Deep learning for ECG Arrhythmia detection and classification: an overview of progress for period 2017–2023

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Outlines

- **Introduction**
- **Methods**
- **Medical Background**
    - Arrhythmias
    - Readings of ECG
- **Public Datasets**
- **Deep Learning Techniques**
- **Results and Discussion**
- **Guideline**
- **Conclusion**

Introduction

Introduction

- Electrocardiography (ECG) serves as a crucial tool for identifying and classifying cardiovascular diseases by capturing the heart's electrical activity.
- It is particularly useful for diagnosing conditions like ischemic heart disease, myocardial infarction, arrhythmias, and cardiomyopathy.
- Its analysis offers non-invasive and repeatable monitoring without discomfort to patients, facilitated by cost-effective equipment.
- Challenges include labor-intensive analysis, limited sensitivity to sporadic arrhythmias, placement-dependent accuracy, and susceptibility to noise and artifacts.

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- Challenges include labor-intensive analysis, limited sensitivity to sporadic arrhythmias, placement-dependent accuracy, and susceptibility to noise and artifacts.

Integration of Machine Learning (ML) and Deep Learning (DL) in ECG Analysis

- ML and DL models show promise in enhancing ECG interpretation, potentially enabling continuous monitoring and improving accuracy.
- These models can automate analysis, standardize interpretations, and handle temporal variations in ECG signals, leading to improved detection and classification of arrhythmias.

Introduction

Progress and Challenges in DL-Based Arrhythmia Detection

- DL methods demonstrate significant advancements in detecting various arrhythmias, leveraging their ability to interpret temporal variations in ECG signals.
- Despite progress, challenges remain in the comprehensive survey and analysis of recent DL works, especially in guiding novice researchers.

Introduction

Contributions

- This work presents an introductory tutorial aimed at enabling new researchers to quickly grasp the technical aspects of arrhythmia detection and classification.
- It focuses on superior-performing DL models, provides a compilation of relevant datasets, and establishes guidelines and pipelines tailored for novice researchers.

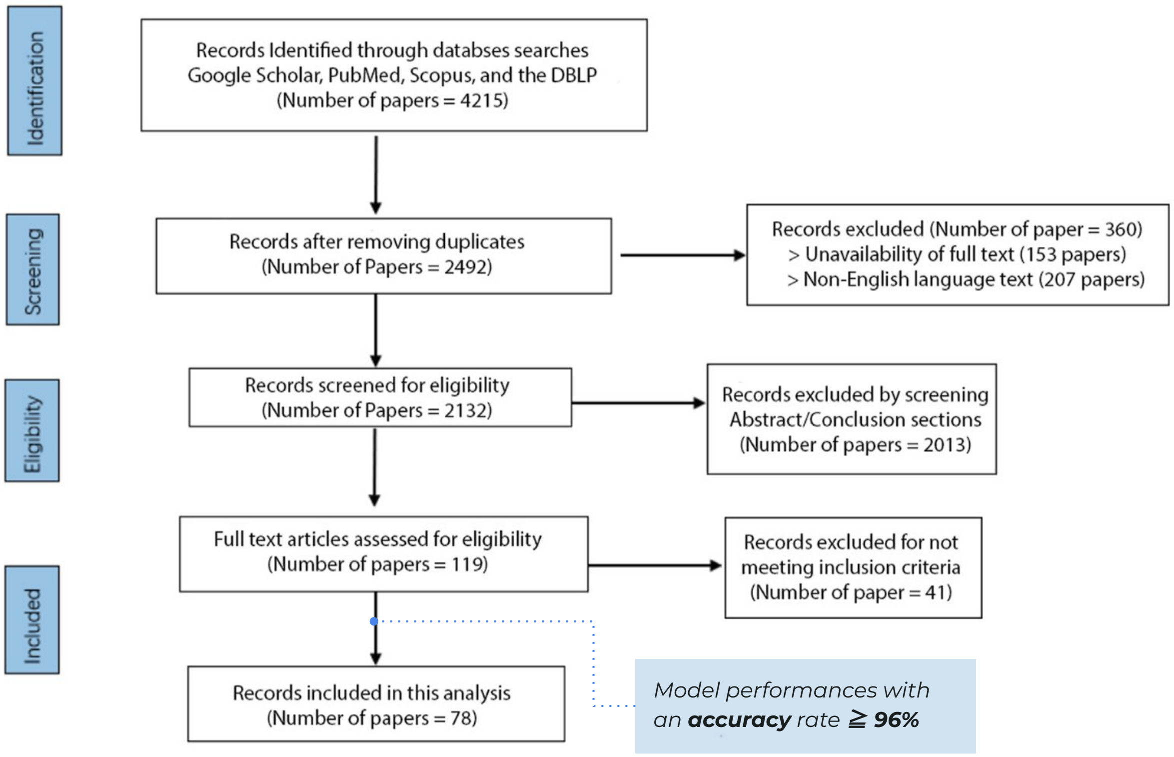
Methods

Methods

The study focused reviewing on studies published from January 2017 to January 2023

Key terms

- “Arrhythmia detection”
- “ECG arrhythmia”
- “Ventricular arrhythmias”
- “Supraventricular arrhythmias”
- “Premature beats”
- “Heart block”
- “Bradycardia”
- “Tachycardia”
- “12-Lead ECG”
- “Cardiac signal processing”
- “Deep learning in ECG”
- “CNN”
- “DNN”
- “LSTM”
- “Transformers”
- “Hybrid models”



Medical Background

Medical Background: Arrhythmias

Normal Sinus Rhythm (NSR)

- Heart rate 60-100 bpm

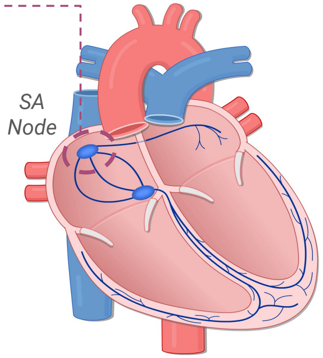


Figure ref. [9]

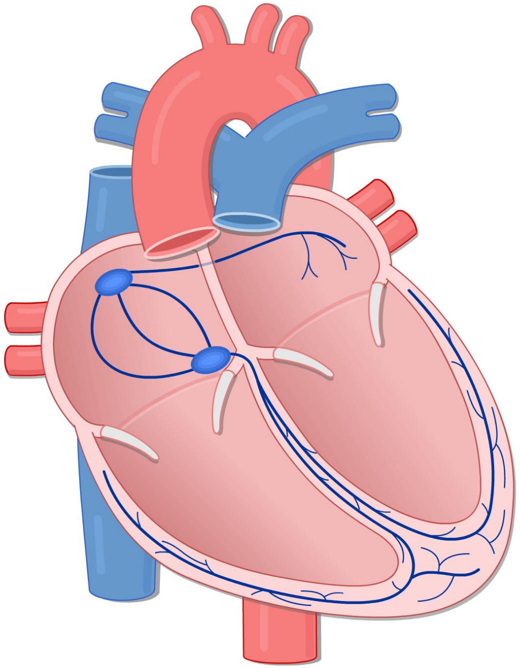
Medical Background: Arrhythmias

Tachyarrhythmias

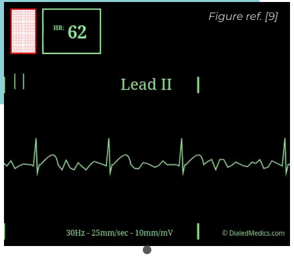
- Supraventricular Tachyarrhythmias
- Ventricular Tachyarrhythmias

Bradyarrhythmias

- Sinus Node Dysfunction
- Atrioventricular (AV) Conduction Disorders



Medical Background: Arrhythmias



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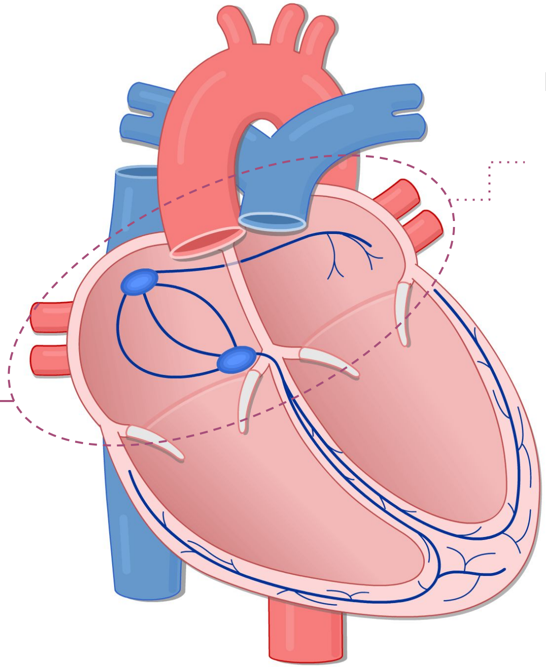
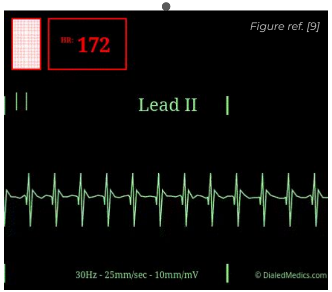


