COMPUTER VISION LAB

PROJECT REPORT

On

Project Name

Five-class classification of ECG signals using the Tunable Q-factor Wavelet Transform

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Submitted By:

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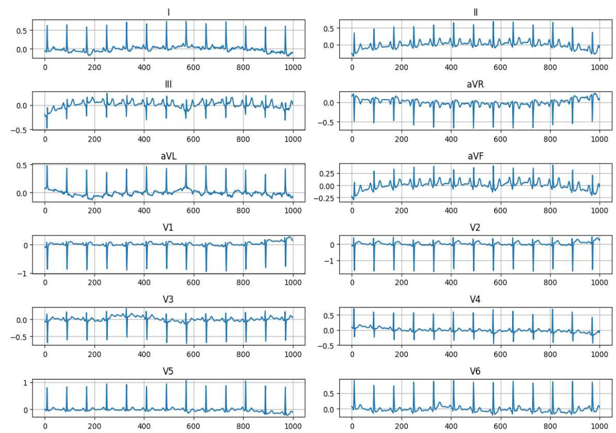
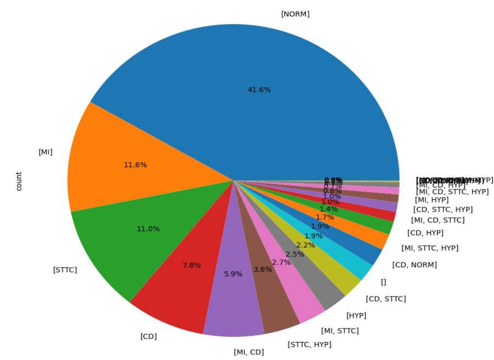
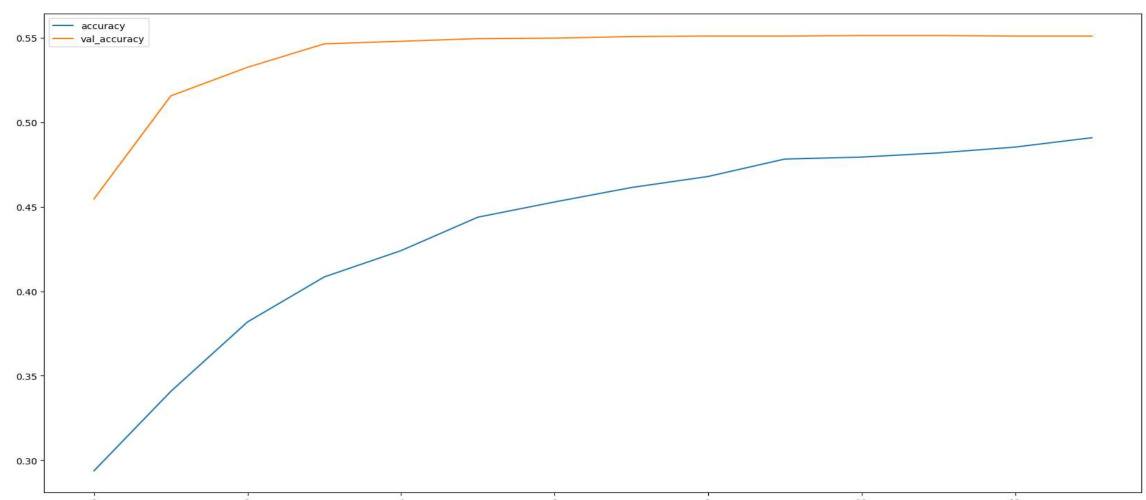


Tunable Q-factor WAVELET TRANSFORMATION



PIE CHART



Accuracy vs Val-Accuracy

LIST OF TABLES

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 1000, 256)	1,792
batch_normalization (BatchNormalization)	(None, 1000, 256)	1,024
max_pooling1d (MaxPooling1D)	(None, 500, 256)	0
conv1d_1 (Conv1D)	(None, 500, 128)	196,736
batch_normalization_1 (BatchNormalization)	(None, 500, 128)	512
max_pooling1d_1 (MaxPooling1D)	(None, 250, 128)	0
conv1d_2 (Conv1D)	(None, 250, 64)	49,216
batch_normalization_2 (BatchNormalization)	(None, 250, 64)	256
max_pooling1d_2 (MaxPooling1D)	(None, 125, 64)	0
flatten (Flatten)	(None, 8000)	0
dense (Dense)	(None, 64)	512,064
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 64)	4,160
dropout_1 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 5)	325

