http://doi.org/10.35784/iapgos.3783 *received: 23.06.2023 | revised: 09.08.2023 | accepted: 27.11.2023 | available online: 20.12.2023*

A GENERATIVE MODEL FOR DEEP FAKE AUGMENTATION OF PHONOCARDIOGRAM AND ELECTROCARDIOGRAM SIGNALS USING LSGAN AND CYCLE GAN

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Abstract. *In order to diagnose a range of cardiac conditions, it is important to conduct an accurate evaluation of either phonocardiogram (PCG) and electrocardiogram (ECG) data. Artificial intelligence and machine learning-based computer-assisted diagnostics are becoming increasingly commonplace in modern medicine, assisting clinicians in making life-or-death decisions. The requirement for an enormous amount of information for training to establish the framework for a deep learning-based technique is an empirical challenge in the field of medicine. This increases the risk of personal information being misused. As a direct result of this issue, there has been an explosion in the study of methods for creating synthetic patient data. Researchers have attempted to generate synthetic ECG or PCG readings. To balance the dataset, ECG data were first created on the MIT-BIH arrhythmia database using LS GAN and Cycle GAN. Next, using VGGNet, studies were conducted to classify arrhythmias for the synthesized ECG signals. The synthesized signals performed well and resembled the original signal and the obtained precision of 91.20%, recall of 89.52% and an F1 score of 90.35%.*

Keywords: arrhythmia, auscultation, electrocardiogram, phonocardiogram, generative networks

GENERATYWNY MODEL Z DEEP FAKE AUGUMENTATION DLA SYGNAŁÓW Z FONOKARDIOGRAMU ORAZ ELEKTROKARDIOGRAMU W STRUKTURACH LSGAN ORAZ CYCLE GAN

Streszczenie. *W celu zdiagnozowania szeregu chorób serca, istotne jest przeprowadzenie dokładnej oceny danych z fonokardiogramu (PCG) i elektrokardiogram (EKG). Sztuczna inteligencja i diagnostyka wspomagana komputerowo, oparta na uczeniu maszynowym stają się coraz bardziej powszechne we współczesnej medycynie, pomagając klinicystom w podejmowaniu krytycznych decyzji. Z kolei, Wymóg ogromnej ilości informacji do trenowania, w celu ustalenia platformy (ang. framework) techniki, opartej na głębokim uczeniu stanowi empiryczne wyzwanie w obszarze medycyny. Zwiększa to ryzyko niewłaściwego wykorzystania danych osobowych. Bezpośrednim skutkiem tego problemu był gwałtowny rozwój badań nad metodami tworzenia syntetycznych danych pacjentów. Badacze podjęli próbę wygenerowania syntetycznych odczytów diagramów EKG lub PCG. Stąd, w celu zrównoważenia zbioru danych, w pierwszej kolejności utworzono dane EKG w bazie danych arytmii MIT-BIH przy użyciu struktur sieci generatywnych LSGAN i Cycle GAN. Następnie, wykorzystując strukturę sieci VGGNet, przeprowadzono badania, mające na celu klasyfikację arytmii na potrzeby syntetyzowanych sygnałów EKG. Dla wygenerowanych sygnałów, przypominających sygnał oryginalny uzyskano dobre rezultaty. Należy podkreślić, że uzyskana dokładność wynosiła 91,20%, powtarzalność 89,52% i wynik F1 – odpowiednio 90,35%.*

Słowa kluczowe: arytmia, osłuchiwanie, elektrokardiogram, fonokardiogram, sieci generatywne

Introduction

Cardiovascular diseases are a group of serious, life-threatening conditions that affect millions of people every year [23]. Cardiovascular disease is typically diagnosed in the clinic using information gathered from a variety of different detection methods. The disorders in heart beat or any abnormality can be termed as arrhythmias, which can range in severity from a minor inconvenience or pain to a life-threatening emergency. When the normal flow of the heart's electrical impulses is interrupted, an arrhythmia develops. It's possible that the heartbeat is too slow, too rapid, or otherwise irregular. Heart illness can be effectively predicted and diagnosed with the help of PCG and ECG signals. Artificial auscultation is a diagnostic tool for the heart that is efficient in terms of both time and money, but it requires clinicians to have extensive training in the field.