For example,

- Atrial Fibrillation (**AF**)
- Atrial Flutter (**AFL**)
- Paroxysmal Supraventricular Tachycardia (**PSVT**)



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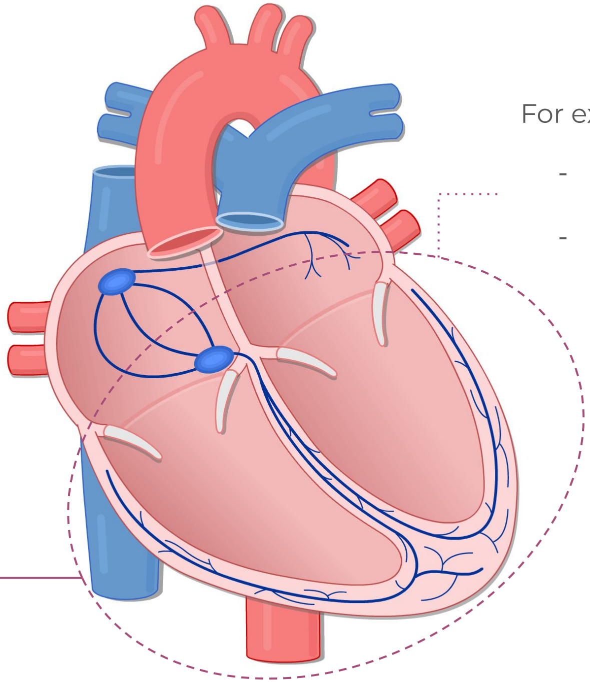
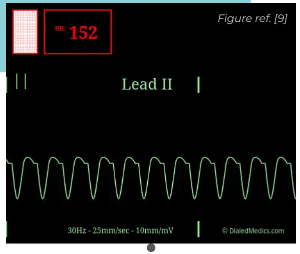
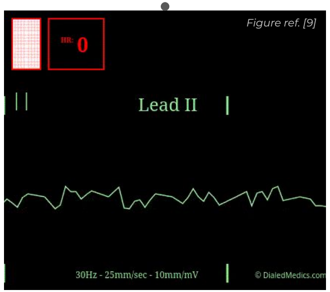




For example,

- Ventricular Tachycardia (**VT**)
- Ventricular Fibrillations (**VF**)



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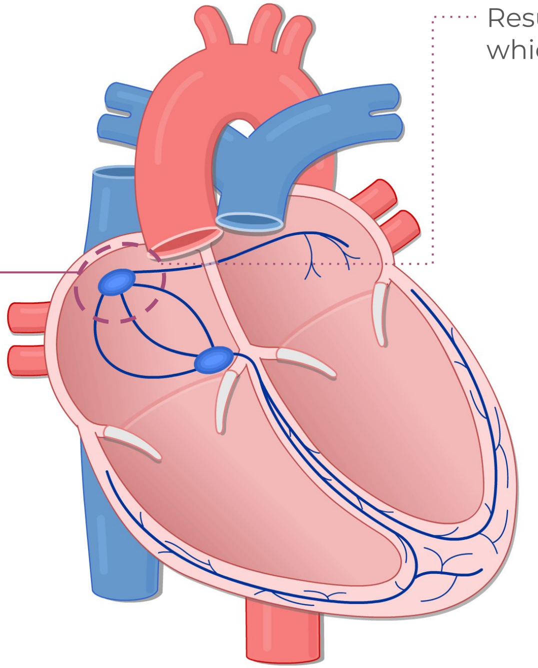
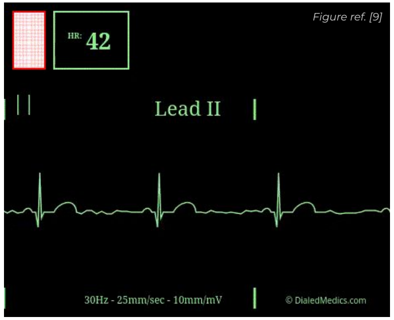


Resulting in slower heart rhythm, which is less than 60 bpm



Medical Background: Arrhythmias

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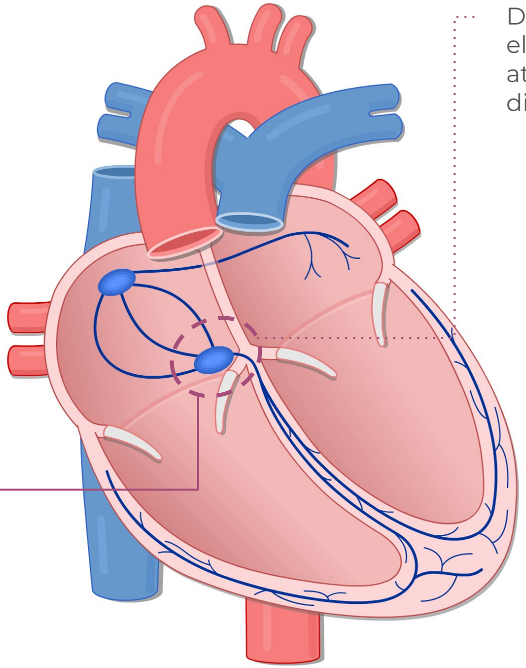


Due to anomalies in the passage of electrical impulses between the atria and ventricles, it can produce different degree of blocks such as

- First degree AV block
- Second degree AV block
- Third degree AV block

Medical Background: Readings of ECG

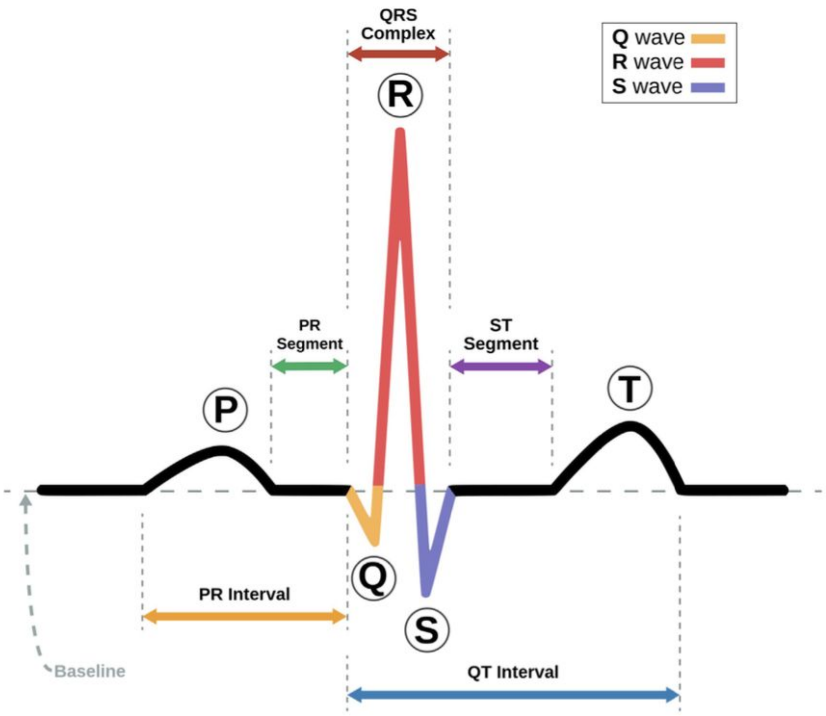
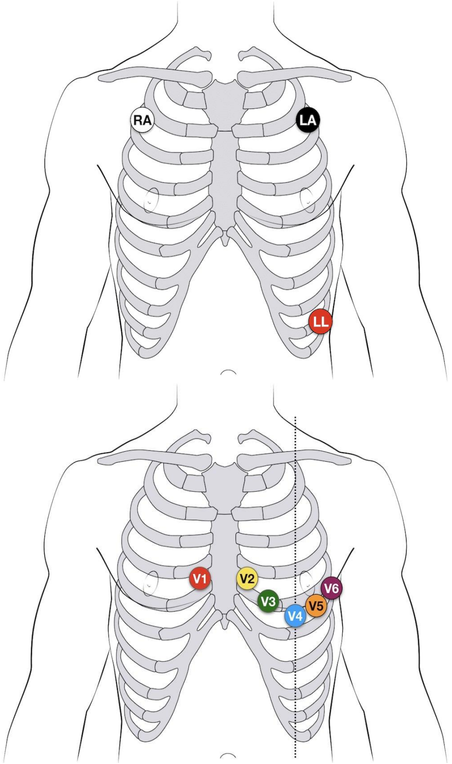
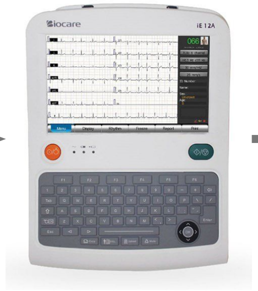


