Network Modeling Analysis in Health Informatics and Bioinformatics (2024) 13:57
https://doi.org/10.1007/s13721-024-00487-w

ORIGINAL ARTICLE

# Detection of heart arrhythmia with electrocardiography

Tarushi Jat[1] · Nagamma Patil[1] · Prajna Bhat[1]

Received: 24 May 2024 / Revised: 12 August 2024 / Accepted: 11 September 2024


**Abstract**

Early detection of cardiac arrhythmia, a prevalent form of cardiovascular disease (CVD) impacting millions globally, is heavily reliant on the accurate analysis of heartbeats. Physicians often recommend that patients wear Holter monitors for 24 h or longer to observe concerning cardiac issues, resulting in the collection of substantial amounts of electrocardiogram (ECG) data. Consequently, there is a need to automate the process of interpreting ECGs to detect cardiac abnormalities efficiently. Current state-of-the-art studies rely on handcrafted feature extraction, which may not effectively capture the intricate temporal relationships inherent in ECG signal data. To address this limitation and facilitate the diagnosis of cardiac diseases, this study proposes a technique that converts electrocardiogram signals into images, subsequently training a deep learning model on the generated images. Image encoding techniques such as Gramian Angular Difference Field (GADF), Gramian Angular Summation Field (GASF) and Markov Transition Field (MTF) are employed to translate the ECG signals into images. The highest accuracy, 96.71%, was achieved by training the Convolutional Neural Network (CNN) model using the concatenation of these three image encoding techniques. The proposed approach is assessed using ECG recordings from the MIT-BIH Arrhythmia Database to detect heart arrhythmia, demonstrating the efficacy of the approach.

**Keywords** ECG · Signals · Images · CNN · Image encoding · GASF · GADF · MTF

## 1 Introduction

Any Heart arrhythmia refers to any deviation from the normal heartbeat rhythm, where the heart rate may be abnormally slow or fast (National Heart Lung and Blood Institute 2011). Any irregular heartbeat is categorized as heart arrhythmia. As per the World Health Organization (WHO) (Cardiovascular Diseases 2021), the majority of deaths are due to cardiovascular diseases among all the reasons for death in the world. Heart arrhythmia is a significant category within cardiovascular disorders. Electrocardiography is the primary tool for detecting cardiac arrhythmia. Dizziness, difficulty in breathing, fainting, and rapid heartbeat are common symptoms of heart arrhythmia. Some heart arrhythmias are harmless; nevertheless, some kinds of arrhythmias, for example, excessive supraventricular ectopic, premature ventricular contractions, and atrial fibrillation, have been linked to a variety of cardiovascular illnesses, including failure of the heart, stroke, and cardiac arrest. ECG is a test that is extremely helpful in identifying various cardiac issues in people of all ages. ECG stands out as the most economical and non-invasive technique for cardiac examination. A crucial component of ECG analysis is the classification of heartbeats.

The three major waves of a typical heartbeat represented in an electrocardiogram are shown in Fig. 1. The first wave on the ECG, known as the P wave, indicates atrial depolarization or the atrial contraction. The QRS complex, featuring the Q, R, and S waves, signifies the process of ventricular depolarization and contraction. The second wave, the R wave, is the most noticeable characteristic of the electrocardiogram, whereas the Q wave and the S wave are descending waves. The T wave represents ventricular repolarization (Taylor 2006). After the QRS complex, the ST segment appears, indicating that the ventricles

Tarushi Jat, Nagamma Patil have made equal contributions to this work.

✉ Prajna Bhat
prajnaudupa.217it002@nitk.edu.in

Tarushi Jat
tarushijat28@gmail.com

Nagamma Patil
nagammapatil@nitk.edu.in

[1] Department of Information Technology, National Institute of Technology, Surathkal, Karnataka 575025, India

Published online: 09 October 2024

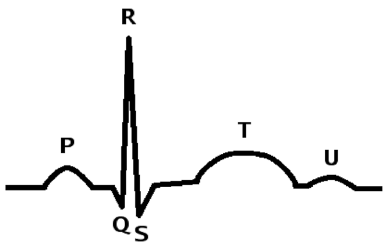


**Fig. 1** Normal systole ECG

are depolarized. Electrocardiography is a procedure that uses a series of electrodes (typically 10) to capture the cardiac electrical activity. It's a popular method for detecting cardiac issues, including arrhythmia. ECG setups vary widely in shape and size. A Holter monitor device, for example, is helpful in carefully monitoring the patient for a lengthy period using a 2-lead ECG (National Heart Lung and Blood Institute 2021).

The electrocardiography process can last up to 48 h. It should be checked by a cardiologist to check for any cardiac issues and this could be tedious and lengthy process. Therefore, it is vital to identify an efficient and automated approach for analyzing and understanding ECG waves. The most crucial factor for ECG details is that they are interpreted using computer-assisted techniques. The current ECG interpretation algorithms still have a high probability of misdiagnosis. The standardization of ECG data digitization and the creation of algorithmic models capable of facilitating large-scale processing of raw clinical datasets offer a chance to revisit traditional ECG analysis methods and bring significant enhancements to computerized ECG interpretation.

Research indicates that utilizing the Synthetic Minority Oversampling Technique (SMOTE) to mitigate class imbalance significantly improved the prediction system's accuracy (Ketu and Mishra 2022). Almost all of the existing automated methods to perform ECG analysis rely on manual feature engineering that fails to capture complex patterns from ECG signals (Kumari et al. 2021). Some Machine Learning (ML) based approaches use ECG templates to make the cardiac disease prediction (Aamir et al. 2022) where the effectiveness relies on the quality of the templates. The effectiveness of these approaches is specific to the samples chosen for the study and demands a more generalized approach (Mandal et al. 2021). To address these limitations, we develop a template-free and generalized heart arrhythmia detection system that captures complex non-linear relationships in the input data without manual intervention and class-balancing techniques. Lastly, the objectives of this study are as follows:

- To convert ECG signals into ECG images with the help of image encoding techniques to facilitate capturing complex patterns from input signals useful for the detection system.
- Apart from detecting heart arrhythmia, the objective is also to determine its type.
- A comparative analysis with existing methodologies.