MODELS USED TO TRAIN: DETAILS

1.INTRODUCTION

1.1 Background and Significance

Electrocardiogram (ECG) signals are crucial diagnostic tools in cardiology, providing valuable insights into the heart's electrical activity and aiding in the detection of various cardiac abnormalities. Traditionally, the interpretation of ECG signals has heavily relied on the expertise of clinicians, who meticulously analyze waveforms to diagnose conditions such as arrhythmias, myocardial infarction, and cardiac hypertrophy. However, manual interpretation is subjective, time-consuming, and prone to errors, especially in cases of subtle abnormalities or complex arrhythmias. Therefore, there's a pressing need to complement traditional methods with automated techniques to enhance diagnostic accuracy, streamline clinical workflows, and improve patient outcomes. Leveraging the power of machine learning, particularly Convolutional Neural Networks (CNNs) with advanced feature extraction techniques like Tunable Q-factor Wavelet Transform (TQWT), we aim to transform ECG signal analysis, ushering in a new era of precision medicine in cardiovascular care

1.2 Motivation

This project is motivated by the imperative to address the challenges associated with manual ECG interpretation and to harness the potential of machine learning in advancing cardiac care. By automating the classification of ECG signals, we aim to streamline clinical workflows, reduce diagnostic errors, and ultimately enhance patient care. The utilization of Convolutional Neural Networks (CNNs), coupled with feature extraction methods like Tunable Q-factor Wavelet Transform (TQWT), holds promise in capturing intricate patterns within ECG signals, which may elude conventional analysis. By leveraging these advanced techniques, we endeavor to develop a robust and scalable solution for accurate ECG signal classification.

1.3 Problem Statement and Objectives

The problem at hand involves developing a robust classification model to accurately categorize ECG signals into five distinct cardiac conditions: normal rhythm (NORM), cardiomyopathy (CD), hypertrophy (HYP), myocardial infarction (MI), and ST-T changes (STTC). This classification task is inherently challenging due to the diverse morphologies and subtle variations present in ECG signals across different cardiac conditions. Our primary objective is to overcome these challenges by leveraging advanced machine learning techniques, particularly Convolutional Neural Networks (CNNs), known for their effectiveness in capturing complex patterns in temporal data. Additionally, we aim to explore the utility of individual lead feature extraction using Tunable Q-factor Wavelet Transform (TQWT) to enhance the discriminative power of our classification model. Through rigorous experimentation and evaluation, our goal is to achieve high accuracy and reliability in automated ECG signal classification, thereby facilitating more accurate diagnoses and improved patient care outcomes.

1.4 Scope and Outline

This report provides a comprehensive overview of our approach to ECG signal classification using CNNs with individual lead feature extraction. We begin by elucidating the background and significance of automated ECG analysis, highlighting the critical need for accurate and efficient diagnostic tools in cardiovascular care. Subsequently, we review pertinent literature on ECG signal classification techniques and machine learning methodologies. We then delineate our proposed methodology, encompassing data preprocessing, feature extraction, model architecture design, and training procedures. Following this, we present the experimental results and discuss the performance of our classification model in detail. Finally, we conclude with a summary of our findings, implications for clinical practice, and avenues for future research and development.

2.LITERATURE REVIEW

Previous research has extensively explored various methodologies for ECG signal classification, with a particular focus on machine learning and deep learning techniques. Convolutional Neural Networks (CNNs) have emerged as a prominent choice due to their ability to automatically extract hierarchical features from temporal data. Additionally, feature extraction methods such as Tunable Q-factor Wavelet Transform (TQWT) have been employed to capture both time and frequency-domain information, enhancing the discriminative power of classification models. Several studies have demonstrated the efficacy of CNNs in accurately classifying ECG signals across multiple cardiac conditions. Furthermore, researchers have investigated novel approaches for feature extraction and model optimization to improve classification performance. By reviewing the existing literature, we gain valuable insights into the state-of-the-art techniques and methodologies, which inform the development of our proposed approach for ECG signal classification..