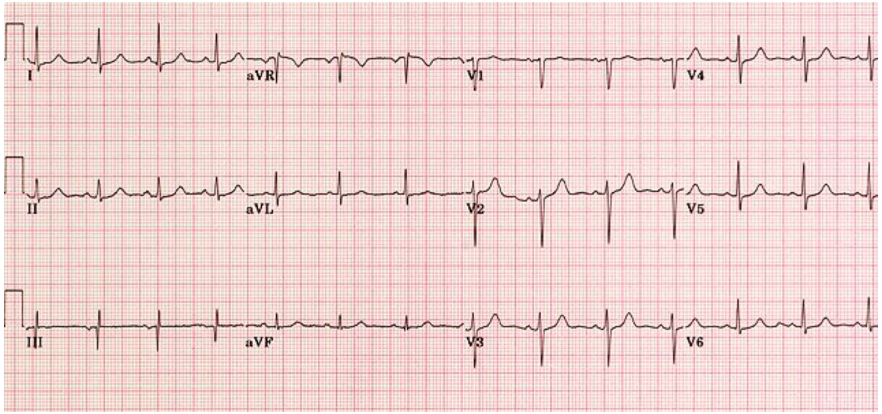
FIGURE 2
Schematic representation of an ECG Signal with its various intervals marked (Adapted with permission from Nayan and Ab Hamid, 2019).

Medical Background: Readings of ECG

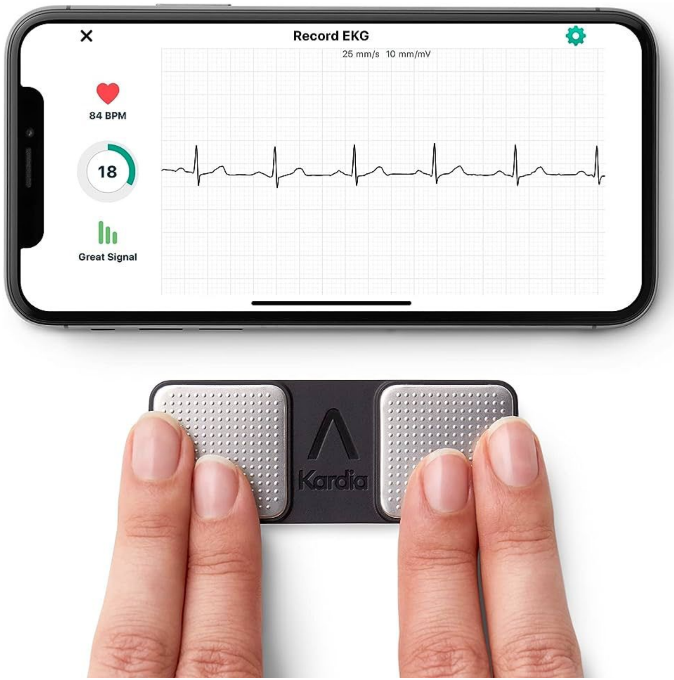


Standard 12-lead ECG





Medical Background: Readings of ECG



Single-lead ECG

Medical Background: Readings of ECG

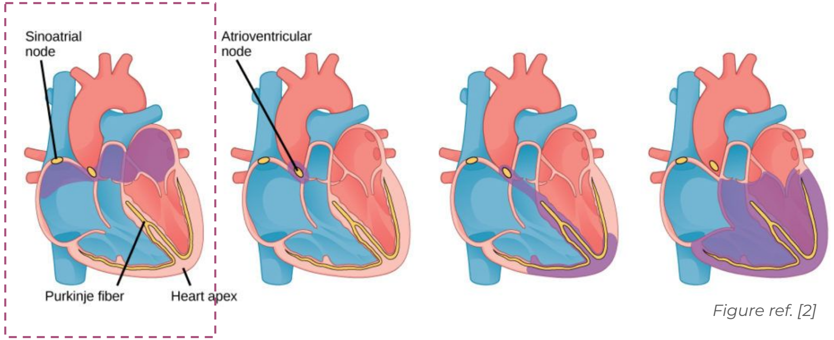
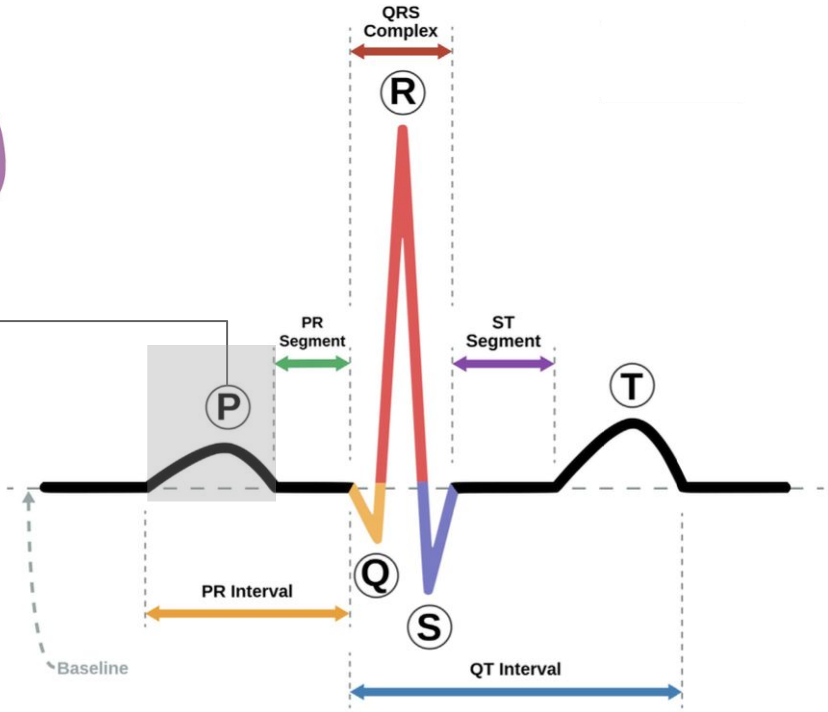


Figure ref. [2]

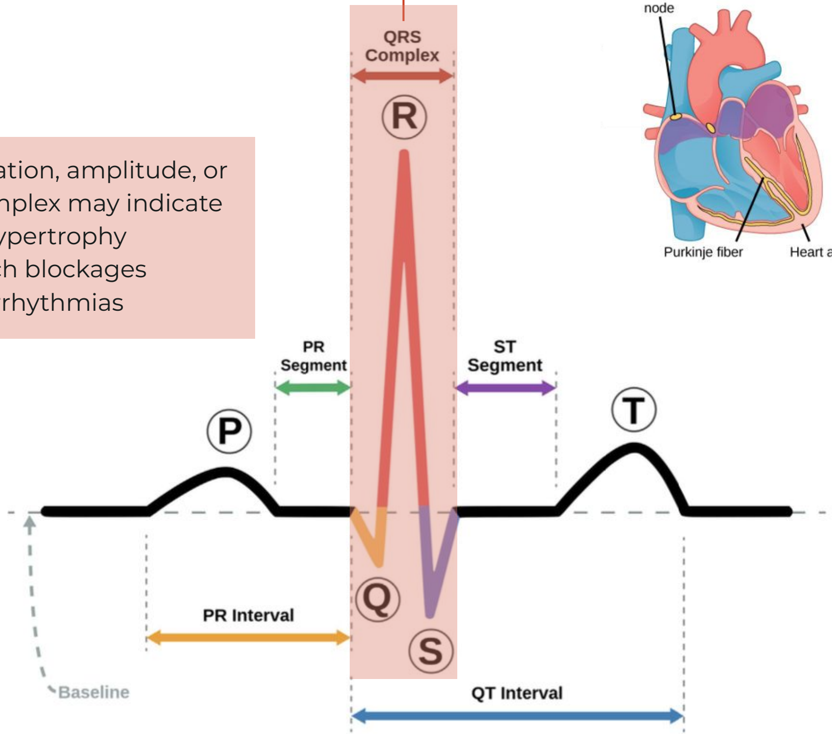
- ***Atrial depolarization***
- *Resulting in atrial contraction and the initiation of ventricular filling*

