achieving optimal performance for specific tasks.

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