3.PROPOSED METHODOLOGY

3.1.Step-1:

Preprocessing:

The dataset is preprocessed to extract individual leads from each ECG signal and prepare the data for feature extraction and model training.

3.2. Step-2:

Individual Lead Feature Extraction:

The Tunable Q-factor Wavelet Transform (TQWT) is a signal processing technique used for feature extraction, particularly suited for analyzing signals with both time and frequency-domain information. Unlike traditional wavelet transforms, TQWT offers the advantage of adjusting the Q-factor parameter, allowing for tailored analysis of frequency resolutions.

Algorithm:

1. **Choose Wavelet:** Select a wavelet function.
2. **Define Q-factor Range:** Specify Q-factor range.
3. **Define Scale Range:** Determine frequency scale range.
4. **Initialize Output Array:** Prepare storage for transformed coefficients.
5. **Iterative Transform:** Apply wavelet transform for each scale and Q-factor.
6. **Feature Extraction:** Extract relevant features from coefficients.
7. **Optional Post-Processing:** Normalize or reduce dimensionality.
8. **Output:** Transformed coefficients or extracted features for further analysis.

3.3. Step-3:

Model Building:

A Convolutional Neural Network (CNN) architecture is designed for ECG signal classification. The CNN architecture consists of convolutional layers, batch normalization, max-pooling layers, and fully connected layers.

Algorithm:

1. **Input**: Extracted features from ECG signals for all leads
2. **Define Model Architecture**:
    - Decide on the number of convolutional layers, filter sizes, activation functions, pooling layers, etc.
    - Consider adding dropout layers for regularization and batch normalization layers for improved convergence.

3. **Initialize Model**:
    - Create a sequential model using a deep learning library like Keras or TensorFlow.
4. **Add Layers**:
    - Add convolutional layers with specified filters, kernel sizes, and activation functions.
    - Optionally add pooling layers (e.g., max pooling) to reduce dimensionality and extract dominant features.
    - Flatten the output of the convolutional layers to prepare for input to the fully connected layers.
    - Add fully connected layers (dense layers) to perform classification.
    - Use appropriate activation functions (e.g., ReLU for hidden layers and softmax for the output layer in multi-class classification).
5. **Compile Model**:
    - Specify the loss function (e.g., categorical cross-entropy for multi-class classification), optimizer (e.g., Adam), and evaluation metric (e.g., accuracy).
6. **Train Model**:
    - Split the dataset into training and validation sets.
    - Train the model using the training data, specifying batch size, number of epochs, and validation data.
    - Monitor training progress and adjust hyperparameters if necessary to prevent overfitting.
7. **Evaluate Model**:
    - Evaluate the trained model on a separate test dataset to assess its performance.
    - Calculate relevant metrics such as accuracy, precision, recall, and F1-score.
8. **Output**: Trained CNN model for ECG signal classification.

3.4. Step-4:

Data splitting:

Data splitting is a fundamental step in machine learning model development aimed at effectively utilizing available data for training, validation, and evaluation.

Algorithm:

1. **Input**: Dataset (features and labels), desired ratios for splitting (e.g., 70-15-15)
2. **Shuffle Data**: Randomly shuffle the dataset.
3. **Split Data**: Divide the shuffled dataset into training, validation, and testing sets based on the specified ratios.
4. **Output**: Training, validation, and testing sets.

3.5. Step-5:

Model Training:

The designed CNN model is trained using the extracted features from the training dataset. The model is optimized using an appropriate optimizer and loss function.