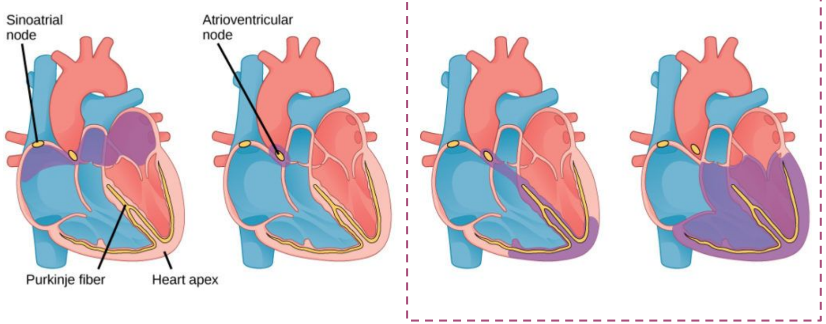
P waveform shape, duration, or amplitude anomalies may indicate conditions including
- Atrial enlargement
- Conduction problems
- Atrial arrhythmias



Medical Background: Readings of ECG

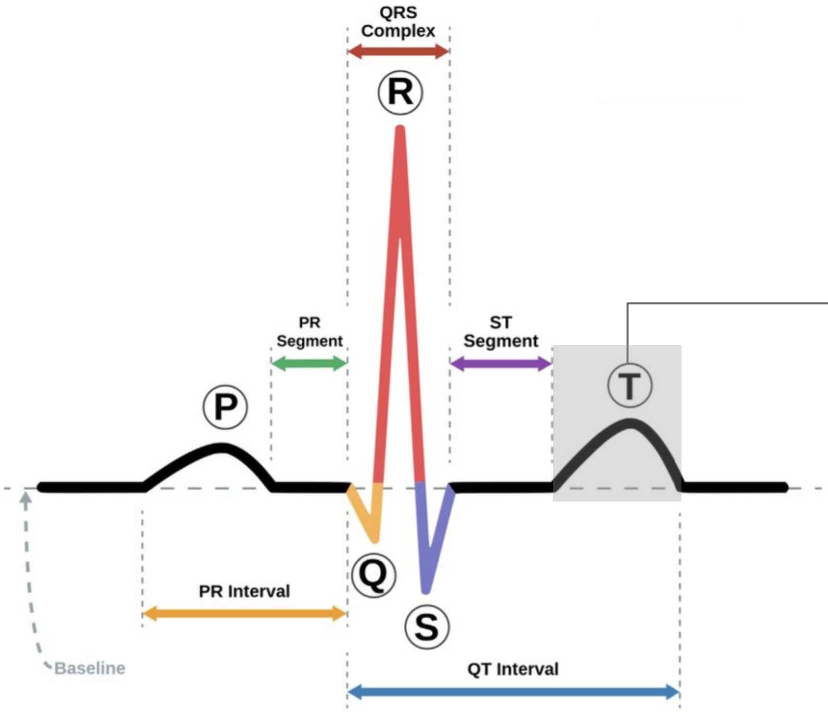
Deviations in the duration, amplitude, or shape of the QRS complex may indicate
- Ventricular hypertrophy
- Bundle branch blockages
- Ventricular arrhythmias

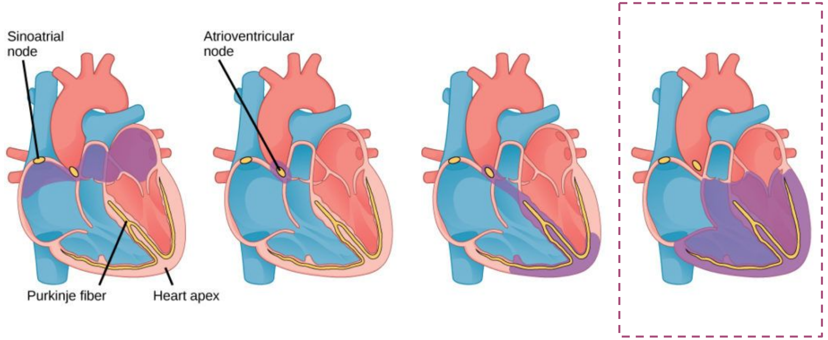




- ***Ventricular depolarization***
- *Resulting in ventricular contraction, or pumping blood out of the ventricles*

Medical Background: Readings of ECG



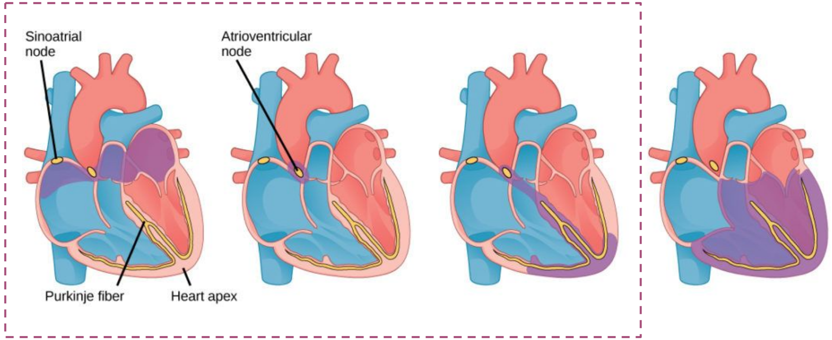


- ***Ventricular repolarization*** *in order to return its resting conditions*

T wave shape, amplitude, or duration changes may suggest

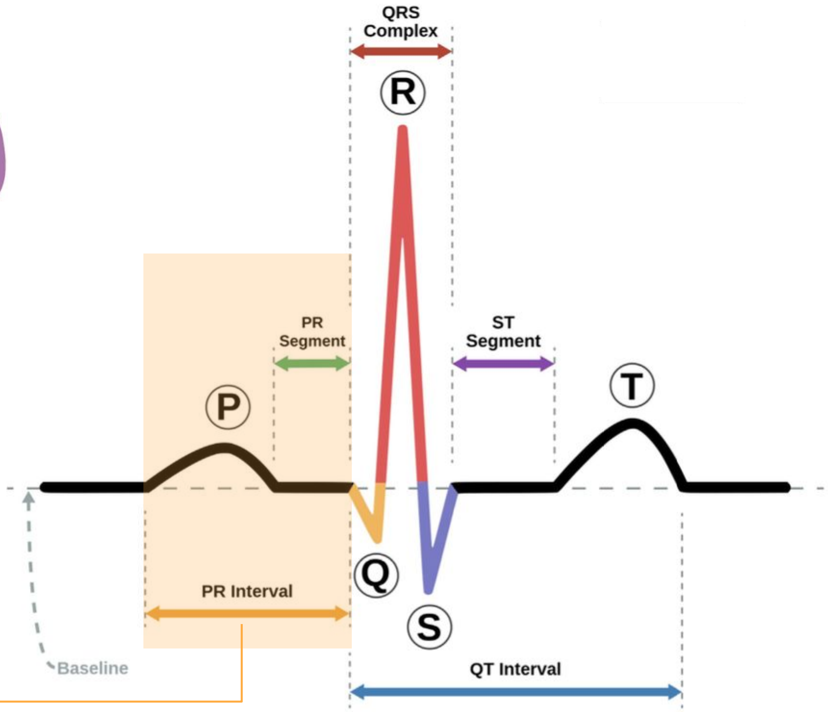
- Myocardial ischemia
- Electrolyte imbalances
- Drug effects