The electrocardiogram is a valuable tool for detecting arrhythmias or abnormalities as it enables the measurement of the bio-electrical activities of the heart whereas the PCG records the heart sounds. The bio-electrical activities of the heart can be recorded by means of an electrocardiogram (ECG), a noninvasive procedure. Electrodes attached to the patient's skin allowed an ECG machine to record the rhythmic contractions and relaxations of the heart. The T wave, the P wave, and the QRS complex are all components of a normal ECG signal. For example, Atrial fibrillation has been linked to abnormalities in the ECG, where there are no P-waves and an irregular ventricular rhythm [1]. Routinely, cardiologists undertake ECG screening for patients, which takes substantial human effort and costly medical procedures to detect heart problems and provide appropriate therapy for those concerns.

Regarding the PCG signals, medical professionals utilize a phonocardiograph to track the auditory manifestations and vibrations generated by the heart, encompassing those arising from the closure of the aortic, pulmonary, and atrioventricular valves. The information is depicted in figure 2. After the atrioventricular and semilunar valves close, the heart makes two distinct sounds, S1 and S2, during systole and diastole, respectively [3].

Due to the comparatively complicated waveform of the Phonocardiogram (PCG) signal in comparison to the Electrocardiogram (ECG), as well as the inherent challenges associated with the collecting approach that often result in significant disturbances, the widespread adoption and application of PCG signal analysis have been limited [16]. The reliability of visually assessing an electrocardiogram (ECG) for detecting heart abnormalities may be limited. The integration of deep network topologies into the automatic processing of ECG and PCG data, as well as other domains within the medical and healthcare industries, has become increasingly prevalent with the rise in popularity of deep learning approaches.

In recent years, the emergence of artificial intelligence as a potential option has been facilitated by technological advancements, particularly in the field of medical applications [7]. While deep learning algorithms are becoming increasingly used in e-health applications, large datasets are still required for the discovery of critical determinants that improve prediction or diagnostic accuracy.

The success of a deep learning model is highly dependent on the availability of both many training samples and a high-quality labelled dataset. Inadequate data or an imbalanced dataset might lead to a non-convergent training phase and biased classification results when training a deep learning model.

A big and well-balanced dataset is required for the Deep Learning model in order to avoid these problems. Despite having access to a big and evenly distributed dataset for training, would be ideal, this is not always possible because to factors such as the rarity of aberrant cardiac events and the scarcity of available cardiologists who can reliably identify (annotate) the waveforms. Because only highly trained doctors are capable of accurately or exactly annotating ECG recordings, the number of recordings that have been annotated is also restricted.

Therefore, there is a need for Deep learning algorithms to strive for the replication of novel artificial or synthetic data by initially comprehending the pattern derived from appropriate training data [8].

The Generative Adversarial Network (GAN) is a widely utilized form of data augmentation model that is employed for the creation of time series data as well as visualizations [10]. Various fields such as health care [22], stock market predictions [25], image segmentation [2], text classification [5] etc., have incorporated the utilisation of GANs.

In this research, we investigate how GANs can be used to generate authentic ECG and PCG signals from scratch. In Section II, we present an overview of relevant published materials. GAN, Least Squares GAN, and Cycle GAN architectures, as well as classification with VGGNet, are discussed in Section III; evaluation criteria are outlined in Section IV; and the simulated results and datasets are discussed in Section V.

1. Literature review

The conventional methods for the classification of electrocardiogram (ECG) and phonocardiogram (PCG) signals rely mostly on the use of traditional supervised machine learning approaches. Using a linear Support Vector Machine (SVM) [5], PCG signals were successfully classified. Numerous studies have used the SVM technique to classify electrocardiogram (ECG) readings [12].

These methods have not been able to scale adequately to incorporate ECGs from a large variety of individuals, even if we disregard the time and work necessary. Each patient's ECG signal will have its own unique dynamics and morphology. After much success in machine learning, researchers have started to take notice of the convolutional neural network's (CNN) potential for ECG and PCG categorization [15]. By coordinating the acquisition of ECG and phonocardiogram signals, Jan Nedoma et al. were able to make direct comparisons between the two methods of monitoring heart rate [19]. ECG signals in the time-frequency domain can be decomposed using wavelet techniques. Popular methods for feature extraction include principal component analysis and the hidden Markov model to name a few [14].

