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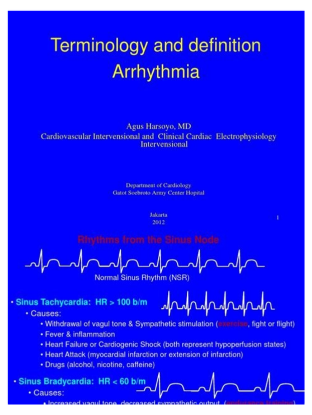
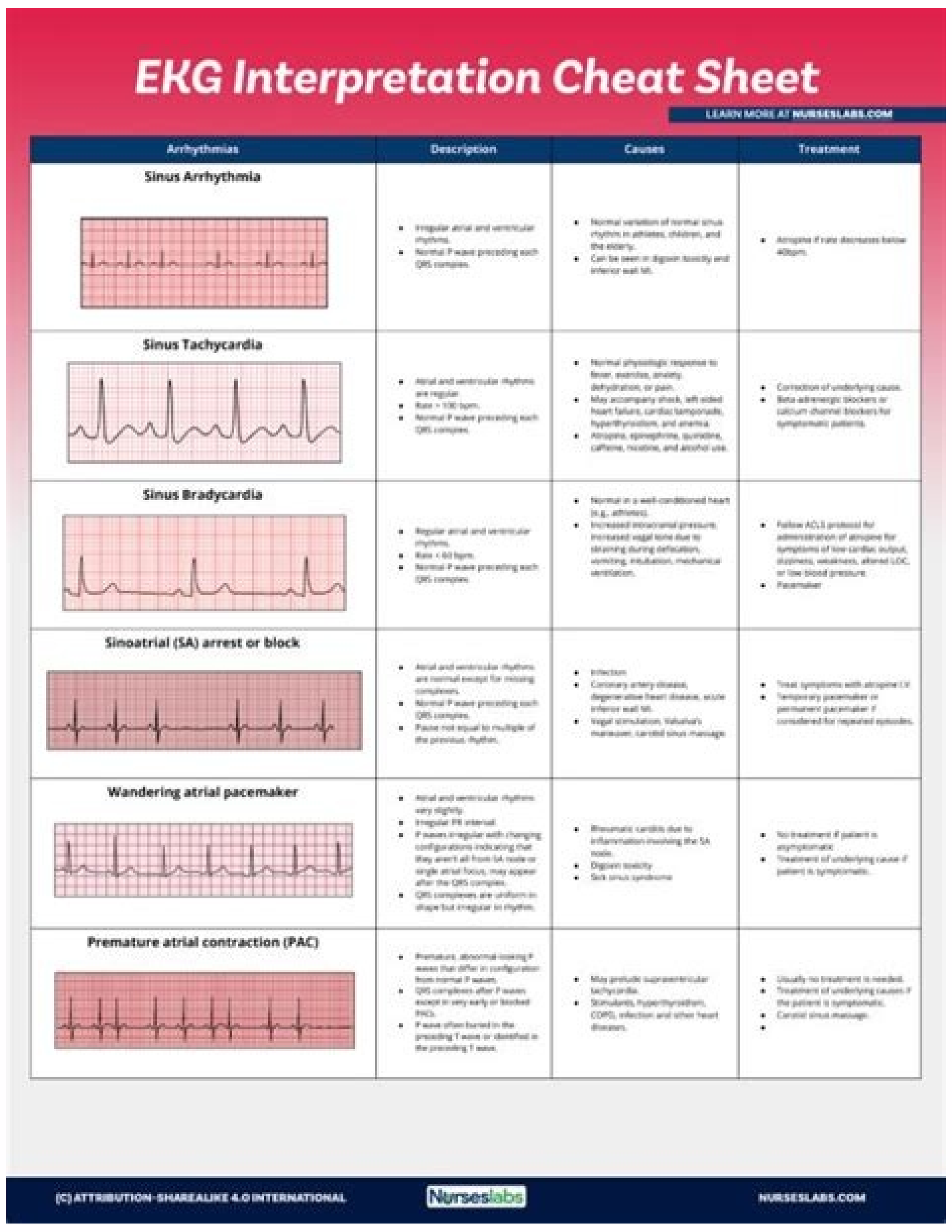

Terminology and definition
Arrhythmia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Arrhythmias
Description
Causes
Treatment
Sinus Arrhythmia
Sinus Tachycardia
Sinus Bradycardia
Sinoatrial (SA) arrest or block
Wandering atrial pacemaker
Premature atrial contraction (PAC)
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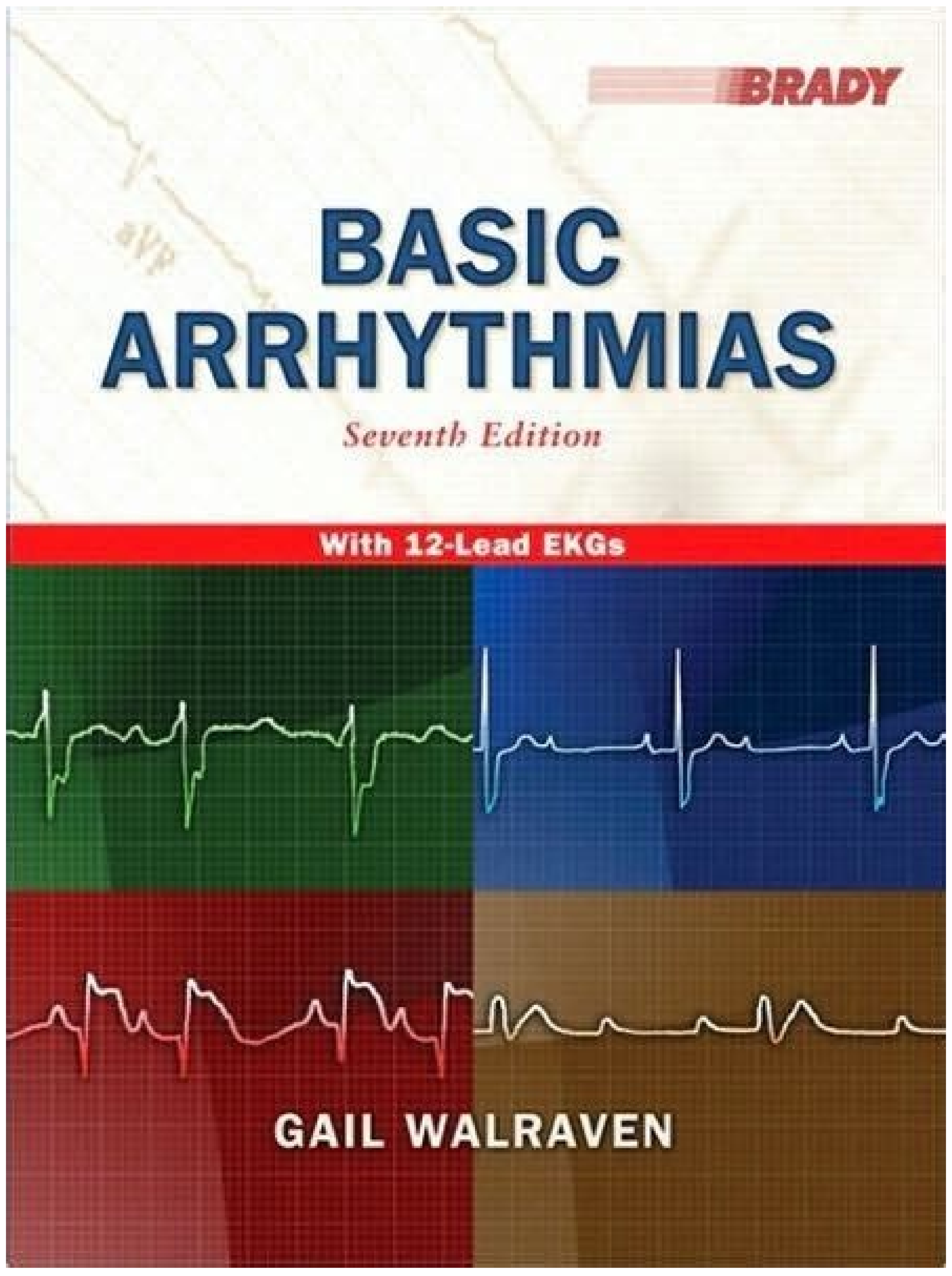
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Sinus P before QRS, then T	Morphing P; hidden, lost in T	Inverted P; before, during/hidden, after QRS
Normal Sinus Rhythm ☐ Regular 60-100 bpm ☐ P Wave: normal upright ☐ PRI: 0.12-0.20s ☐ QRS: <0.12s	**Wandering Pacemaker** ☐ Slightly irregular 60-100 bpm ☐ P Wave: morphology changes, difficult to see, change every complex ☐ PRI: 0.12-0.20s, changes every complex ☐ QRS: <0.12s	**Premature Junctional Contraction** ☐ Underlying rhythm and rate ☐ P Waven: inverted; before, during, after QRS ☐ PRI: measured before QRS, <0.12s ☐ QRS: <0.12s
Sinus Bradycardia ☐ Regular <60 bpm ☐ P Wave: normal upright ☐ PRI: 0.12-0.20s ☐ QRS: <0.12s	**Premature Atrial Contraction** ☐ Regular underlying except for PAC, 60-100 bpm, just one beat ☐ P Wave: flattened, notched, lost in T wave ☐ PRI: 0.12-0.20s, >0.20s ☐ QRS: <0.12s	**Junctional Escape Rhythm** ☐ Regular 40-60 bpm ☐ P Waven: inverted; before, during, after QRS ☐ PRI: measured before QRS, <0.12s ☐ QRS: <0.12s
Sinus Tachycardia ☐ Regular >100 bpm ☐ P Wave: normal upright ☐ PRI: 0.12-0.20s ☐ QRS: <0.12s	**Atrial Tachycardia** ☐ Regular 150-250 bpm ☐ P Wave: different, lost in T wave ☐ PRI: 0.12-0.20s ☐ QRS: <0.12s	**Accelerated Junctional Rhythm** ☐ Regular 60-100 bpm ☐ P Waven: inverted; before, during, after QRS ☐ PRI: measured before QRS, <0.12s ☐ QRS: <0.12s
Sinus Arrhythmia ☐ Irregular 60-100 bpm ☐ P Wave: normal upright ☐ PRI: 0.12-0.20s ☐ QRS: <0.12s	**Atrial Flutter** ☐ Regular; atrial rate 250-350 bpm ☐ P Wave: sawtooth ☐ PRI: unable to determine ☐ QRS: <0.12s	**Junctional Tachycardia** ☐ Regular 100-180 bpm ☐ P Waven: inverted; before, during, after QRS ☐ PRI: measured before QRS, <0.12s ☐ QRS: <0.12s
	Atrial Fibrillation ☐ Grossly irregular >350 bpm <100: controlled vs. >100: uncontrolled ☐ P Wave: fibrillatory ☐ PRI: unable to measure ☐ QRS: <0.12s	**Supraventricular Tachycardia** ☐ Regular rapid arrhythmia ☐ P Waven: invisible ☐ PRI: unable to measure ☐ QRS: narrow
	Paroxysmal Atrial Tachycardia ☐ Random atrial tachycardia that breaks to normal	**Paroxysmal Supraventricular Tachycardia** ☐ Normal then sudden random SVT burst ☐ Obscure regular rhythm ☐ No P, rates vary

Eina Jane & Co. ©2008 Last Updated: 06 October 2008

Walraven, G. (2006). *Basic arrhythmias*. Upper Saddle River, New Jersey: Brady Prentice Hall/Health.

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When the pacemaker stimuli finds the refractory ventricles, he cannot capture. Gail Walraven, Basic Arrhythmias, Sixth Edition ©2006 by Pearson Education, Inc., Upper Saddle River, NJ 16 Competition This track shows pacemaker peaks at a rate of 100 beats per minute, with an underlying ventricular tachycardia/fibrillation. The pacemaker is competing for heart control, but the annoying ventricular follicles are gaining. Main article: History of Education, Culture, Education, Culture Gail Walraven, Basic Arrhythmias, Sixth Edition ©2006 by Pearson Education, Inc., Upper Saddle River, NJ 24 Pacemaker Failure to Depolarize consistently, Indicating Lead Fracture or Displacement Gail Walraven, Basic Arrhythmias, Sixth Edition ©2006 by Pearson Education, Inc., Upper Saddle River, NJ 25 Ventricular Pacemaker with 100% CaptureGail Walraven, Basic Arrhythmias, Sixth