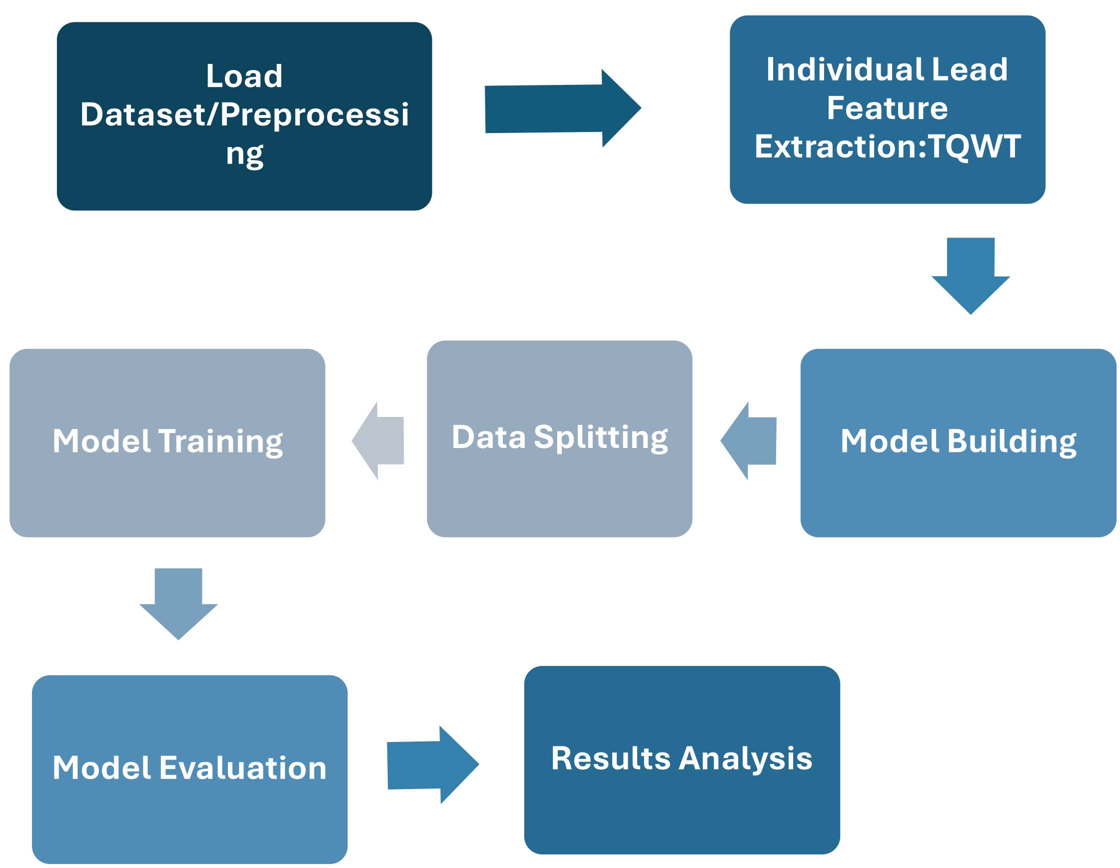
3.6. Step-6:

Model Evaluation:
The trained model is evaluated on a separate test dataset to assess its performance in classifying ECG signals into different cardiac conditions.

3.7. Step-7:

Results Analysis:
The results obtained from the model evaluation are analyzed to understand the model's performance, identify strengths, weaknesses, and areas for improvement.

Block Diagram:



4.RESULTS AND DISCUSSION

4.1.Experimental setup

- **Dataset:** ECG signals categorized into five cardiac conditions.
- **Preprocessing**: Extraction of individual leads and feature extraction using Tunable Q-factor wavelet transform(tqwt).
- **Model:** Convolutional Neural Network (CNN) with multiple convolutional and pooling layers, batch normalization, and dropout regularization.
- **Hyperparameters:** 64, 128, and 256 filters in convolutional layers, kernel size of 5, ReLU activation, softmax output, Adam optimizer with learning rate=0.0001, categorical cross-entropy loss.
- **Training:** 80:20 split for training and testing sets, batch size of 32, early stopping based on validation loss.
- **Evaluation:** Performance metrics including accuracy, sensitivity, specificity, precision.