There are a number of deep learning methods that show promise for cardiovascular diseases classification and detection, but they need a lot of training instances to be truly effective. Due to the rarity of potentially lethal arrhythmias, there is a lack of data for training which is required for deep algorithms. There is a scarcity of deep PCG and ECG signals for rare diseases that are acceptable for clinical application because of the extensive heartbeat categorization challenge. To address this problem, we train deep learning models with simulated PCG and ECG signals depicting a variety of arrhythmias.

As a result, the need for medical image augmentation evolved. Basic data augmentation techniques encompass flipping, snipping, and introducing noise. In addition to these techniques, some other basic data augmentation techniques such as spatial inversion [11], time-spatial inversion [6], baseline wandering [20] are also applied to ECG signals. However, when it comes to the management of complex data such as medical imaging, these basic techniques are inadequate. The variational autoencoder (VAE) [20] is a deep model that has received less attention compared to other more widely adopted techniques. Nevertheless, a prominent concern revolves around the recurrent occurrence of hazy and indistinct output images.

2. Generative Adversarial Networks

In 2014, a group of researchers or academicians led by Ian Goodfellow [8] proposed the concept of GANs. Generative models, which include GANs, are a broad category. Therefore, GANs are based on the concept of zero-sum games, in which each player intentionally strives to maximise his or her own advantage at the expense of everyone else. The results of the GAN are a joint effort of a Generator and a Discriminator neural network. The Generator's goal is to perfect its ability to mislead the Discriminator with artificial distributions, whereas the Discriminator's goal is to perfect its capacity to recognise and reject fake distributions generated by the Generator. The figure 1 gives the architecture block diagram of GAN.

The GAN's effectiveness as a deep generative model can be attributed to its two main components, the generator and the discriminator. The generator (G) takes in a latent vector (z) with a Gaussian distribution and produces fake images or data. A discriminator trained on both forms of data x will produce an answer as to whether the created data is fake or real in its output (D). The goal function of a GAN is written out in the form of a min-max optimisation, as shown in equation 1.

In this study, we developed an LSGAN and Cycle GAN capable of producing realistic ECG and PCG signals, as well as a discriminator that can distinguish between the real and fake. Next these signals are given to a VGG-Net classifier to classify arrhythmias.

$$min_G max_D V(D,G) = \\ = E_Z \log\Big(1 - D\big(G(z)\big)\Big) + E_x \log\big(D(x)\big) \quad (1)$$

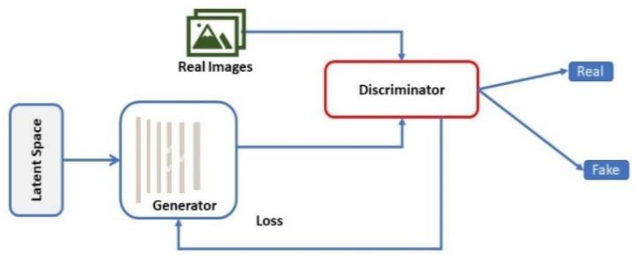

Fig. 1. Architecture of GAN

2.1. Cycle GAN

Cycle GANs can autonomously learn to translate between two visual inputs [27] when given just those two sets. Together, the two GANs in a Cycle GAN undergo training at the same time. The objective here is to preserve the constancy of the cycle at all times. In addition to the pair loss terms inherent in a GAN, a cycle loss term is included. It is necessary to optimise both GAN pairings in addition to the cycle loss term. The concept of "cycle loss" is visualised here. Take the task of teaching the Cycle GAN to convert summer (X) to winter (Y) landscapes as an example. To convert data from domain X to domain Y, we first train the initial generator, designated by F, to produce a winter image from a summer input image. DY is used to tell Y apart from the real thing. The second GAN pair does the opposite operation, converting X to Y and differentiating Y from X. While learning, the second GAN could invert Y into X. Therefore, while switching from summer to winter and back again, the images must remain visually consistent. This is shown in the figure 3 [27].

2.2. Least square GANs

GANs where the least-squares loss is utilised as a discriminator are called LSGANs [18]. Lowering the LSGAN's goal function has the same effect as minimising the Pearson 2 divergence. There are two benefits of LSGANs over classic GANs. First, unlike regular GANs, LSGANs can generate images of higher quality. Second, when it comes to teaching and learning, LSGANs are more reliable.