Edition ©2006 by PearsonEht .Lacitirc Ro sselmrah Eb nac Hcihw taebtraeh eht fo mhtyhr lambon eht in denifed aimhtyra .]6[,] FO noitcncnuf llarevo eht stceffa of ,yltneuqesnoc .]6[seiretra fo s or ot Evitpeer Erom Semoceb Dna Rekaew Sworg Metasys Ralucsavoidrara Ruo .dlrow eht ot ,] yb Elbuod Eb ot detcepxe ya)red dna sraey 06 (notitopop gniworg ,eromrettruf .0302 yb noillib 4.1 ot noillim 109 morf 100.65 yb worg 0ore evo evoee 03. na gnicaf si dlrow eht ,5102 by Snoitan Detino eht yb troper eht ot ot ot ot ot ot ot ot ot ot tnidroccattnoc dna sthgir teg210.40.7102.sni.j/6101.01/gro.iod//:spth09-18 Sagap ,7102 rebmetpes ,5 -6991 Â©Ã JN ,reviR elddaS reppU ,.cnI ,noitacudE nosraeP yb 6002Â©Ã noitidE htxiS ,saimhtyhrrA cisaB ,nevarlaW liaGerutpaC %001 gniwohS rekamecaP ralucirtneV 92 JN ,reviR elddaS reppU ,.cnI ,noitacudE nosraeP yb 6002Â© Ã noitidE htxiS ,saimhtyhrrA cisaB ,nevarlaW liaGrekamecaP dnameD ralucirtneV 82 JN ,reviR elddaS reppU ,.cnI ,noitacudE nosraeP yb 6002Â©Ã noitidE htxiS ,saimhtyhrrA cisaB ,nevarlaW liaG pirtS fo dnE ta rekamecaP htiw gnitepmoC aidracyhcaT ralucirtneV ot gnitrevnoC ,pirtS fo traP tsriF ni mhtyhR ralucirtnevarpuS htiw gnitepmoC rekamecaP gnirutpac-noN 72 JN ,reviR elddaS reppU ,.cnI ,noitacudE nosraeP yb 6002Â©Ã noitidE htxiS ,saimhtyhrrA cisaB ,nevarlaW liaGerutpaC %001 htiw rekamecaP lairtA 62 JN ,reviR elddaS reppU ,. Cnin fibrillation (Afib), atrial flutter (Afl), and ventricular fibrillation (Vfib) are the recurrent types of arrhythmias reported in the elderly [6]. Afib is a commonly occurring arrhythmia due to various health complications. During Afib, the contraction of the atria is asynchronous due to the rapid firing of electrical impulses from various parts of the heart reentry [2]. The reentry occurs when a impulse does not die after normal heart activation and continues to recite the heart. In fact, Afib's electrocardiogram (ECG) rhythm is fast and beating at a rate of 150 to 220 beats in a minute. Has an abnormal R-R range, irregular and fast ventricular contraction, and the wave P is absent in the ECG signal [29]. In Afl, atrial contracts quickly between 240 and 360 beats per minute and have a replicating saw tooth waveform known as flutter wave. Afl occurs when the atria suffers chaotic electrical signals [2]. Vfib is usually caused by rapid heartbeat known as ventricular tachycardia (VT). This abnormal heartbeat is due to abnormal electrical impulses in the ventricles. During this, the ventricles contract kaotically and hafazardly. It can be seen in the morphology of the ECG, which records an indefinite and erratic fluctuation of the ECG signal with the absence of complex QRS wave [29]. Typical portions of Nsr, Afib, Afl and Vfib ECG signals are shown in Fig. 1 and 2. Therefore, the morphology of the ECG signals contains vital details about the conditions of the heart. Thus, the ECG signal is beneficial in the detection and diagnosis of heart health [2]. However, the ECG signals are highly non-linear and any changes in the ECG signals are difficult to observe, as their amplitude is in millivolts [2], [13]. In addition, the indications of cardiac abnormalities are faithfully indicated in the ECG signals during the recording of Holter 24 hours. Thus, the manual interpretation of ECG signals can be due to the long recordings. Moreover, there is a great possibility that important information captured in the ECG morphology may be overlooked. Hence, a computer-aided diagnosis (CAD) system can be employed to reduce subjective variabilities in the diagnosis and reduce the time taken to analyze the ECG signals [25].Table 8 shows the studies conducted on CAD system to automatically detect arrhythmias and categorize different types of arrhythmia into their respective classes. Wang