4.2.Dataset Description

- The dataset consists of ECG signals representing various cardiac conditions: normal rhythm (NORM), cardiomyopathy (CD), hypertrophy (HYP), myocardial infarction (MI), and ST-T changes (STTC).
- Each signal includes data from 12 leads, providing comprehensive information about the cardiac activity.
- Data preprocessing involves extracting individual leads from the ECG signals, enabling focused analysis on each lead's unique characteristics.
- Tunable Q-factor wavelet transform(tqwt) is applied to extract relevant features from each lead, capturing both time and frequency-domain information essential for classification.

4.3.Performance matrices

		Precision		Recall		f1_score	
Lead No.	Lead Names	Random classifier	CNN	Random classifier	CNN	Random classifier	CNN
0	I	0.343437	0.303890	0.411511	0.550939	0.374405	0.391715
1	II	0.356054	0.481678	0.446907	0.554632	0.396341	0.400772
2	III	0.362491	0.408596	0.393660	0.551862	0.377433	0.393236
3	aVR	0.352274	0.379154	0.439212	0.554940	0.390969	0.404272
4	aVL	0.354110	0.303873	0.385349	0.551247	0.369070	0.391779
5	aVF	0.354763	0.343243	0.420129	0.551247	0.384689	0.392482
6	V1	0.455951	0.303873	0.413666	0.551247	0.387435	0.391779
7	V2	0.447326	0.343337	0.411511	0.551247	0.375585	0.392560
8	V3	0.470804	0.303873	0.436750	0.551247	0.399017	0.391779
9	V4	0.526121	0.402832	0.445060	0.559557	0.404238	0.411497
10	V5	0.368415	0.435268	0.453370	0.577101	0.406501	0.455998
11	V6	0.357857	0.582927	0.449369	0.580486	0.398426	0.458250
2,4,6,12		0.6919893753655412	0.4431524319869994	0.6620498614958449	0.5063096337334565	0.025626130354158557	0.46316064892333586

Overall, the performance metrics suggest that the classification model achieves moderate accuracy in distinguishing between the five classes of ECG signals. However, there may be room for improvement, especially if the goal is to achieve higher precision, recall, and F1-scores across all classes. Further analysis and optimization of the model may be necessary to enhance its performance.

4.4.Results and discussion

		ACCURACY	
LEAD NO.	LEAD NAME	CNN	Random Forest classifier
0	I	0.562327	0.611881
1	II	0.572176	0.639581
2	III	0.563866	0.633426
3	aVR	0.592490	0.626039
4	aVL	0.556787	0.618960
5	aVF	0.551862	0.629117
6	V1	0.571868	0.627578
7	V2	0.577101	0.619575
8	V3	0.586950	0.669437
9	V4	0.568175	0.667590
10	V5	0.598030	0.664820
11	V6	0.604186	0.659895
ALL 12 LEADS	ALL	0.4488	0.7122191443521083
2,4,6,12	II,aVR,aVF,V6	0.5361	0.6620498614958449

5.CONCLUSION

- Our study presents a comprehensive approach to ECG signal classification using CNNs with individual lead feature extraction. While the model demonstrates moderate performance, there is room for improvement. Future work may involve fine-tuning the model architecture and exploring additional feature extraction techniques to enhance classification accuracy further.

6.REFERENCES

- ECG Signal Classification Using Deep Learning Techniques Based on the PTB-XL Dataset. (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8469424/)
- Python methods and libraries. (https://www.python.org/)
- Sample codes Provided along with the problem.

Roll No.	Name	Tasks performed	Weightage (%)	Signature
121CS0149	HARSH BENUSKAR	PPT Making	20	Harsh Benuskar
121CS0151	CHODISETTY BHUVANESWARI	Code	30	CHODISETTY BHUVANESWARI
121CS0152	AKASH KUMAR BISWAL	Report Making	20	AKASH KUMAR BISWAL
121CS0153	GOURAV KUMAR BISWAL	Code, PPT Making, Report Making	30	GOURAV KUMAR BISWAL