2.3. Arrhythmia classification

For the arrythmia classification, VGGNet architecture is used in this research. The VGGNet stands for Visual Geometry Group Network [21]. It was introduced in 2014, which was two years after AlexNet. The primary objective behind the development of this model was to investigate the influence that depth has on the level of precision achieved by picture classification training models. The model's speed and accuracy both saw substantial boosts after VGG was introduced. As the number of layers with smaller kernels was utilised, non-linearity improved, which is a desirable property in deep learning.

The VGG-Net is divided into VGG-16 and VGG-19 architectures. The VGG-16 network is a deep convolutional model that was trained using data from ImageNet. The major data set classification in this paper was accomplished using the VGG-16 model. Pooling layers, Convolution layers, and fully linked layers make up the network model. Figure4 depicts the network diagram of VGG-16's structural design. The VGG-16 architecture is shown in the figure 4.

The "16" in VGG stands for the number of layers in the deep neural network used by the VGGNet architecture. The VGG-16 architecture consists of 13 convolutional layers and three fully connected layers. The convolutional layer generates a feature map by applying a kernel matrix to the input matrix. By spreading the Kernel matrix over the input matrix, we are able to carry out a mathematical operation known as convolution. The feature map is the accumulated output of element-by-element matrix multiplication at each node. The output feature map of the convolutional layer remembers the exact position of the features in the input, which can be problematic. This means that the feature map will vary drastically if the input image is trimmed, or altered in any other way. As a solution, we employ down sampling in our convolutional layers. The ability to down sample can be achieved by introducing a pooling layer after a non-linearity layer. When the input is translated slightly, the representation becomes roughly invariant thanks to pooling.

In a convolutional neural network, the final Fully Connected Layer receives the output of the final Pooling Layer. There may be one, two, or all of these layers depending on the situation. To be fully connected, all of the first-layer nodes must have links to all of the second-layer nodes.

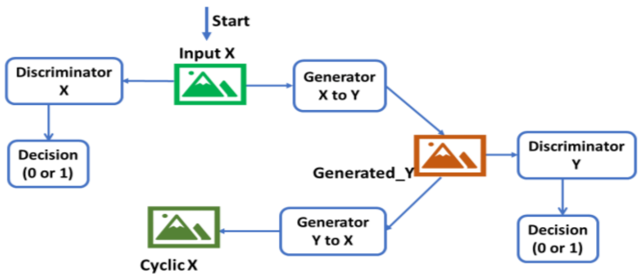

Fig. 2. Architecture of Cycle GAN

Fig. 3. Summer to winter [27]

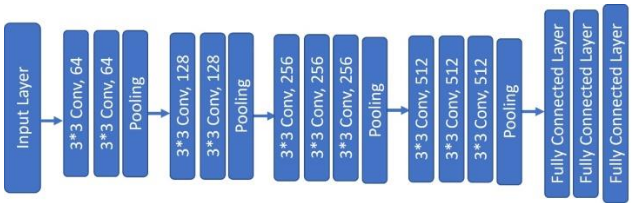

Fig. 4. Network Architecture of VGG-16

3. Evaluation metrics

Peak signal to noise ratio

The peak signal-to-noise ratio (PSNR) is the maximum pixel intensity divided by the distortion power, and it is calculated using the mean square error. Like MSE, the PSNR metric requires little effort to compute but may not correlate well with subjective evaluations of quality.

Structural similarity index

One metric for evaluating the quality of digital still photographs is the SSIM index. To calculate the SSIM of two images, x and y, we use the following formula. The Structural Similarity Index Approach is an interpretation-based framework. This approach sees image degradation as a shift in how we interpret the underlying structural details of an image. It works in tandem with other perceptual facts that are as crucial, such as the masking of brightness and contrast.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(c_1^2 + \mu_x^2 + \mu_y^2)(c_2^2 + \sigma_x^2 + \sigma_y^2)}$$

σ_y^2 – variance of y,
σ_x^2 – variance of x,
σ_{xy} – covariance of y and x,
μ_x – mean of x,
μ_y – mean of y.

Cross correlation coefficient

Cross-correlation assessment is a method of deducing properties of a signal from its correlation with another signal.

Accuracy

The degree of accuracy can be thought of as a representation of the probability that the values that were provided are accurate. A key measurement to take into account is the proportion of instances that the classifier correctly labelled.

$$Accuracy = \frac{TN + TP}{TP + FP + TN + FN}$$

TP indicates True Positive, FP indicates False Positive, FN indicates False Negative, and TN indicates True Negative.