et al. [34] performed short-time multifractal characterization of Afib, Vfib, and VT classes of ECG beats and recorded an accuracy of 99.40% for Afib, 97.20% for Vfib and 97.80% for VT using fuzzy Kohonen network classifier. Martis et al. [26], [27] have conducted a three-class study to automatically diagnose Afib, Afl, and Nsr ECG signals. In [27], they have employed higher order spectra methods on 641 Nsr, 855 Afib, and 887 Afl ECG beats. Then these ECG beats are subjected to independent component analysis (ICA) to select highly significant features. Their method yielded an accuracy, sensitivity, and specificity of 97.65%, 98.16%, and 98.75% with the k-nearest neighbor classifier. In their another study [26], they performed a discrete cosine transform combined with ICA on the ECG beats. Their proposed technique attained an average accuracy of 99.45%.In addition, Fahim et al. [10] employed a data mining approach with expectation-maximization-based clustering on 50 compressed ECG signals obtained from an open-source database. They used correlation-based feature subset selection technique to reduce the number of features. Then, the selected features are fed into the classifier. They detected Afib, premature ventricular contraction, and Vfib with an average accuracy of 97.00% using the rule-based system. Acharya et al. [1] proposed a CAD system to automatically detect and identify same four ECG classes (Nsr, Afib, Afl, Vfib) using the entire (614,526 ECG beats) obtained from an open code database [14]. Extracted characteristics of ECG signal entropy. These extracted characteristics were subject to the reduction of resources and the 14 significant characteristics selected were fed on the decision -making classifier, producing a precise 96.30%, sensitivity of 99.30% and specificity of 84.10%. In addition, it is, I challenge et al. [8] It also implemented a CAD system to diagnose four -class arrhythmia (AFIB, AFL, NSR and VFIB). However, they used a smaller data set (3858 ECG beats) obtained from the same open code database [14] in their work. They applied the dwarf dwarf parano of quantification for remembrance for ECG beats. Then the characteristics are organized according to the F-VALE. They reached a precise of 98.37% with the forest classifier of rotation. However, from literature [1], [8], [10], [26], [27], it can be noted that these systems are a standardized workflow by which signs are prted -In first, then segmented. Then the signals are subjected to the extraction of resources, followed by the selection of resources to select only significant characteristics for classification. In this study, we do not follow the conventional process of an automated CAD system. This is different from the previous work recorded in Table 8, as no extraction or selection of resources is implemented in this work. We employ a convolutionary neural network of eleven layers (CNN) to automatically classify the four ECG signal classes (NSR, AFIB, AFL and VFIB). Thus, in this study, there is no need to try different characteristics of characteristics or determine which classifier performs the best with the extracted characteristics. CNN was recently employed in the automated classification ECG Signs. Kiranyaz et al. [21] They studied the patient categorization system and monitoring of the patient using CNN of Train Layers with only R-Peak wave. They reached a precise of 97.60% and 99.00% in the detection of ectal beats and ventricular ectal beats respectively. Zubair et al. [36] Used CNN with 44 ECG signal recordings obtained from the MIT-BIH database. They extracted R-PEAK ECG beats for the formation of the CNN of TRANS SHEETS. They reached 92.70% precise in the detection of the ecg beats in their respective classes (normal, fuse