The structure of this paper is as follows. A literature survey of heart arrhythmia detection with electrocardiogram signals is described in Sect. 2. The approaches employed for ECG arrhythmia classification, which includes different encoding techniques for images and a Convolution Neural Network based classifier, are discussed in Sect. 3. The experimental outcomes of ECG arrhythmia detection with electrocardiogram signals are discussed in Sect. 4. In Sect. 5, we review our results and suggest avenues for future research.

## 2 Literature survey

### 2.1 Related work

The studies in the field of heart arrhythmia detection using electrocardiogram records are discussed in this section. In Carnevale et al. (2020), the authors built a reliable and scalable distributed processing system with improved response time for analyzing large data and locating cardiac beats and heart arrhythmias with electrocardiograms; the authors utilized the Menard algorithm. However, all analyses performed in this approach were specific to a particular ECG signal type. The authors in fariha et al. (2018) present a review of the various detection methods for heart arrhythmia on the highly imbalanced MIT-BIH database. This review highlighted the significance of the extracted features in the detection process. 2/2

In Savalia and Emamian (2018), authors used deep learning techniques for the identification of heart arrhythmia among other cardiovascular diseases using electrocardiograms. The authors designed a CNN and a Multi-Layer Perceptron (MLP) to classify electrocardiogram signals into one of the many diseases. Although MLPs outperform CNNs, it was observed that misinterpretation of certain features resulted in false positives. In Alarsan and Younes (2019), the authors presented some machine-learning approaches for classifying heart arrhythmia through manual feature extraction and selection. Despite achieving a high-performance system, the classification is done only using three classes of heartbeats.

There are several research studies in which the researchers worked on identifying whether a person is suffering from a heart arrhythmia. But, in Mustaqeem et al. (2018), authors also focused on identifying the subtype of heart arrhythmia in electrocardiogram signals. They proposed a Support Sector Machine (SVM) classifier with its variants to detect heart arrhythmia and used a wrapper method for feature selection from the electrocardiogram dataset.

The research in Wu et al. (2021) introduces a highly effective 12-layer deep 1D CNN to accurately classify the five distinct heartbeat categories found in the MIT-BIH Arrhythmia archive. However, this approach introduces additional computational complexity that needs to be overcome. The authors in Lanata et al. (2011) proposed the use of a K Nearest Neighbor (KNN) and Mixture Of Gaussian (MOG) classifiers on the bispectrum features extracted from the electrocardiogram signals of the MIT-BIH database where the KNN classifier outperforms the MOG classifier.

In Essa and Xie (2021), the authors propound an ensemble of the CNN-LSTM (Long Short Term Memory) model that captures the local and temporal features and the RRHOS-LSTM model that integrates the classical features from the ECG data. A bagging model with a weighted loss function is designed using this ensemble to handle the class imbalance problem effectively. A meta-classifier combines the model outputs to generate the final prediction. The authors in Sun (2023) propose an automated classification model that integrates CNNs and Recurrent Neural Networks (RNNs) to differentiate between various cardiac arrhythmias.

From the literature, it is evident that almost all works derive attributes from the ECG signal analysis and perform feature selection to determine the best feature set for arrhythmia detection. This approach fails to capture the complex temporal relationships between the input signals. Moreover, misinterpretation of selected features can affect the model performance. The significance of converting time-series information into images in the classification task is discussed in Wang and Oates (2015). We extend this idea to the arrhythmia detection task to facilitate the integration of complex and meaningful temporal features. Most models are machine learning and deep learning classifiers Hannun et al. (2019), whereas a few approaches use the CNN model (Essa and Xie 2021; Sellami and Hwang 2019; Hassan et al. 2022; Zhou and Tian 2020; Xu et al. 2020). We employ a CNN architecture in our study as they are found to learn the features for the detection task effectively. Some of the approaches try to handle the class imbalance through the use of weighted loss functions and data sampling methods (Ketu and Mishra 2022; Essa and Xie 2021). Still, we try to design a robust model to the class imbalance without any explicit imbalance handling techniques.

# 3 Methodology

## 3.1 MIT-BIH arrhythmia database

The MIT-BIH database (Moody and Mark 2001) is a well-known resource, extensively employed in most studies focused on detecting heart arrhythmias using electrocardiogram signals. The dataset contains samples from the five classes. The first is NOR (Normal heartbeat signal), and the remaining four classes represent sub-types of heart arrhythmia, which are PVC (Premature Ventricular Contraction beat) and APC (Atrial Premature Contraction beat), LBB (Left Bundle Branch block beat), RBB (Right Bundle Branch block beat). The dataset contains the data of 60% inpatients and 40% outpatients. The dataset comprises ECG signals obtained from dual-channel ambulatory recordings.

## 3.2 Method overview

As mentioned earlier, all ECG signals are obtained from the MIT-BIH Arrhythmia dataset. The MIT-BIH dataset primarily includes three types of files for each recording: signal files, header files, and annotation files. MIT signal files contain binary-encoded information that stores digitized signal samples, header files describe the content of signal files, and annotation files contain annotations. The WFDB (WaveForm DataBase) package was utilized to read, write, and process the files. This package is especially valuable for managing the different file formats within the MIT-BIH ECG database.

To read the binary signal files, the function wfdb.rdsamp() was used. This function reads the signals and returns them as a NumPy array, making it convenient for further processing in Python. The header files were read to extract metadata such as the sampling frequency, signal names, and gain, which are necessary for converting the signals into physical units. The digitized signals in the binary files were converted to physical values using the gain and baseline values provided in the header files. This conversion ensures that the signals are in meaningful units (e.g., millivolts). Annotation files were processed to extract the timing and types of annotations, which are crucial for labelling the ECG signals during training and evaluation. The physical signal values were standardized to have a zero-centered distribution with unit variance, which helps stabilize the neural network training process.

Each sample was then encoded using the three image encoding techniques, which are Gramian Angular Difference Fields (GADF), Gramian Angular Summation Fields (GASF), and Markov Transition Field (MTF) (Wang and

Oates 2015). Encoded images can detect complex relationships in the time series data that traditional methods might miss. Techniques like GASF and GADF can capture higher-order interactions between time points, which can be crucial for anomaly detection or classification (Rahadian et al. 2023). These techniques can help in reducing noise and emphasizing important patterns in the temporal data, making the generated images more informative for the learning algorithms (Sharma et al. 2022).