Medical Background: Readings of ECG

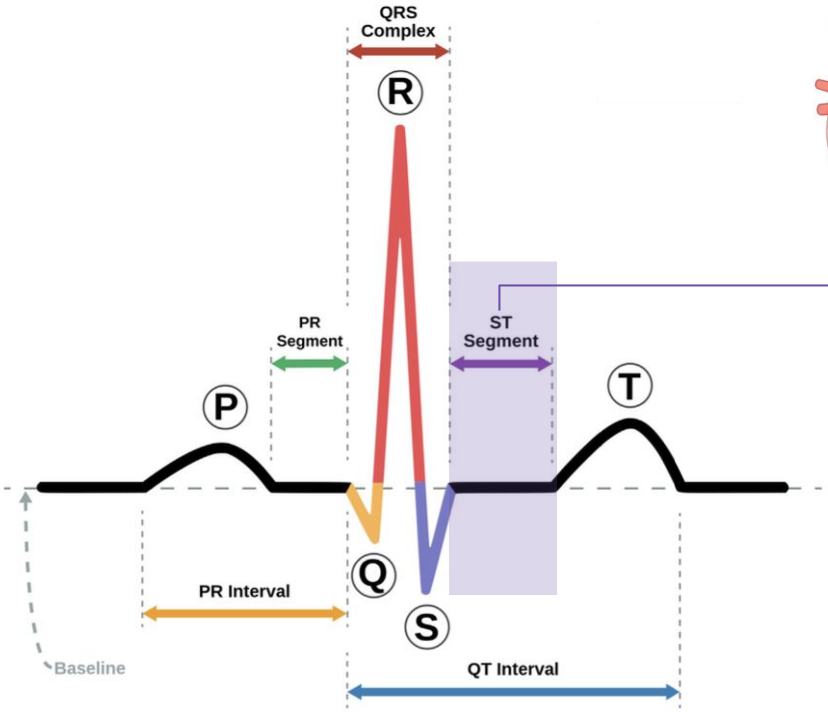


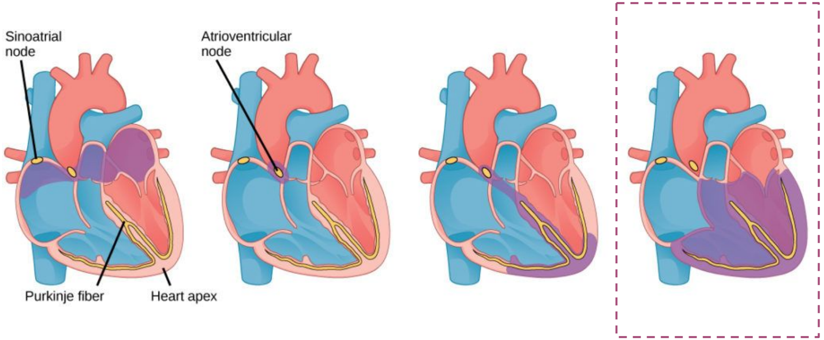
- *PR interval represents the time necessary to initiate atrial depolarization, atrioventricular conduction, and ventricular depolarization*

Prolonged PR intervals might indicate
- AV conduction delays or AV blocks.



Medical Background: Readings of ECG

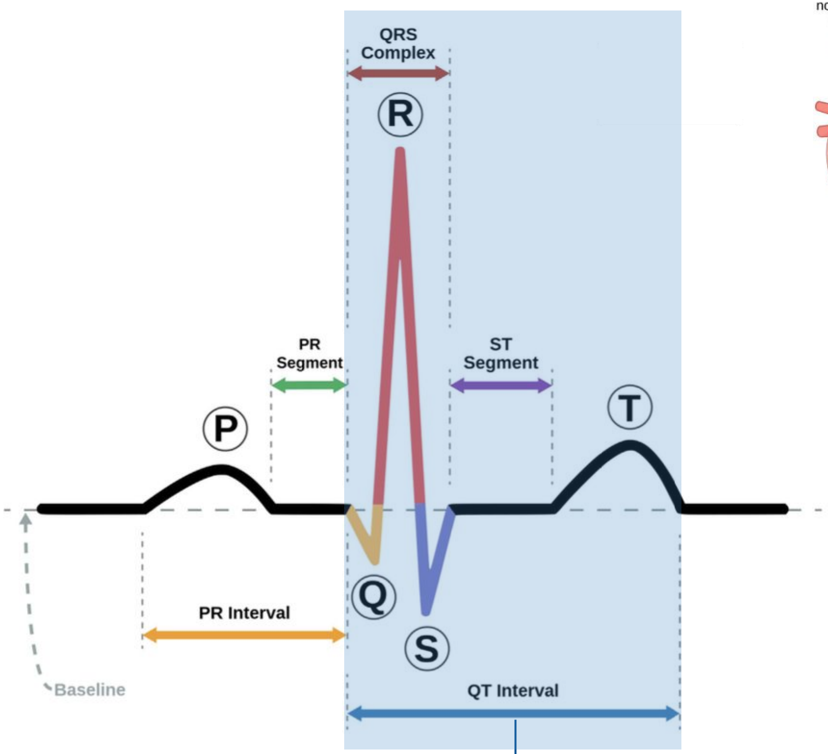


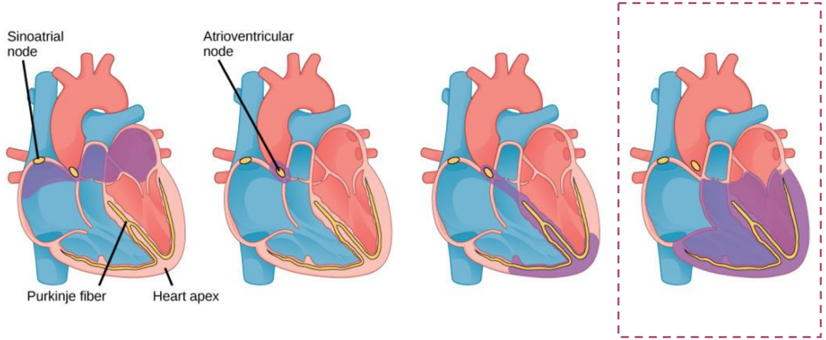


- *ST segment stands for the time elapsed between depolarization (QRS) and repolarization (T-wave) of ventricles.*

Changes in the ST segment, such as elevation or depression, might provide important information about myocardial ischemia or damage.

Medical Background: Readings of ECG





- *QT interval denotes the whole period of ventricular contractions*

QT prolongation can increase the risk of ventricular arrhythmias, which could lead to death.

Public Databases

Datasets

Annotation types coresponding to cardiac events and conditions	Notable	Databases	Records	Leads	Time	Source
Atrial Fribillation (AF)	*The standard dataset*	Long-Term AF Database (LTAFDB)	84 records	2	24–25 h each	Boston's Beth Israel Deaconess Medical Center
Atrial Fribillation (AF)	*The standard dataset*	MITBIH Atrial Fibrillation Database	25 records	2	10 h each	Massachusetts Institute of Technology (MIT) + Boston's Beth Israel Deaconess Medical Center
Ventricular arrhythmias	*The standard dataset*	MIT BIH Malignant Ventricular Ectopy Database	22 records	2	30 min each	Massachusetts Institute of Technology (MIT) + Boston's Beth Israel Deaconess Medical Center
Ventricular arrhythmias	*The standard dataset*	Sudden Cardiac Death Holter Database (SCDDB)	23 records	2–3	24–48 h each	Boston area hospitals
Ventricular arrhythmias	*The standard dataset*	The Creighton University Ventricular Tachyarrhythmia Database (CUDB)	35 records	1	8 min each	Creighton University Cardiac Center
Normal Sinus Rhythm (NSR)	*The standard dataset*	MIT BIH Normal Sinus Rhythm Database	18 records	2	24 h each	Massachusetts Institute of Technology (MIT) + Boston's Beth Israel Deaconess Medical Center
Normal Sinus Rhythm (NSR)	*The standard dataset*	Normal Sinus Rhythm RR Interval Database (NSRDB)	18 records	NA	24 h each	Washington University School of Medicine + Columbia-Presbyterian Medical Center
Multiclass arrhythmias with *multiclass labels*	*- Arrhythmia detection* *- Automated diagnosis of heart conditions* *- Signal qaulity assessment* *- Anormaly detection*	China Physiological Signal Challenge 2018 (CPSC 2018)	6,877 records	12	6–60 s each	11 hospitals across China
Multiclass arrhythmias		PTB Diagnostic ECG Database	549 records	12	10 s each	Physikalisch-Technische Bundesanstalt (PTB), the National Metrology Institute of Germany
Multiclass arrhythmias	*The dataset is widely used for **its large number of data points and patient pool***	Georgia 12-Lead ECG Challenge Database (GA12ECG)	20,672 records	12	5–10 s each	Emory University, Atlanta, Georgia, United States of America
Multiclass arrhythmias	***Is the most utilized** for detecting and classifying arrhythmia*	**MIT-BIH Arrhythmia Database**	48 records	3	23–48 s each	Massachusetts Institute of Technology (MIT) + Boston's Beth Israel Deaconess Medical Center
Multiclass arrhythmias	*The standard dataset*	St Petersburg INCART 12-lead Arrhythmia Database (INCARTDB)	32 records	12	30 min each	St. Petersburg Institute of Cardiological Technics (Incart), St. Petersburg, Russia
Multiclass arrhythmias	*The standard dataset*	The PhysioNet Computing in Cardiology Challenge 2017 (AFDB)	12,186 records	1	30–60 s each	Compiled by PhysioNet aliveCor healthcare device
Supraventricular arrhythmia (SVT)	*The standard dataset*	MIT-BIH Supraventricular Arrhythmia Database (SVDB)	78 records	3	30 min each	Massachusetts Institute of Technology (MIT)
ST and T-wave change	*The standard dataset*	European ST-T Database	90 records	2	2 h each	CNR Institute for Clinical Physiology + European Society of Cardiology
Arrhythmia detector assessment in noisy settings	*The standard dataset*	MIT-BIH Noise Stress Test Database (NSTDB)	12 records	2	30 min each	Massachusetts Institute of Technology (MIT) + Boston's Beth Israel Deaconess Medical Center
Presence of Apnea	*The standard dataset*	Apnea-ECG Database	70 records	1	7–10 h each	Phillips-University, Marburg, Germany

Datasets

The Association for the Advancement of Medical Instrumentation (AAMI) recommends training and detecting _only a few types of arrhythmia_ by using these 15 classes, which are classified then into five superclasses.