beaten, supraventricular ectary beat, unknown beat and ventricular ectary beat). These works [21], [36] detected the QRS wave in its automated classification. However, in our study, no detection of the QRS wave is implemented. In this paper, ECG signs were obtained from a publicly available arrhythmia database. We obtained VFIB signs (vetricular fibrililation) ECG from the University of Creighton Tachyarrhythmia ventricular, affib (atrial fibrilation) and AFL (Atrial Flutter) ECG signs of atrial mit-bih fibrililation, and affib (affib Atrial Fibrillation), AFL (Aturus Flutter) and NH In this work, we use lead signs of lead II. The ECG Signs Details of the University of Creighton Tachyarrhythmia Ventricular and Atrial Mit-Bih fibrililation sampled at a 250 Hz frequency, while ECG signals from the Mit-Bih Arrhythmia are sampled at a 360 frequency Hz. In addition, the ecg signals are segmented and classified according to the cardan we train our algorithm in a work of two Intel Xeon 2.40 GHz processor (E5620) and a 24GB RAM. It took a day of 557,812 s to complete one to training for network A and 256.332 s to network B. Tables 5 and 6 show the confusion matrix for the two seconds and five seconds respectively segment segment . It can be seen in Table 5 that; 93.13% of ecg segments are correctly classified as class. 92.89% of the ECG segments are correctly classified as Afib. A total of 8.64% of Afl ECG segments is incorrectly The number of Vfib segments (Table 2) used in this work are few (163 and 65 ECG segments in the A network and in the B network respectively) and therefore resulted in low sensitivity and PPV. Thus, CNN performance is affected by the number of subjects (data) used in each class. In this work, the five-second ECG network (ECG signal) did a little better than the A network (two-second ECG signal) as there are three additional seconds of additional information on the morphology of the ECG. However, the results of twogenerally, the presence of arrhythmia is reflected in the ECG morphology. Essentially, with many elderly people affected by severe arrhythmias, there is a need to design an efficient and robust CAD system to accurately detect and automatically detect various types of arrhythmias. In this work, we have developed a CNN to automatically classify the four classes (Nsr, Afib, Afl and Vfib) using 21.709 ECG segments of segments A and 8683 ECG liquids B. Our proposed algorithm achieved a accuracy of 92.50%B.N. Singh et al. R.J. Martis et al. R.J. Martis et al. R.J. Martis et al.G.V. Chow et al. U.R. Acharya et al. U.R. Acharya et al. S. BawanyC. Berry et al. J. Bouvrie. Notes on the convolutional neural network, D.C. Ciresan et al. U. Desai et al. R.O. Duda et al. S. Fahim et al.K. FukushimaX. Glorot et al. A.L. GoldbergerA.L. Goldberger et al. We test principles that could lead to future cognitive aid that offers an interpretation of the physiological state of the newborn during the resurrection after birth. Using the agreement between the interpretations of specialists of newborn vital signal patterns as an approximation to an algorithm that could provide an interpretation of the state of the newborn, we explore the reliability and generality of the â â sodicsan-m©Ãcer odnartsom sacif¡Ãrg sair³Ãtejart ed serap otio mariv siatanoen satsilaicepse ezoD .satsilaicepse ed Rate saturation and oxygen records complemented with differential diagnoses previously triggered from other specialists. each pair of trajectories included a trajectory in which the original differential diagnoses had been based and a similar but new trajectory, to which the original differential diagnoses were now generalized. for each trajectory, experts rated differential diagnoses according to their probability. we calculate how similar the