For this study, a total of 3205 images are used with each of the image encoding techniques. These images are divided into an 80:20 ratio. CNN model is trained separately with the images generated using three image encoding schemes, and performance analysis is performed on each of the trained models. Finally, the three image encoding schemes are merged, and then the CNN model is trained. Figure 2 provides a comprehensive illustration of the proposed model.

### 3.3 Gramian angular summation fields

GASF (Rahadian et al. 2023) utilizes the polar coordinate system to transform ECG temporal data into image representations. In a polar coordinate two-dimensional system, we represent every point with the help of one reference point. In the polar coordinate system, the location of a point is defined by its distance from a central reference point and the angle it forms with a reference direction. Similarly, in our time series, we have N timestamps, assuming their respective values to be x, which can be considered as N different points of the polar coordinate system. For each timestamp, we calculate the angle $\phi$ and the distance r as given in Eqs. 1 and 3, correspondingly.

$$\phi_I = arccos\left(x_I\right) \tag{1}$$

$$r_I = I/N \tag{2}$$

After calculating $\phi$ and r for each timestamp, we construct the Gram matrix GG, as illustrated in Eq. 4.

$$G = \begin{bmatrix} cos(\phi_1 + \phi_1) & \dots & cos(\phi_1 + \phi_N) \\ cos(\phi_2 + \phi_1) & \dots & cos(\phi_2 + \phi_N) \\ \dots & \dots & \dots \\ cos(\phi_N + \phi_1) & \dots & cos(\phi_N + \phi_N) \end{bmatrix} \tag{3}$$

In this gram matrix G, the diagonal represents the original time series, where the top left represents the start of the series, and the bottom right represents the end. All the other entries of the gram matrix G represent the temporal correlation with different timestamps of our time series. This Gram matrix can be represented as a 2D image.

### 3.4 Gramian angular difference fields

The idea of GADF (Wei et al. 2024) image encoding is very similar to that of the GASF image encoding scheme. The calculation of the angle $\phi$ and r for every timestamp is similar, as explained above. The difference exists in the calculation of the gram matrix G. Instead of using the cos summation in the gram matrix, in GADF, we use the sin difference. The GASF encoding is turned into an inverse mapping as a result. The equation for the gram matrix calculation for GASF and GADF is given in Eqs. 4 and 5.

$$GASF = \left[cos\left(\phi_I + \phi_J\right)\right] \tag{4}$$

$$GADF = \left[sin\left(\phi_I - \phi_J\right)\right] \tag{5}$$

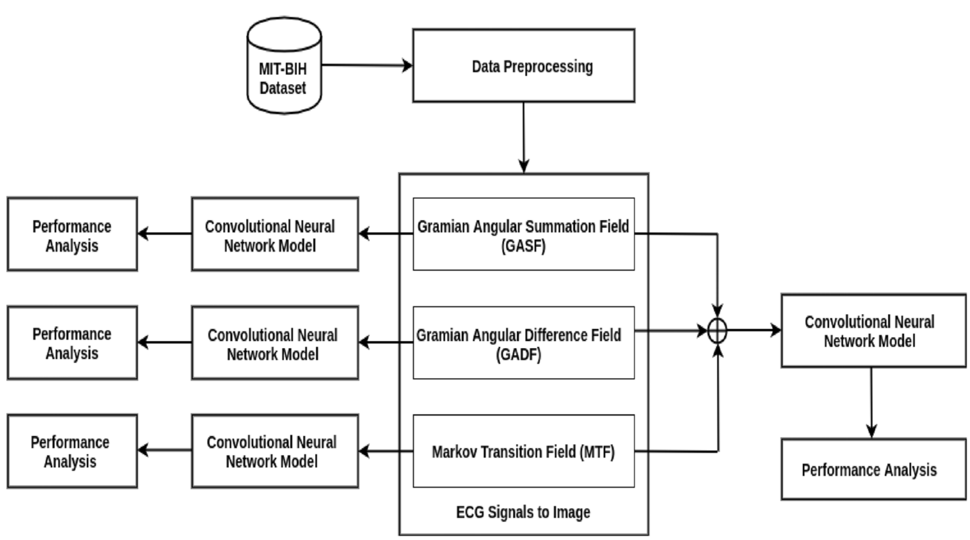


**Fig. 2** Detailed proposed methodology

### 3.5 Markov transition field

The time-series data is used to construct a Markov Transition Matrix, which bins the various values the time series may take on as states in a Markov Chain. Within a first-order Markov chain, the elements of W reflect the movement between quantile bins along the temporal axis. After normalization, W becomes a time-insensitive matrix. To mitigate the loss caused by the absence of temporal dependence, the Markov Transition Field is defined as specified in Eq. 7. By spreading out matrix values and considering the temporal locations of the bins, this is turned into a Markov Transition Field. So, the MTF (Rahadian et al. 2023) picture may be considered dynamic information about the time series and the waveform amplitudes at a particular temporal point.

$$M = \begin{bmatrix} w_{ij|x_1 \epsilon qi, x_1 \epsilon qj} & \cdots & w_{ij|x_1 \epsilon qi, x_n \epsilon qj} \\ w_{ij|x_2 \epsilon qi, x_1 \epsilon qj} & \cdots & w_{ij|x_2 \epsilon qi, x_n \epsilon qj} \\ \cdots & \cdots & \cdots \\ w_{ij|x_n \epsilon qi, x_1 \epsilon qj} & \cdots & w_{ij|x_n \epsilon qi, x_n \epsilon qj} \end{bmatrix} \tag{6}$$

### 3.6 Convolution neural network architecture

Research shows that CNNs are effective when combined with image encoding methods in anomaly detection studies (Baloglu et al. 2019; Acharya et al. 2018; Sun 2023). This encouraged us to use the CNN architecture to detect cardiac arrhythmia. We empirically determined the network architecture by gradually increasing the number of convolutions and filters. No explicit hyperparameter tuning was performed. The architecture comprises thirteen 2D convolutional layers with varying filters: 64 for the first two layers, 128 for the next two layers, 256 for the subsequent three layers, and 512 for the remaining six layers. Each convolutional layer utilizes a $3 \times 3$ filter size. Batch normalization was added after every convolutional layer. To enhance generalization and prevent overfitting, dropout layers are strategically placed throughout the network. Specifically, dropout is applied after the following layers: the 1st, 3rd, 5th, 6th, 8th, 9th, 11th, and 12th layers. These dropout layers contribute to robust learning by randomly deactivating a portion of the input units during each update throughout the training process, thus preventing the network from becoming too reliant on specific pathways. Max pooling with a pool size of $2 \times 2$ is used after every two convolutional layers for the first four convolutions and after every three layers in the following convolutions. Lastly, we used two dense layers. We applied the ReLU (Bazi et al. (2013) activation function throughout the convolutional and dense layers, reserving the Softmax (Yang et al. 2018; Lin and Yang 2014) activation function for the output layer. The architecture is shown in Fig. 3.