Precision

The proportion of actual positive results relative to the total number of expected results is a measure of precision.

$$Precesion = \frac{TP}{TP + FP}$$

Recall

It evaluates a model based on how effectively it can provide accurate predictions.

$$Recall = \frac{TP}{TP + FN}$$

F1 score

It's a function that takes into account both accuracy and recall. It is the harmonic mean of recall and precision.

$$F1\ Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

4. Results and discussion

4.1. Datasets

To evaluate the method's performance, we used two databases, PTB and MIT-BIH [9]. The PTB diagnostic database contains 549 records, representing 290 individuals. Each record contains data from fifteen consecutive measurements of the same signal. One thousand samples per second of digital data are taken from each signal. There is a wide variety of data available, including that pertaining to heart failure, myocardial hypertrophy, intra-cardiac, healthy persons, and more. There are 25 recordings with junctional, supra-ventricular, and heart block arrhythmias, and 23 healthy recordings with sequential numbers between 100 and 124 in the MIT-BIH database.

The PASCAL Heart Sound Challenge [4] dataset, the Heart Sound and Murmur Library [13], and the PhysioNet CinC Challenge dataset [17] are only a few examples of openly accessible datasets for PCG recordings.

Dataset 'A' and dataset 'B' are two subsets of the Pascal HSC database. Dataset 'A' was collected with the help of the iStethoscope Pro iPhone software, whereas dataset 'B' was compiled in a hospital setting with the help of the digital stethoscope. There is a total of 176 and 656, respectively, of auscultations in the two data sets. Both sets of data include recordings of regular heartbeats, as well as those with murmurs and additional systoles. The PhysioNet CinC database version 2016 was also created for a competition. The dataset includes heart sounds from clinical as well as non-clinical environments. The 'normal,' 'uncertain,' and 'abnormal' sound categories are all part of the test.

There is also the Heart sound and Murmur Library from the Michigan University Health Systems, which is a publicly available dataset containing many types of heart murmurs and sound, such as normal heart sounds, S1, single S2, split S2 transient, and more.

4.2. Simulation results

The real and artificial ECG and PCG signals generated by LS GAN are displayed in figure 5 and figure 6, respectively whereas figure 7 shows real and artificial ECG and PCG signals generated using Cycle GAN. The similarity results between real and artificial (or Generated) signals are shown in the table 1 whereas table 2 gives the arrhythmia classification results.