These 15 classes

- *(Nou.) Normal Beat*
- *(L) Left Bundle Branch Block Beat*
- *(R) Right Bundle Branch Block Beat*
- *(e) Atrial Escape Beat*
- *(j) Nodal (Junctional) Escape Beat*
- *(A) Atrial Premature Beat*
- *(a) Aberrated Atrial Premature Beat*
- *(J) Nodal (Junctional) Premature Beat*
- *S Supraventricular Premature Beat*
- *(V) Premature Ventricular Contraction*
- *(E) Ventricular Escape Beat*
- *(F) Fusion of Ventricular and Normal Beat*
- *(Pou) Paced Beat*
- *(f) Fusion of Paced and Normal Beat*
- *(U) Unclassified Beat*

TABLE 2 Classes of ECG Signals used to training.

Superclasses				
Normal (N)	**SupraVentricular Ectopic Beat (SVEB)**	**Ventricular Ectopic Beat (VEB)**	**Fusion Beat (F)**	**Unknown Beat (Q)**
(Nou.) Normal Beat	**(A)** Atrial Premature Beat	**(V)** Premature Ventricular Contraction	**(F)** Fusion of Ventricular and Normal Beat	**(Pou)** Paced Beat
(L) Left Bundle Branch Block Beat	**(a)** Aberrated Atrial Premature Beat	**(E)** Ventricular Escape Beat		**(f)** Fusion of Paced and Normal Beat
(R) Right Bundle Branch Block Beat	**(J)** Nodal (Junctional) Premature Beat			**(U)** Unclassified Beat
(e) Atrial Escape Beat	**S** Supraventricular Premature Beat			
(j) Nodal (Junctional) Escape Beat				

Deep Learning Techniques

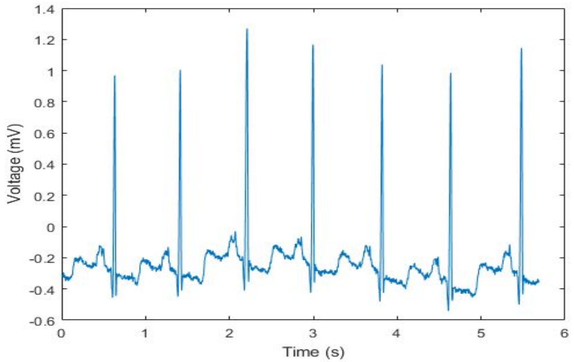
Deep Learning Techniques

- Multilayer Perceptron (MLP)
- Convolutional Neural Network (CNN)
- Recurrent Neural Network (RNN)
- Long Short-Term Memory (LSTM)
- Gated Recurrent Unit (GRU)
- Deep Belief Network (DBN)
- Transformer

Deep Learning Techniques

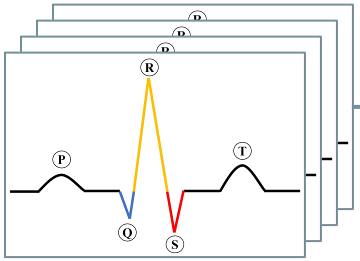
- Input data

A fixed-length segment



OR

Heartbeat segments



DL models

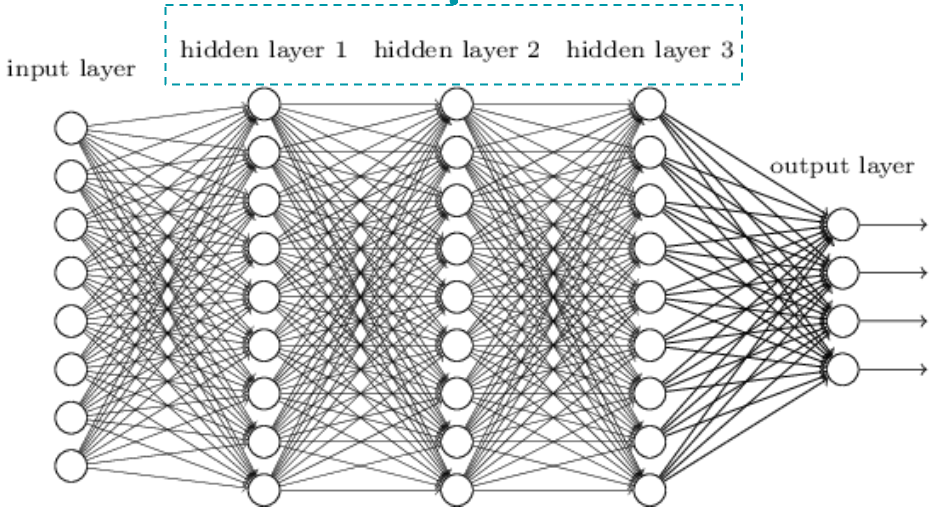
- Output

(N) *Normal Beat*
(SVEB) *SupraVentricular Ectopic Beat*
(VEB) *Ventricular Ectopic Beat*
(F) *Fusion Beat*
(Q) *Unknown Beat*

Deep Learning Techniques

- Multilayer Perceptron (MLP)

The model can capture complex patterns related to various arrhythmias because *the hidden layers learn to extract higher-level representations and patterns* from the input data.



Deep Learning Techniques

- Convolutional Neural Network (CNN)

They are fit at identifying spatial hierarchies or patterns using stacked *trainable small filters called kernels,* which these kernels may *effectively extract local information from the context of ECG data*, such as the shape and duration of heartbeats.

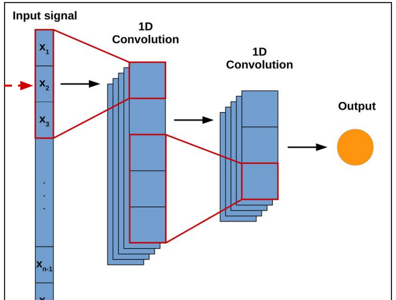
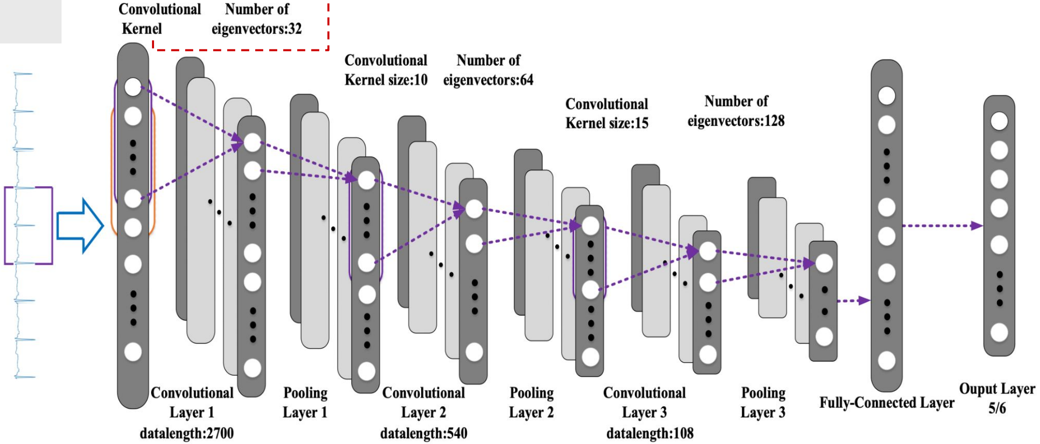


Figure ref. [4]



1D Conventional Neural Network | Figure ref. [3]

Deep Learning Techniques

- Recurrent Neural Network (RNN)

The network is equipped with *feedback mechanisms* that are fit to *capture temporal correlations from time series data*, which are exceptionally well suited for ECG analysis, where the sequential nature of cardiac rhythms is essential for spotting anomalies.