## 4 Experiments and results

### 4.1 Images obtained from Image Encoding Techniques

Firstly, images are generated for each ECG signal using the GASF encoding scheme. Figure 4 illustrates the GASF images corresponding to the different classes of cardiac

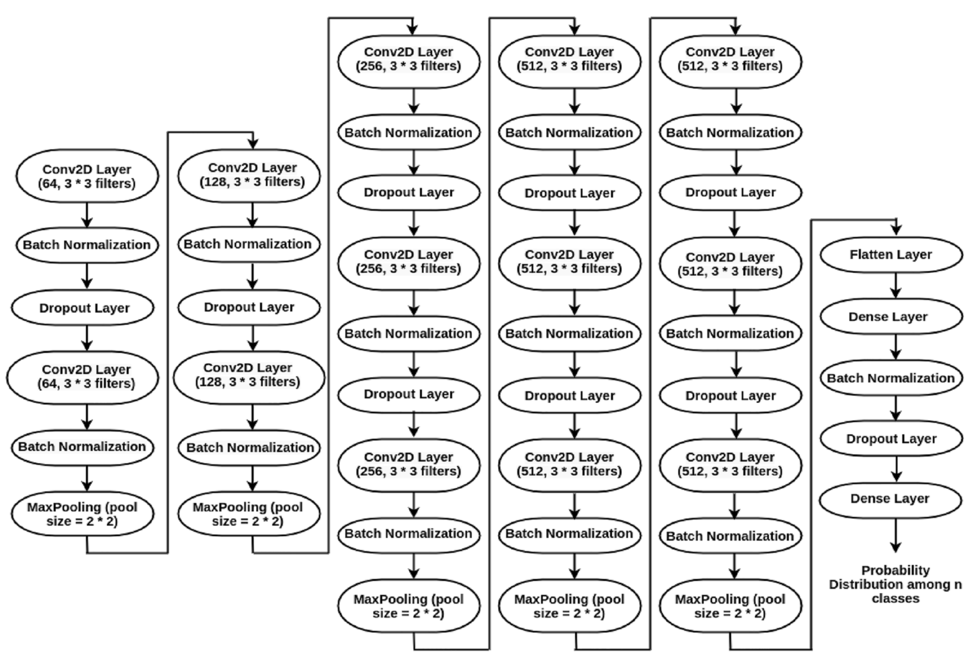


**Fig. 3** Architecture of the proposed CNN model

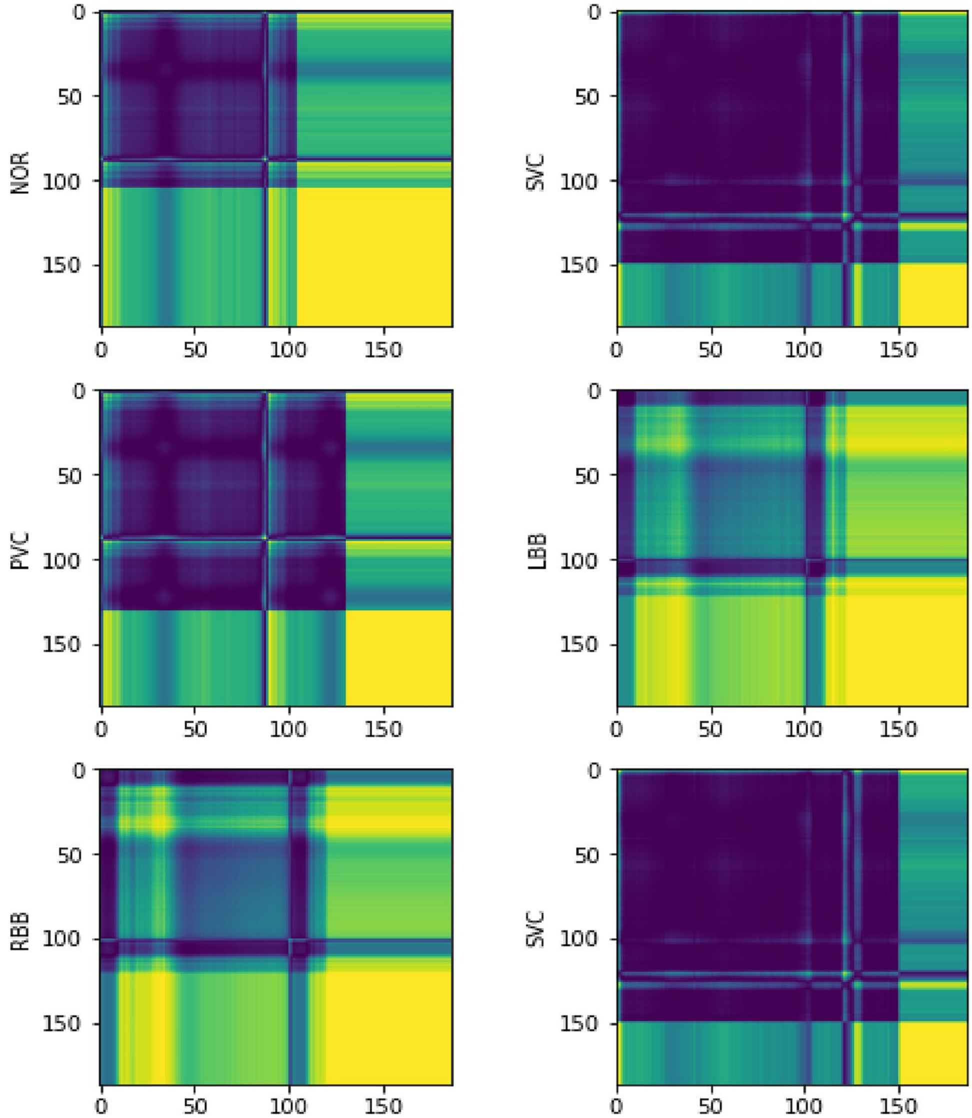


**Fig. 4** Gramian angular summation field representations

arrhythmia, with the y-axis representing signal amplitude and the x-axis indicating time.