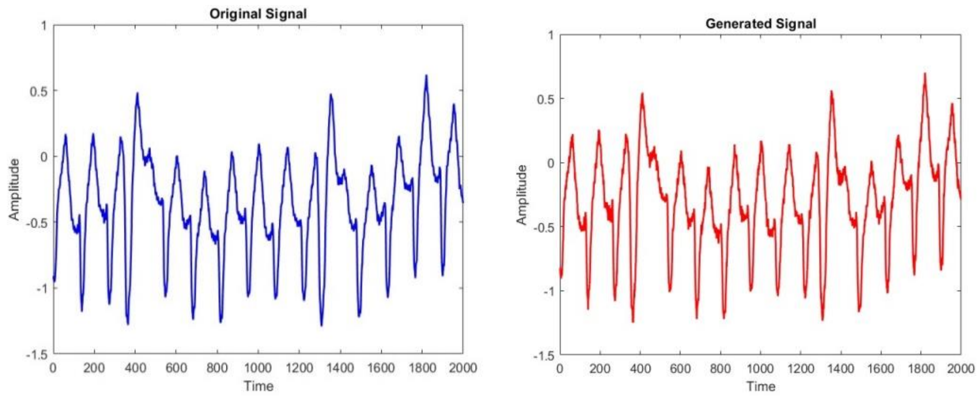

Fig. 5. Real and fake (generated) ECG Signals using LSGAN

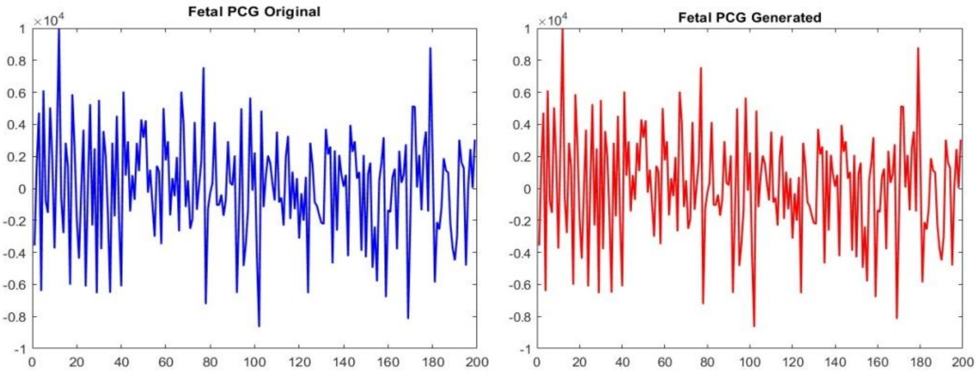

Fig. 6. Real and Fake (Generated) PCG Signals using LS GAN

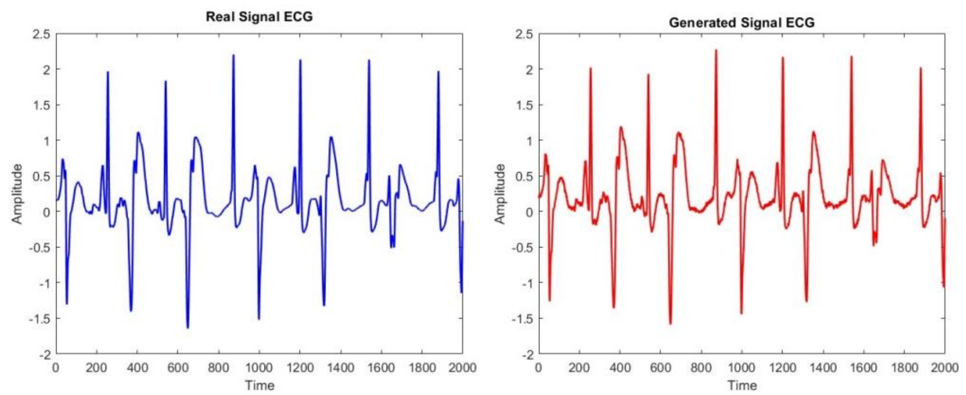

Fig. 7. Real and Fake (Generated) ECG Signals using Cycle-GAN

Table 1. Similarity results between synthesised and Real ECG and PCG signals

Method	Signal	MSE	SSIM
LSGAN	ECG	0.0702	0.9705
LSGAN	PCG	0.0728	0.9702
CycleGAN	ECG	0.0651	0.9823
CycleGAN	PCG	0.0699	0.9805

Table 2. Arrhythmia classification results

Method	Signal	Precision	Recall	F1 Score
LSGAN	ECG	0.9002	0.8569	0.8780
LSGAN	PCG	0.8959	0.8412	0.8676
CycleGAN	ECG	0.9120	0.8952	0.9035
CycleGAN	PCG	0.9054	0.8897	0.8974

5. Conclusion

There are a number of constraints that could make it difficult to get extensive patient information. The synthesis of realistic data has emerged as an attractive new topic of research in healthcare, particularly medicine. This is mostly due to the fact that it enables supervised machine learning classifiers to be better trained on datasets. In this research, ECG and PCG data were created using Least Squares GAN and Cycle GAN. Furthur, using VGGNet, studies were conducted to classify arrhythmias for the synthesized ECG signals. The synthesized signals performed well and resembled the original signal and the obtained precision of 96.99%, recall of 97.81% and an F1 score of 97.22%.