new ranking of the experts was to the ranking of the original specialists for original and new trajectories. we use descriptive categories to interpret the strength of similarity. there were mainly small differences in the similarity scores between the original and new trajectories paired; less than 25% of the participants suggested an alternative differential diagnosis. the agreement of the interpretations of the specialists could serve as an approximation of the physiological state of the newborn, and the interpretations could be widespread. the results can jotify the search for an algorithm to sustain a cognitive help. as research on computer aided arrhythmia detection deepens, the application in clinical practice is still challenging due to poor generalization capability. the use of the previous knowledge of the previous patient can be an effective approach to solving the problem and finally architecting a suitable network for clinical oo. a deep neural network incorporated into inverted blocks (irbednn) is proposed to accurately detect arrhythmias based on processed ecgs. first, continuous ecgs are segmented into individual heartbeats based on peak information. to simulate the real clinical scenario, these heartbeats are converted into two-dimensional images of heartbeat without any processing. Then, selected heartbeats are fed into the proposed IRBEDNN which combines CNN and inverted residual block (IRB) to extract implicit features. Also, patient-specific knowledge is exploited in the network to enhance arrhythmia detection. Finally, 24 data records from the MIT-BIH arrhythmia database are utilized to validate the method¢ÃÂÃs effectiveness and superiority. The effect on utilizing different duration of patient-specific information to the final experimental results is investigated and analyzed in detail, which demonstrates the effectiveness of using patient-specific information. On the 24 data-segment tests, the highest classification accuracy could reach 100%, while the overall ACC is 96.326%, higher than that of the existing comparison models. The precision of the S class can reach 0.816, also higher than comparison methods. After the boosting method, the recall reaches 0.852 for the S class and 0.921 for the V class, which outperforms the other comparison methods on average. Ablation experiments is conducted to investigate the performance of the IRBEDNN. Results show that the proposed IRBEDNN-based method achieves good generalization ability with promising accuracy on both the MIT-BIH arrhythmia database and the INCARTDB. Therefore, the proposed IRBEDNN could accurately and efficiently detect arrhythmias and has positive significance to clinical applications.Nowadays, deep learning algorithm has been widely used for automatic electrocardiogram (ECG) classification. However, most algorithms can only classify single heartbeat, which requires complex heartbeat extraction preprocessing. In addition, the traditional software implementation on CPU or GPU platform faces the challenge of low computing efficiency and high resource consumption. In this work, a deep one-dimensional (1D) U-net is proposed, which can classify the original continuous ECG segment at the pixel level. And an efficient The architecture is presented to implement the U 1D network. A two -step winograd structure is designed to increase the efficiency of computing. A 3D (PE) processing element matrix is developed to improve the use of resources and the general transfer rate. Implemented on the Xilinx Zynq ZC706 plate, the experimental results show that the UP proposed 1D network reaches a 95.55% day -to -day precision for classification at the level of the five cards. In terms of hardware performance, resource efficiency and computing efficiency reach 