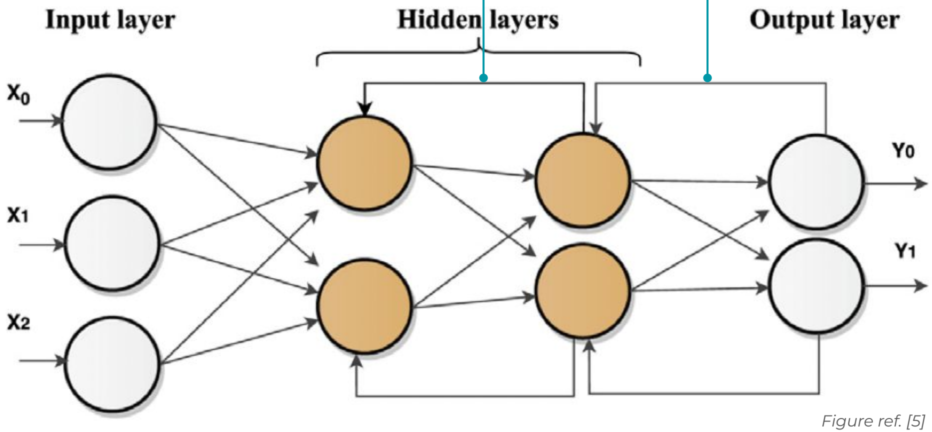


Figure ref. [5]

Deep Learning Techniques

- Long Short-Term Memory (LSTM)

LSTMs present *Memory cells* that *retain information and Gates that govern the flow of information into and out of these cells*, which these gates allow LSTMs to learn and retain longer sequences.

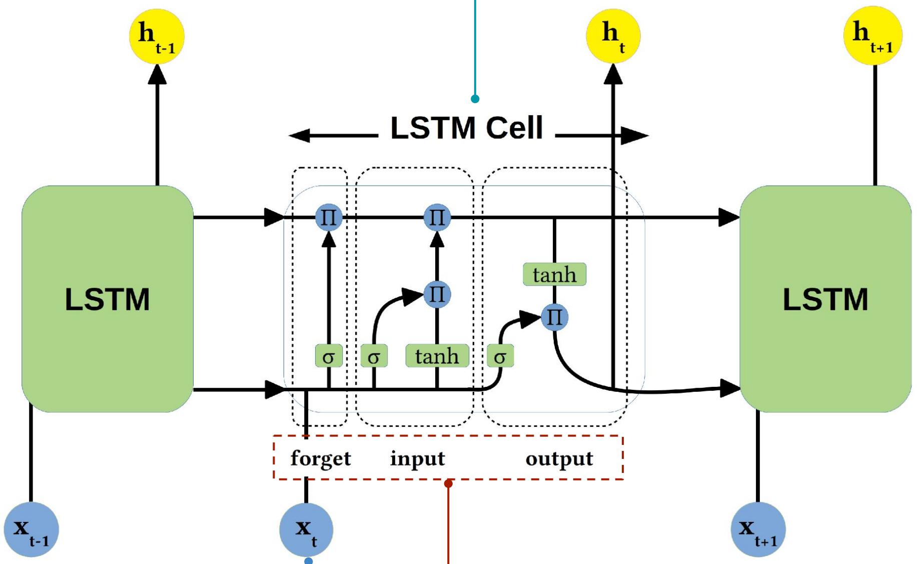


Figure ref. [4]

Deep Learning Techniques

- Gated Recurrent Unit (GRU)

GRUs, which distinguish themselves from LSTMs by their _update_ and _reset gates_, manage the flow of information by *selectively remembering pertinent information and discarding*.

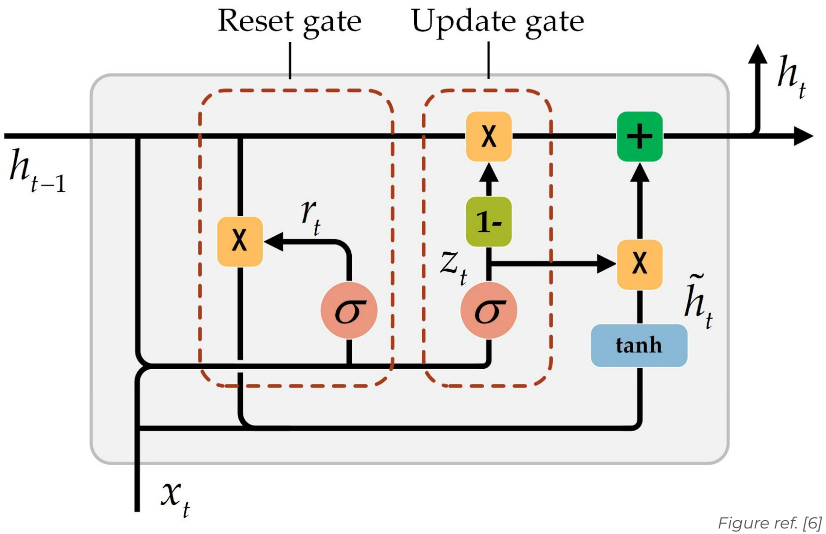


Figure ref. [6]

Deep Learning Techniques

- Deep Belief Network (DBN)

- DBN comprises several layers of latent variables or 'hidden units', which are *typically made up of [Restricted Boltzmann Machines (RBMs)]* by creating overlapping stacks of the RBM models since the hidden layer of one model is the visible layer of the next one.

- DBNs help *develop robust and discriminative models* by discovering complex patterns inside datasets using *the probabilistic model*, which enables them to generate top-down models.

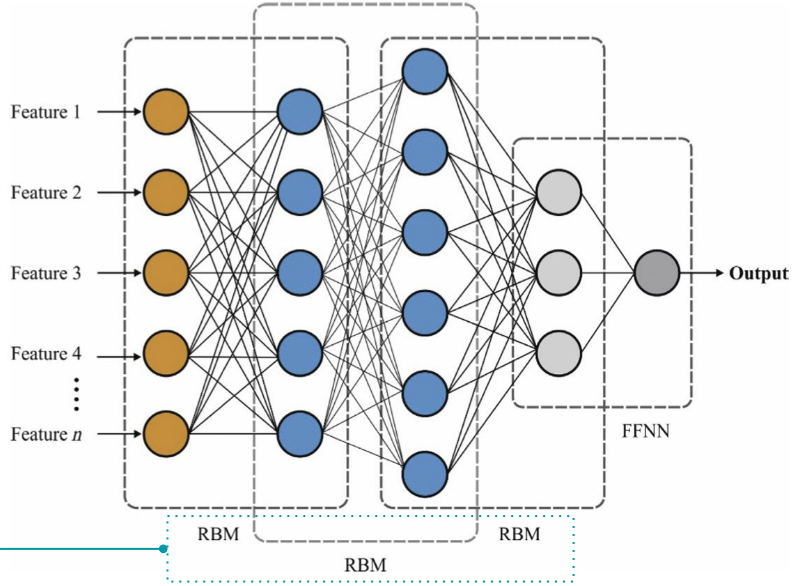


Figure ref. [7]

Deep Learning Techniques

- Transformer

Transformers employ *self-attention mechanisms* to *learn complicated patterns and connections within time-series data*, which allows the model to assess both local and global patterns at the same time.

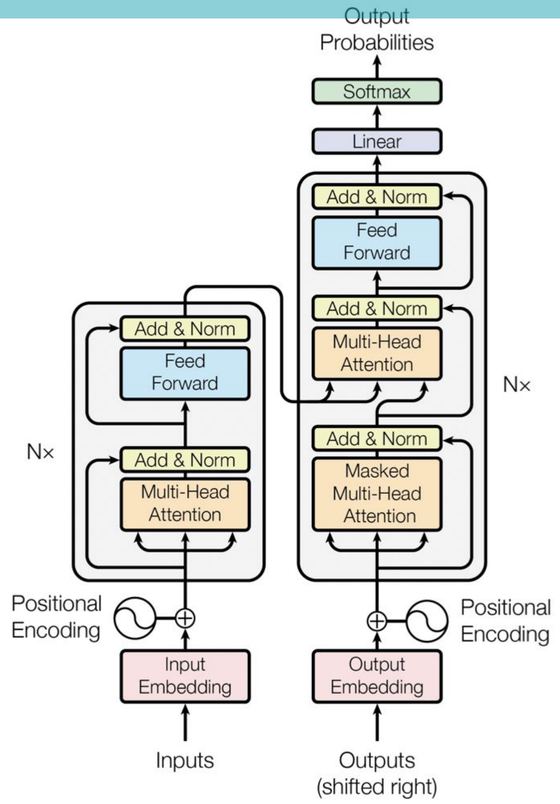


Figure ref. [8]

Deep Learning Techniques

To be summarized...