References

[1] Ahmed N., Zhu Y.: Early Detection of Atrial Fibrillation Based on ECG Signals. Bioengineering 7(1), 2020, 16 [http://doi.org/10.3390/bioengineering7010016].
[2] Akkaradamrongrat S. et al.: Text generation for imbalanced text classification. 16th International Joint Conference on Computer Science and Software Engineering (JCSSE), 2019, 181–186.
[3] Aziz S. et al.: Phonocardiogram Signal Processing for Automatic Diagnosis of Congenital Heart Disorders through Fusion of Temporal and Cepstral Features. Sensors 20(13), 2020, 3790 [http://doi.org/10.3390/s20133790].
[4] Bentley P. et al.: Classifying Heart Sounds Challenge. 2011 [http://www.peterjbentley.com/heartchallenge/index.html]
[5] Bouril D. et al.: Automated classification of normal and abnormal heart sounds using support vector machines. Computing in Cardiology Conference – CinC, Vancouver 2016, 549–552.
[6] Cayce G. I. et al.: Improved Neural Network Arrhythmia Classification Through Integrated Data Augmentation. IEEE MetroCon, Hurst 2022, 1–3.
[7] England J. R., Cheng P. M.: Artificial intelligence for medical image analysis: a guide for authors and reviewers. American journal of roentgenology 212(3), 2019, 513–519.
[8] Garcea F. et al.: Data augmentation for medical imaging: A systematic literature review. Computers in Biology and Medicine 152, 2023, 106391 [http://doi.org/10.1016/j.compbiomed.2022.106391].
[9] Goldberger A. L. et al.: PhysioBank, PhysioToolkit and PhysioNet: components of a new research resource for complex physiologic signals. Circulation 101, 2000, 215–220.
[10] Goodfellow I. et al.: Generative adversarial networks. Communications of the ACM, 63(11), 2020, 139–144 [http://doi.org/10.1145/3422622].
[11] Guo G. et al.: Multimodal Emotion Recognition Using CNN-SVM with Data Augmentation. IEEE International Conference on Bioinformatics and Biomedicine, Las Vegas 2022, 3008–3014.
[12] Houssein E. H.: ECG signals classification: a review. International Journal of Intelligent Engineering Informatics 5(4), 2017, 376–396.
[13] Judge R., Mangrulkar R.: Heart Sound and Murmur Library. [http://open.umich.edu/education/med/resources/heart-sound-murmur-library/2015].
[14] Khalifa Y et al.: A review of Hidden Markov models and Recurrent Neural Networks for event detection and localization in biomedical signals. Information Fusion 69, 2021, 52–72.
[15] Li H. et al.: Dual-input neural network integrating feature extraction and deep learning for coronary artery disease detection using electrocardiogram and phonocardiogram. IEEE Access 7, 2019, 146457–146469.
[16] Li J., Ke L., Du Q., Ding X., Chen X.: Research on the Classification of ECG and PCG Signals Based on BiLSTM-GoogLeNet-DS. Applied Sciences 12(22), 2022, 11762.
[17] Liu C. et al.: An open access database for the evaluation of heart sound algorithms. Physiological Measurement 37(12), 2016, 2181.
[18] Mao X. et al.: Least Squares Generative Adversarial Networks. arXiv, 2017 [http://arxiv.org/abs/1611.04076].
[19] Nedoma J. et al.: Comparison of BCG, PCG and ECG signals in application of heart rate monitoring of the human body. 40th International Conference on Telecommunications and Signal Processing – TSP, 2017, 420–424.
[20] Rahman, M. M. et al.: A Systematic Survey of Data Augmentation of ECG Signals for AI Applications. Sensors, 23(11), 2023, 5237 [http://doi.org/10.3390/s23115237].
[21] Simonyan K., Zisserman A.: Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv, 2015 [http://arxiv.org/abs/1409.1556].
[22] Skandarani Y. et al.: GANs for medical image synthesis: An empirical study. Journal of Imaging 9(3), 2023 [http://doi.org/10.3390/jimaging9030069].
[23] Sreeniwas Kumar A., Nakul S.: Cardiovascular Disease in India: A 360 Degree Overview. Medical Journal Armed Forces India 76(1), 2020, 1–3 [http://doi.org/10.1016/j.mjafi.2019.12.005].
[24] Wang T. C. et al.: High-resolution image synthesis and semantic manipulation with conditional gans. IEEE Conference on computer vision and pattern recognition. Salt Lake City, 2018, 8798–8807.
[25] Wu J. L. et al.: A prediction model of stock market trading actions using generative adversarial network and piecewise linear representation approaches. Soft Comput 27, 2023, 8209–8222 [http://doi.org/10.1007/s00500-022-07716-2].
[26] Xiong P. et al.: Deep Learning for Detecting and Locating Myocardial Infarction by Electrocardiogram: A Literature Review. Frontiers in Cardiovascular Medicine 9, 2022 [http://doi.org/10.3389/fcvm.2022.860032].
[27] Zhu J. Y. et al.: Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. arXiv [http://arxiv.org/abs/1703.10593].

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