Secondly, images are produced for each ECG signal using the GADF encoding scheme. Figure 5 presents the GADF images for each class of cardiac arrhythmia, where the y-axis denotes signal amplitude and the x-axis represents time.

Additionally, images are generated using the MTF encoding scheme for each ECG signal. Figure 6 displays the MTF images associated with each cardiac arrhythmia class, with the y-axis showing signal amplitude and the x-axis reflecting time.

## 4.2 Performance measures

- Accuracy: Among all the predictions made by the model, how many predictions are correctly made is accuracy.

$$Accuracy = (TP + TN)/(TP + FP + FN + TN) \tag{7}$$

- Precision: Precision assesses the fraction of true positives among all the instances predicted as positive by the model.

$$Precision = TP/(TP + FP) \tag{8}$$

- Recall: Recall indicates the fraction of true positives among the total number of actual positive cases captured by the model.

$$Recall = TP/(TP + FN) \tag{9}$$

- F1 Score: The F1 score merges precision and recall into a comprehensive metric through their harmonic mean, delivering an integrated assessment of the model's effectiveness.

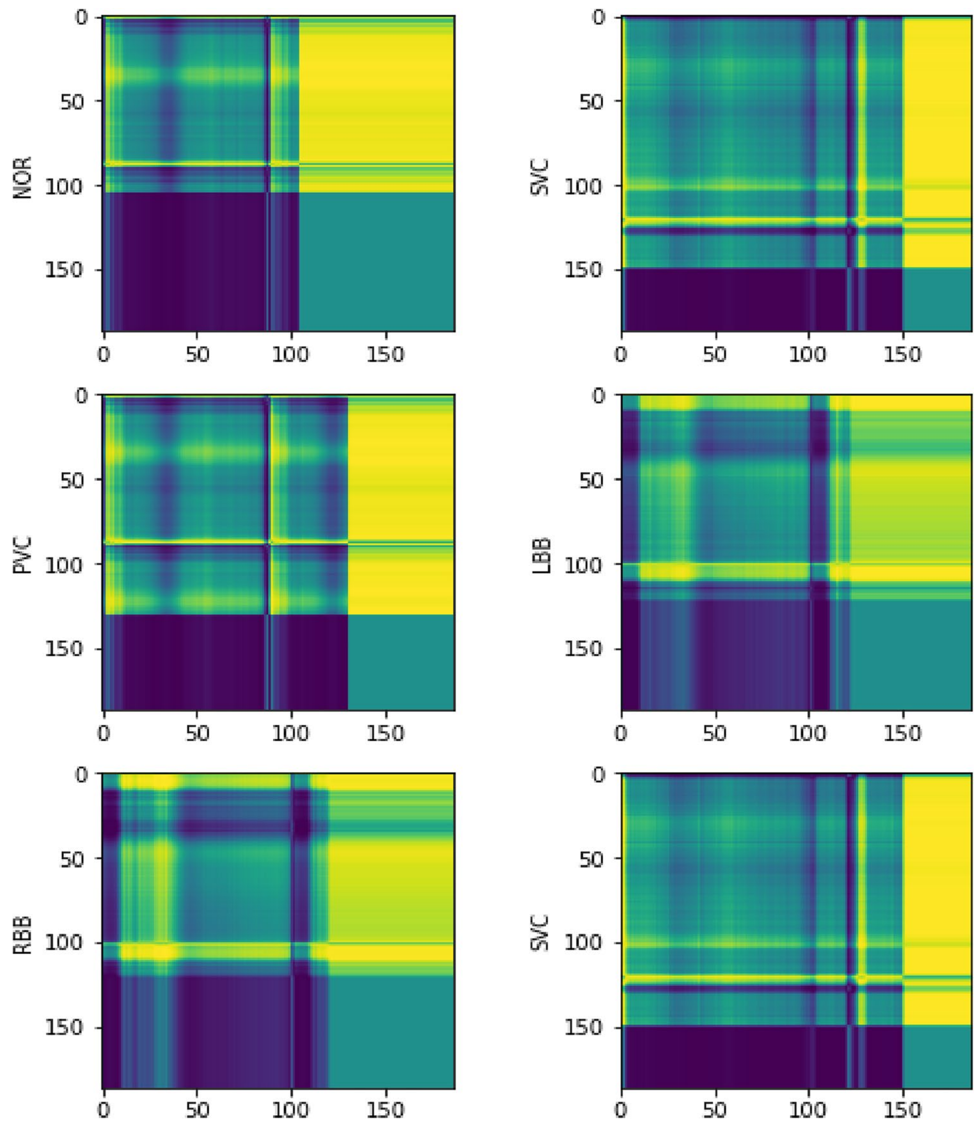


**Fig. 5** Gramian angular difference field representations

$$F1Score = 2 * (Recall * Precision)/(Recall + Precision) \quad (10)$$

## 4.3 Result analysis and comparison with existing work

The CNN model was subjected to 50 epochs of training with images of $187 \times 187$ pixels as input. We employed the Adam optimizer, configuring it with a learning rate of 0.00001. Sequential training of the model was conducted with images derived from each image encoding method detailed in the methodology. Initially, training was performed using images encoded with the GASF technique. This was followed by training with images encoded using the GADF technique. Subsequently, training was conducted with images encoded by the MTF technique. Finally, the model was trained using images generated from concatenating all three encoding schemes. Figure 7 presents the accuracy graph for the GASF encoding scheme. Figure 8 displays the accuracy graph for the GADF encoding scheme. Figure 9 shows the accuracy graph for the MTF encoding scheme, and Fig. 10 illustrates the accuracy graph for the combined GASF+GADF+MTF encoding scheme.