8.27 gops/klut and 123%, respectively, in the 200 MHz relief frequency. Patients with risk of high disease disease may be provided with computerized electrocardiogram devices (ECG) to detect arrhythmia. This requires long quality ECG segments that, however, can be missed from episode. To overcome this, we proposed a deep learning approach, where the scalogram obtained by a containment of Wavelet (CWT) is classified by the network based on the corresponding signing. The CWT of the records is obtained and used to train the 2D Convolutional Neural Network (CNN) for Arrhythmia Automal Detection. The proposed model is trained and tested to identify five types of heartbeat, such as normal branch block, left package, right, atrial premature, premature premature premature block. The model shows a sensitivity, specificity and precise child precise in 98.87%, 99.85%and 99.65%, respectively. The result shows that the proposed model can effectively detect short ECG segments and have the potential to be used for custom and digital health care. The telemetry system will involve the following steps: the acquisition of the electrocardiogram signal, the electrocardiogram signal processing and in case of emergencies. This system will help the doctor at first as well as an accurate analysis of heart disease. A wireless sensor network electrocardiogram monitoring system is currently being developed for electrocardiogram signal analysis. In the past, convolutional neural networks were employed to solve various artificial intelligence problems with good results. Even so, designing the architecture of convolutional neural networks remains an accomplice procedure as well as meticulous that needs the involvement of field specialists. This work has explored the application of neuro-evolution to the automatic design of topologies of convolutional neural networks and also developed a new solution that is based on the artificial bee colony as well as the Grey Wolf Optimizer. In addition, this work gave the proposed hybrid algorithm Grey Wolf Optimizer-Artificial Bee Colony, in which wolves will adopt the information sharing strategy to promote their exploration ability, continuing with their original strategy of hunting strategy for maintaining their exploration capacity. The experimental results demonstrate the superior performance of the proposed algorithm on other existing algorithms. Atrial fibrillation (AF) is a common arrhythmia worldwide. The visual examination for electrocardiogram is the main diagnostic method, which is usually costly and inefficient. In this work, a long-term bidirectional memory frame (IB-LSTM) is specially designed for intelligence-based AF signal classification. Based on the existing B-LSTM architecture, a scale factor is installed on the IB-LSTM network that allows the model system to effectively relocate information representation and thus learn better representation. After several steps of pre-processing, such as denoization, these results etnetsisnoc etnetsisnoc ohnepmesed With the precision of 98.2% and 97.5% against existing and lower computer costs than B-LST with the two MIT-BIH and arrhythmia databases. The IB-LSTM Network proposed is capable of negotiating between the precision of the model and computing resources. In particular, this research provides the first empathic exploitation of B-LSTM redesign architecture to relieve the cost of computing and redundancy of information, which shows major perspectives as auxiliary tools efficient for the diagnosis of Mother. See all articles on scopus in this article, we propose a new approach based on deep learning for active classification of electrocardiogram signals (ECG). To this end, we learn a representation of proper resources of the Gross ECG data in no supervised