Deep Learning Methods	Distinctive features	Limitations
Multilayer Perceptron (MLP)	Pattern recognitions	Lack of temporal connections
Convolutional Neural Network (CNN)	Pattern recognitions	Lack of long-term dependency due to a fixed receptive field size
Recurrent Neural Network (RNN)	Temoral connections	Lack of long-term dependency probplem due to the vanishing gradient
Long Short-Term Memory (LSTM)	Long-term dependencies in the temporal data	Computationally more expensive than straightforward models like RNNs or MLPs
Gated Recurrent Unit (GRU)	Long-term dependencies in the temporal data	Computationally more expensive than straightforward models like RNNs or MLPs
Deep Belief Network (DBN)	Pattern recognitions	Requires huge data to perform better techniques and much computation
Transformer	Pattern recognitions and long-term dependencies	Less simple, require much computation, and need different hyperparameters to adjust

Results and Discussion

Results and Discussion

TABLE 3 Summary of deep learning models for ECG arrhythmia detection and classification.

Study	Database	# Cl	Classifier	Acc (%)	Se (%)	Sp (%)
Luo et al. (2017)	MIT-BIH	4	DNN-SDA	98.80	71.40	99.80
Majumdar and Ward (2017)	MIT-BIH	4	SVM-RBF	97.00	100.0	90.12
Zhang et al. (2017)	MIT-BIH	5	RNN	99.40	97.60	99.70
Xia et al. (2017)	MIT-BIH	3	CNN	98.63	98.79	97.87
Nguyen et al. (2018)	CUDB MIT-BIH (VFDB)	2	FCN	99.26	97.07	99.44
Jun et al. (2018)	MIT-BIH	4	2D CNN	99.05	99.57	97.85
Yildirim (2018)	MIT-BIH	4	Bi-directional LSTM	99.39	95.66	98.11
Sannino and De Pietro (2018)	MIT-BIH	4	DNN	99.68	99.48	99.83
Faust et al. (2018)	MIT-BIH	5	BiLSTM	98.51	98.32	98.67
Xia and Xie (2019)	MIT-BIH	4	1D CNN + Active Learning	99.20	95.73	98.73
Lui and Chow (2018)	MIT-BIH	4	ML-CNN	96.00	95.40	97.37
Xia et al. (2018)	MIT-BIH Wearable Device	4	DNN	99.80	99.40	99.90
Wang et al. (2019)	MIT-BIH	2	GRNN	97.40	86.70	98.30
Hanbay (2019)	MIT-BIH	4	DNN	96.40	86.41	96.41
Wang and Zhou (2019)	BIDMC-CHF + MIT-BIH NSR + Fantasia	5	LSTM	99.22	99.22	99.72
Chen et al. (2020)	MIT-BIH	4	CNN-LSTM	99.32	97.50	98.70
Fu et al. (2020)	PTB	6	CNN-BiGRUt	99.11	99.02	98.23
Sharma et al. (2021)	MIT-BIH	5	SVM + FFBPNN	98.53	98.24	95.68
Ojha et al. (2022)	MIT-BIH	4	CNN-SVM	99.53	98.24	97.58
Sepahvand and Abdali-Mohammadi (2022)	Chapman ECG DB	12	Distilled Models	98.15	97.11	98.45
Midani et al. (2023)	MIT-BIH	5	CNN + BiLSTM	99.46	97.01	99.57
Kumar et al. (2023)	MIT-BIH	5	Fuzz-ClustNet	98.66	98.92	93.88

TABLE 4 F1-scores of deep learning models for ECG arrhythmia detection and classification.

Study	Database	# Cl	Classifier	F1-Score(%)
Luz et al. (2016)	MIT-BIH	5	GRNN	99.00
Sujadevi et al. (2017)	MIT-BIH	4	GRU	99.99
Faust et al. (2018)	MIT-BIH	5	BiLSTM	98.00
Tan et al. (2018)	Fantasia + INCARTDB	2	CNN-LSTM	99.52
Xiang et al. (2018)	MIT-BIH	8	1D CNN	99.99
Hammad et al. (2020)	MIT-BIH	5	DNN	95.30
Mahmud et al. (2020)	MIT-BIH	5	1D CNN	99.10
Ullah et al. (2020)	MIT-BIH	8	2D CNN	98.00
Peimankar and Puthusserypady (2021)	QT DB	4	CNN-LSTM	99.56
Islam et al. (2022)	MIT-BIH	5	BiGRU + BiLSTM	98.41
Hong et al. (2022)	MIT-BIH	4	ECG Delineator	96.11
Zahid et al. (2022)	MIT-BIH	5	1D Self ONN	99.51
Kim et al. (2022)	MIT-BIH	5	ResNet + BiLSTM	99.20
Sepahvand and Abdali-Mohammadi (2022)	Chapman ECG DB	12	Distilled Models	97.55
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Results and Discussion

Accuracy *assesses overall model performance*

Sensitivity *measures the ability to detect arrhythmias accurately*

Specificity *indicates the ability to avoid incorrect diagnoses*

Together, these metrics offer a nuanced evaluation ensuring balanced performance across all categories.

F1 scores *provide a balanced assessment of model performance, revealing effectiveness in identifying and classifying arrhythmias.*

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Results and Discussion

Results and Discussion: Deep Learning Techniques analysis

- CNNs are typically preferred for ECG due to strong feature extraction, while RNNs fit time series nature.
- Transformers with attention mechanisms signify significant progress in DL models.
- Hybrid DL models, especially with transformers, outperform shallow ones, using CNNs for initial extraction and transformers/RNNs for precise features.
- Hybrid models improve accuracy but raise computational complexity.
- Trends include combining Vision Transformers and MLPMixer with traditional models.
- Interpretable DL models are crucial for clarity in ECG classification.
- Integrating DL with AI frameworks like active learning enhances diagnostic accuracy.
- Systematic optimization of DL architectures and hyperparameters boosts efficiency.
- Challenges include mapping complexity and data scarcity in increased categories.
- Constant innovation and optimization are key to advancing ECG arrhythmia classification.

Results and Discussion: Arrhythmia Data analysis

- Intertextual analysis of literature reveals insights into current research directions and limitations, focusing on data quality, public ECG database use, and data imbalance.
- Data quality is essential for robust classification, emphasizing the need for diverse training data.
- Reliance on public ECG datasets has limitations, requiring more diverse samples.
- Rising model complexity demands comprehensive ECG data for practical training.
- Merging data from multiple databases is crucial but necessitates careful evaluation.
- Imbalance in data categories is a significant hurdle, addressed by augmentation and focal loss.
- Acquiring new data in abnormal categories is practical but poses challenges.
- Arrhythmia detection and classification involve a complex multiclass task.
- Studies use databases like MIT-BIH, CUDB, and AFDB for classification and detection of significant arrhythmias.
- PhysioNet/CinC Challenge datasets classify AF, NSR, and other rhythms considering noise.
- Patient-specific characteristics impact arrhythmia types, emphasizing tailored methodologies.
- A broader perspective highlights the multifaceted nature of arrhythmia classification research, emphasizing the need for customized solutions.
- Insights illustrate complexities, indicating areas for further research and innovation.

Guideline

Database selection stage

- Use the standard MIT-BIH database, allowing for impartial comparisons with previous studies.
- Examine the model's generalization capabilities by including the INCART database into the assessment procedure

Preprocessing stage

- Use standard signal filtering techniques to permit direct comparisons with current literature.
- Employ the unfiltered raw signal as the ground truth to correctly assess the model's performance.

Segmentation stage

- Introduce variability to the R-location annotation during the assessment process to evaluate the model's resilience.

Feature extraction stage

- Utilize state-of-the-art feature selectors to extract salient features
- The use of class-oriented feature selection can provide useful insights into selecting significant features for various forms of arrhythmias

Classification stage

- Implement a k-fold cross-validation training pipeline to ensure unbiased model training.
- Address dataset imbalances associated with certain heartbeat types by using data augmentation techniques.

Evaluation stage

- Employ standardized metrics to enable fair and unbiased comparisons between the proposed methodology and existing literature.

Conclusion

DL algorithms show promise for ECG arrhythmia detection, with potential for clinical use. The review in this study offers tailored suggestions for novice researchers, highlighting the importance of exploring diverse ECG databases, developing integrated DL models, and facilitating adoption in clinical practice.

Next Presentation

As mentioned previously in the discussion part that CNNs are traditionally favored for ECG detection and classification, next presentation would be provided regarding an application of the CNN-based architecture utilizing Transfer learning technique to detect AF, which is the most common heart arrhythmia.

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