Upon comparing the operational outcomes of the CNN model trained with each image encoding technique and their concatenation, it was noted that the peak accuracy was attained when the model was trained with the combined use of GASF, GADF, and MTF encoding techniques. Table 2 displays the results, showing that the model achieved an accuracy of 88.81% when trained with the GASF encoding technique. The model's accuracy with the GADF encoding technique was 86.98%, while the accuracy with the MTF encoding technique was 89.99%. When trained with the combined GASF+GADF+MTF encoding technique, the CNN model reached an accuracy of 96.71%.

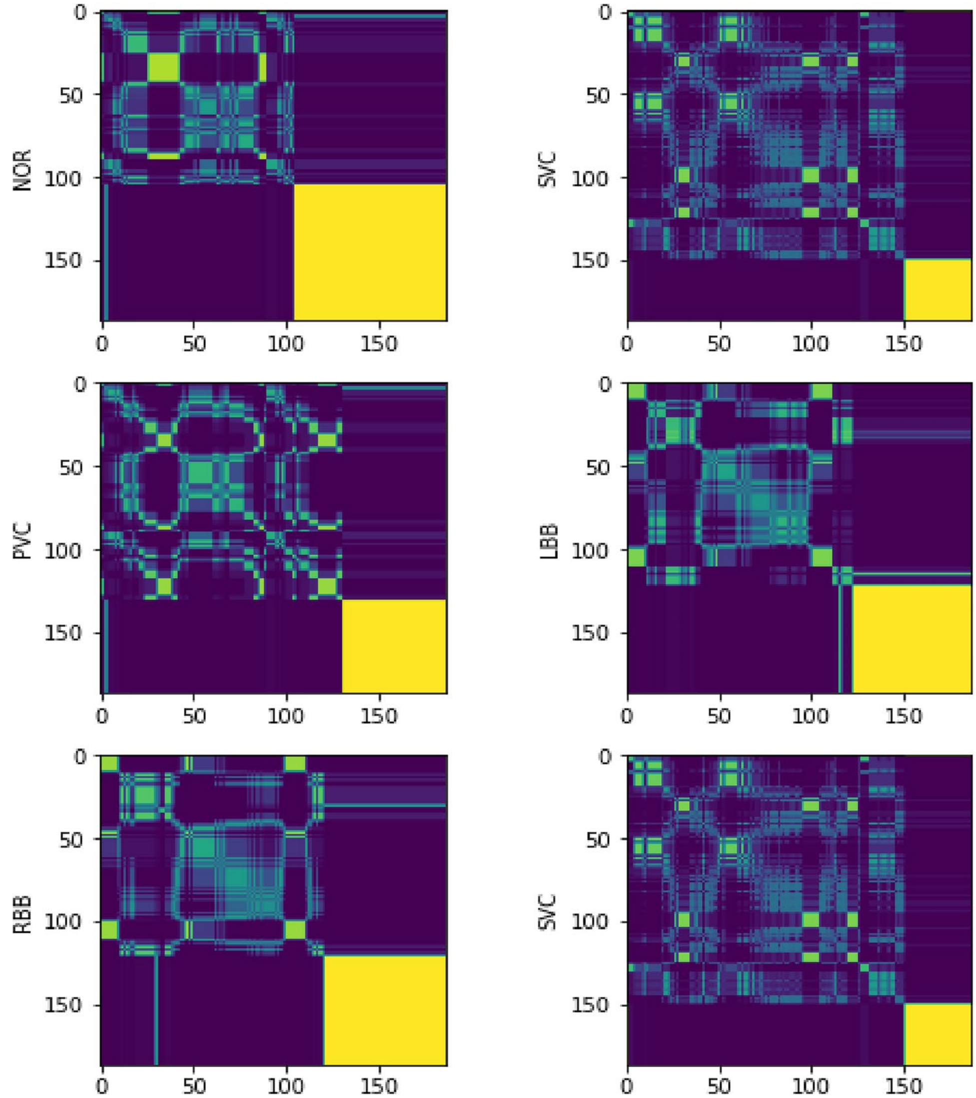


**Fig. 6** Markov transition field images

**Table 1** Precision comparison of all the image encoding techniques

| Heartbeat type | GASF | GADF | MTF | GASF+GADF+MTF |
|---|---|---|---|---|
| NOR | 81% | 83% | 81% | 94% |
| APC | 89% | 76% | 98% | 94% |
| PVC | 91% | 98% | 87% | 95% |
| LBB | 87% | 89% | 97% | 97% |
| RBB | 95% | 98% | 95% | 99% |

**Table 2** Accuracy comparison of all the image encoding techniques

| | GASF | GADF | MTF | GASF+GADF+MTF |
|---|---|---|---|---|
| Accuracy | 88.81% | 86.98% | 89.99% | 96.71% |

**Table 3** Recall comparison of all the image encoding techniques

| Heartbeat type | GASF | GADF | MTF | GASF+GADF+MTF |
|---|---|---|---|---|
| NOR | 82% | 78% | 96% | 97% |
| APC | 85% | 90% | 85% | 80% |
| PVC | 89% | 80% | 99% | 99% |
| LBB | 96% | 95% | 66% | 70% |
| RBB | 96% | 96% | 99% | 99% |

Table 1 provides a comparative analysis of precision achieved by training the CNN model with each image encoding technique across the five classes of cardiac arrhythmia. Table 3 compares recall, following the training of the CNN model with each image encoding technique, across the same five arrhythmia classes. Table 4 compares the F1 score for the CNN model, evaluated using each image encoding technique for each of the five classes of cardiac arrhythmia. Our

**Table 4** F1 Score comparison of all the image encoding techniques

| Heartbeat Type | GASF | GADF | MTF | GASF+GADF+MTF |
|---|---|---|---|---|
| NOR | 82% | 80% | 81% | 95% |
| APC | 87% | 82% | 91% | 86% |
| PVC | 90% | 88% | 93% | 97% |
| LBB | 91% | 92% | 80% | 81% |
| RBB | 95% | 95% | 99% | 99% |

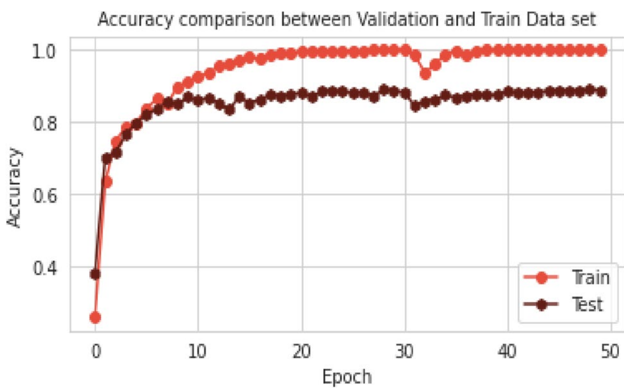


**Fig. 7** Accuracy graph (GASF)

study computes macro averages for all the considered evaluation metrics.