manner using stacking self -enclosure (SDAES) with sparsity restriction. After this resource learning phase, we add a layer of softmax regression at the top of the resulting hidden representation layer that produces the so -called Deep Neural Network (DNN). During the interaction phase, we allow the expert in each iteration to label the most relevant and uncertain ecg beats in the test record, which is used to update DNN weights. As classification critics, the whole depends on the later probabilities of DNN to associate confidence measures, such as entropy and breakage-ties (BT) with each test beaten in the ECG register in dwarf . In experiments, we validate the whole in the well-known MIT-BIH Arrhythmia Database, as well as two other databases called Incart and SVDB, respectively. In addition, we follow the recommendations of the association for the advancement of instrumentation (AAMI) for class labeling and results presentation. The results show that the newly proposed approach provides significant improvements in precision with Less specialized and more rude online retreatment compared to the last generation. O o (ECG) is a standard test used to monitor the activity of the heart. Many heart abnormalities will be manifested in the ECG, including arrhythmia, which is a general term that refers to an abnormal heart rate. The basis of arrhythmia diagnosis is the identification of normal versus abnormal individual heartbeats, and their correct classification in different diagnoses, based on ECG morphology. Heartbeats can be subdivided into five categories: ectopic, supraventricular, ventricular ectopic, fusion and unknown beats. It is challenging and time consuming to distinguish these heartbeats in the ECG as these signals are typically corrupted by noise. We have developed a deep 9-layer convolutional neural network (CNN) to automatically identify 5 different categories of heartbeat in ECG signals. Our experience was conducted in original and attenuated sets of ECG signals derived from a publicly available database. This set was artificially increased even out the number of instances the 5 classes of heartbeat and filtered to remove high frequency noise. CNN was trained using the increased data and achieved an accuracy of 94.03% and 93.47% in the diagnostic classification of heartbeat in original and noiseless ECGs respectively. When CNN was trained with highly unbalanced data (original dataset), CNN accuracy reduced to 89.07%% and 89.3% in noisy and noiseless ECGs. When properly trained, the proposed CNN model can serve as a tool for ECG tracking to quickly identify different types and frequency of arrhythmatic heartbeats. Fibrillations and flutters are serious diseases influence the normal functioning of the heart. Among the most frequent heart disorders occur belong to atrial fibrillation (Afib), atrial flutter (Afl), and ed ed odirefsnart lanis o odnanimaxe)GCE(amargoidracortele ovitisopsid olep sadatceted etnemlapicnirp o£Ãs sacaÃdrac sahlaf sa ,aid me ejoH .)bifV(ralucirtnev placed on the human body to the output display. The signal is examined by professional health personnel, who are looking for an obvious pattern representing the normal or abnormal rhythm of the heart. Nevertheless, information from ECG can be distorted by noise on data transmission. Moreover,problematic pattern does not have to be so much different from normal and it can be difficult to recognize them just by human eye even by an expert in the field. An automated computer-aided diagnosis (CAD) is an approach to make decision support for elimination of these lacks. For early diagnosis, CAD tool should work in like real-time system without big time consuming and dependency on data and measuring differences of each device. This paper proposes