Classifying heart arrhythmias using the MIT-BIH dataset across multiple categories is a complex process due to inadequate data for lesser-known classes. In such cases, performance metrics like precision, recall, and F1 score are better parameters than accuracy. In the current study, the precision, recall, and F1 score results are not biased towards any particular class. The high accuracy and balanced performance metrics across different classes of cardiac arrhythmia in our CNN model suggest its strong potential for clinical application. Importantly, the model's competence in labelling arrhythmias with precision and recall that is not biased toward any particular class is essential for reliable diagnosis in real-world settings. Misclassification in a clinical environment can have significant consequences: false positives may cause undue stress and lead to unnecessary diagnostic procedures. In contrast, false negatives could delay diagnosis and treatment, compromising patient outcomes. By leveraging the combination of GASF, GADF, and MTF encoding techniques, our approach enhances the model's proficiency in recognizing and analysing subtle variations in ECG signals, thereby improving the accuracy of arrhythmia detection. This careful balance between precision and recall helps minimize misclassification risks, ensuring that patients receive appropriate care-neither subjected to unnecessary interventions nor deprived of timely treatment. As such, this model holds promise for improving early detection, timely intervention, and overall patient outcomes, particularly in situations where swift and precise ECG analysis is essential. A comparative review of different machine learning and deep learning strategies for heart arrhythmia detection using the MIT-BIH dataset can be found in Tables 5 and 6.

**Table 5** Table of Comparative Methods for Detecting Arrhythmias through ECG Signals

| Literature | Features | Classifier | Accuracy |
|---|---|---|---|
| de Chazal et al. (2004) | ECG morphology, heartbeat intervals, RR-intervals | Linear discriminants (LD) | 86.24% |
| Chazal and Reilly (2006) | Morphology, heartbeat interval | LDA | 85.9% |
| Lin et al. (2008) | Morlet wavelet | Adaptive Wavelet Network | 90% |
| Melgani and Bazi (2008) | ECG morphology features, QRS complexes duration | SVM | 91.67% |
| Park et al. (2008) | HOS and HBF | Hierarchical SVM | 85% |
| Soria and Martinez (2009) | VCG, RR-Intervals, morphological + FFS | Weighted LD | 90% |
| de Lannoy et al. (2010) | ECG-Intervals, morphological, HBF, HOS coefficients | Weighted SVM | 83% |
| Llamedo and Martínez (2011) | VCG + SFFS, Wavelet | Weighted LD | 93% |
| Mar et al. (2011) | Morphological, statiscial features + SFFS, Temporal Features | Weighted LD, MLP | 89% |
| Lanata et al. (2011) | HOS | MOG, kNN | 85% |
| Kumar and Kumaraswamy (2012) | QRS Complex | RFT | 92.16% |
| Ye et al. (2012) | Morphological features, RR-Peaks | SVM | 86.55% |
| Yeh et al. (2012) | Morphological, RR-interval, QFS | Clustering | 94% |
| Zhang et al. (2014) | Multiple feature set | One-versus-one SVM | 88.34% |
| Lin and Yang (2014) | Normalized RR-interval | Weighted LD | 93% |
| Kumar and Kumaraswamy (2013) | RR-intervals | RBF, CART, MLP, IOAW-FFNN | 92% |
| Herry et al. (2017) | SST derived features | SVM | 82.70% |

**Table 6** Comparison Table for Methods Used for Arrhythmia Detection using ECG Signals

| Literature | Features | Classifier | Accuracy |
|---|---|---|---|
| Raj and Ray (2018) | Set of 4 features | SVM, k-NN, PNN, RBFNN | 90.27% |
| Mathews et al. (2018) | ECG morphology, RR Intervals | RBM, DBN | 75.50% |
| Sellami and Hwang (2019) | Raw waveform | CNN | 88.35% |
| Shi et al. (2019) | Wavelet method | XGBoost | 91.87% |
| Essa and Xie (2021) | QRS complex, R-Peak | CNN, LSTM, CNN-LSTM, RRHOS-LSTM, Fusion Classifier | 95.81% |
| Sun (2023) | Waveform features of the unprocessed ECG signals | Attention-based CNN + GRU | 84.65% |
| Proposed Work | GASF, GADF, MTF Image Encoding Techniques | CNN | 96.71% |