a novel approach of a CAD system to the detection of fibrillations and flutters by our 8-layer deep convolutional neural network. Proposed model requires only basic data normalization without pre-processing and feature extraction from raw ECG samples. We have achieved the accuracy, specificity, and sensitivity of 98.45%, 99.27%, and 99.87% respectively. Designed system can be directly implemented like decision support system in clinical environment.Long-short term memory networks (LSTMs), which have recently emerged in sequential data analysis, are the most widely used type of recurrent neural networks (RNNs) architecture. Progress on the topic of deep learning includes successful adaptations of deep versions of these architectures. In this study, a new model for deep bidirectional LSTM network-based wavelet sequences called DBLSTM-WS was proposed for classifying electrocardiogram (ECG) signals. For this purpose, a new wavelet-based layer is implemented to generate ECG signal sequences. The ECG signals were decomposed into frequency sub-bands at different scales in this layer. These sub-bands are used as sequences for the input of LSTM networks. New network models that include (ULSTM) and two-way structures (BLSTM) are designed for performance comparisons. Experimental studies were conducted for five different types of heartbeat obtained from the MIT-BIH arrhythmia database. These five types are Normal Sinus Rhythm (NSR), Ventricular Premature Contraction (VPC), Paced Beat (PB), Left Bundle Branch Block (LBBB) and Right Bundle Branch Block (RBBB). The results show that the DBLSTM-WS model gives a high recognition performance of 99.39%. It was observed that the wavelet-based layer proposed in the study significantly improves the recognition performance of conventional networks. This proposed network structure is an important approach that can be applied to similar signal processing problems. Arrhythmia is a heart condition caused by abnormal electrical activity of the heart, and an electrocardiogram (ECG) is the non-invasive method used to detect arrhythmias or heart abnormalities. Due to the presence of noise, the non-stationary nature of the ECG signal (i.e., the changing morphology of the ECG signal over time) and the irregularity of the heartbeat, doctors face difficulties in the diagnosis of arrhythmias. Computer assisted analysis of the results of the ECG helps doctors to detect cardiovascular diseases. The development of many existing arrhythmia systems depended on the findings of linear experiments in ECG data that achieve high performance in noiseless data. However, non-linear experiments characterize the most effectively sense ECG signal, extract hidden information in the ECG signal, and achieve good performance under noisy conditions. This article investigates the ability to represent linear and non-linear characteristics and proposes a combination of such characteristics to improve the classification of ECG data. In this study, five types of classes of arrhythmia beats, as o£Ãs o£Ãs acid©ÃM o£Ã§Ãatnemurtsnl ed o§ÃnavA ed o£Ã§ÃaicossA alep taht si ydutS siht fo snoitubirtnoc tnacifingis eht fo enO. devresbo saw %0.99 revo fo ycarucca na dna ,etar)drp(ecnereffid erauqs naem toor egatnecrep %07.0 egareva na yb darpmoc erew slangis gce ,esabatad aimhtyhrra : L .staeb cimhtyhrra fo ezis langis eht ecuder ot detnemelpmi si erutcurts noisserpmoc raenilnon desab)eac(redocne-otua lanoitulovnoc :Proposed approach can significantly reduce the duration of time when using LSTM networks for data dwarf. Thus, a new and effective approach was proposed for ECG signal compress, and its high performance automatical recognition with very low computational cost. See full text

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