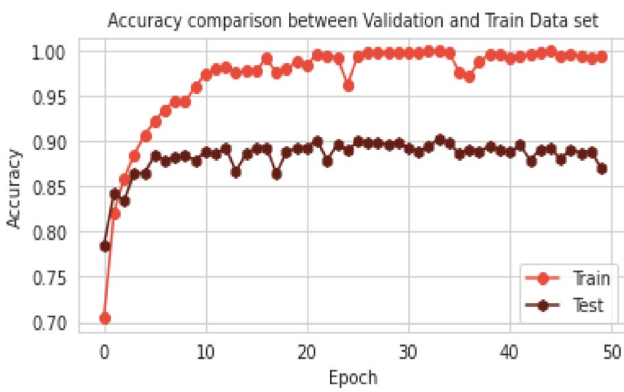


**Fig. 8** Accuracy graph (GADF)

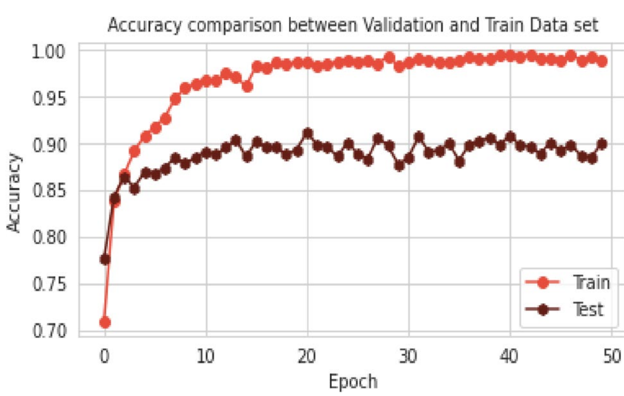


**Fig. 9** Accuracy graph (MTF)

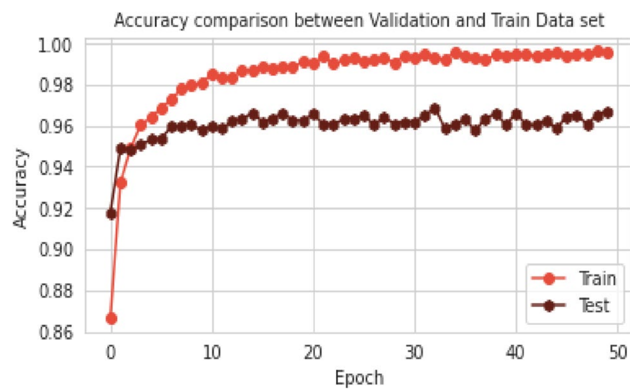


**Fig. 10** Accuracy graph (GASF + GADF + MTF)

The proposed CNN model, utilizing a combination of GASF, GADF, and MTF image encoding techniques, achieved an impressive accuracy of 96.71%, setting a new benchmark for heart arrhythmia classification. This performance exceeds that of several leading techniques documented in the literature, demonstrating the efficacy of our approach.

Among the earlier studies, Chazal et al. (2004) employed a linear discriminant approach (LDA) with ECG signal morphology and beat interval parameters, achieving an accuracy of 86.24%. A similar methodology in a later study by Chazal et al. (2006) resulted in a slightly lower accuracy of 85.9%, using LDA on morphology and heartbeat intervals. Lin et al. (2008) enhanced classification performance by integrating a Morlet wavelet with an adaptive wavelet network, reaching an accuracy of 90%. Melgani and Bazi (2008) and Soria and Martinez (2009) employed SVM and weighted LD classifiers, respectively, achieving accuracies of 91.67% and 90%, emphasizing the significance of feature selection in enhancing model performance.

Kumar and Kumaraswamy (2012) achieved 92.16% accuracy using random forest techniques (RFT) with QRS complex features, indicating the potential of ensemble methods in ECG classification. Similarly, Llamedo and Martínez (2011) employed weighted LD, achieving 93% accuracy with wavelet and VCG features. Their results highlight the effectiveness of combining temporal and morphological features for arrhythmia detection. More recent works, like Sellami and Hwang (2019), who used a CNN with raw waveform data, achieved 88.35% accuracy, underscoring the challenge of directly classifying raw ECG signals without extensive preprocessing. Shi et al. (2019) improved classification to 91.87% by applying a wavelet method with XGBoost, showcasing the power of gradient boosting in time-series analysis.

EHAB ESSA (2021) employed a fusion classifier combining CNN, LSTM, and RRHOS-LSTM, achieving a remarkable 95.81% accuracy, which was one of the highest reported before our study. This approach highlights the potential of hybrid models in capturing both temporal and spatial aspects of ECG signals. However, our model's ability to integrate the strengths of three distinct image encoding techniques (GASF, GADF, and MTF) allowed us to surpass this performance, achieving an accuracy of 96.71%.

In summary, while various approaches have demonstrated significant advancements in heart arrhythmia classification, our proposed method stands out due to its superior accuracy and the innovative use of multiple image encoding techniques. This comprehensive comparison underscores the potential of our model to set new standards in the field, particularly in clinical settings where precision is paramount.

## 5 Conclusion and future work

Using the MIT-BIH Heart Arrhythmia dataset, ECG signals were converted into images to facilitate their classification into five arrhythmia categories. To translate the time series ECG data into graphical formats, three distinct image encoding techniques were employed: GASF, GADF, and MTF. A two-dimensional CNN was trained on images generated by each of these encoding techniques individually, as well as on images produced by concatenating all three techniques. The CNN model achieved its highest accuracy of 96.71% when trained with the concatenated image encoding approach, which combines GASF, GADF, and MTF. Additionally, a comparative analysis of the model's precision, recall, F-score and accuracy was conducted across the different image encoding methods and their concatenated form.

For future work, there are several avenues to enhance the classification and detection capabilities of our model. Firstly, expanding the model to classify a broader range of heart arrhythmia types would significantly increase its utility. Expanding the model's evaluation to include a wider range of datasets beyond the MIT-BIH Heart Arrhythmia dataset would be instrumental in assessing its robustness and generalizability. Potential datasets for consideration include PhysioNet's CinC Challenge datasets, which offer various arrhythmia types and are widely used in ECG research. The ECG-ID Database, which includes ECG signals from multiple individuals and various heart conditions, provides a broader range of arrhythmias. Advanced feature learning algorithms could be employed to further improve classification accuracy. Techniques such as deep autoencoders, transformers, and self-supervised learning can be integrated to enhance feature extraction and representation. For example, applying models pre-trained on comprehensive ECG datasets could aid in transferring learned features and improving task-specific performance. In future efforts, we aim to carry out extensive hyperparameter optimization to enhance the model's effectiveness in arrhythmia detection.

**Author contributions** Tarushi J. Implementation of the work and Writing the Manuscript, Nagamma P. Verification of the work and Reviewing the Manuscript, Prajna B. Revising the Manuscript

**Funding** The study was conducted without any external funding.

**Data availability statement** Access the MIT-BIH Arrhythmia Database at: George Moody, Roger Mark: MIT-BIH Arrhythmia Database. PhysioNet (2005) https://physionet.org/content/mitdb/1.0.0/.

## Declarations

**Conflict of interest** No Conflict of interest relevant to the manuscript have been disclosed by the authors.

**Research involving human and/or animals** Not Applicable

**Informed consent** Not Applicable

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