

Heart beats classification method using a multi-signal ECG spectrogram and convolutional neural network with residual blocks

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ABSTRACT

The paper describes a process of formulating a classifier on the basis information contained by MIT-BIH arrhythmia database. This data source contains electrocardiographic signals from two sensors. Both were used, which represent not a typical phenomenon. In the learning process, the classifier uses only information with high certainty. Data are based on expert endorsements and the errors found have been corrected over the years. Specific types of heartbeats were divided into special groups according to the standard "Association for the Advancement of Medical Instrumentation" (AAMI). It recommends splitting the specific types into five separate groups according to physiological origin. Rare heartbeats have a limited number of occurrences. For one group, modifying methods were used which allowed to increase sufficiently the amount of data in training sets. This had a beneficial impact on the results. The solution includes features extraction. The main module of the classifier is a deep neural network. Good result was obtained with tools supporting automatic hyperparameter selection. In ECG signal diagnostics, the most significant task is to properly separate the group of supraventricular and ventricular beats. The study managed to obtain this error at an exceptionally low level and an overall accuracy of 98.37%.

1. Introduction

Cardiovascular disease is still one of the most frequent causes of death. In many illnesses, including cardiological ones, the decision about life-saving and therapeutic methods depends on quick and correct diagnosis of the disease. Many of the symptoms describe a whole range of illnesses. Making a diagnosis with a significant probability remain not a trivial task. Over time doctors will make greater use of tools that support them take decisions in real time. Medicine already accepts many different solutions, mostly based on artificial intelligence methods. Algorithms frequently use artificial neural networks, Bayesian networks, genetic algorithms, decision trees and fuzzy logic. When a short electrocardiographic record (ECG) analysis is needed, an experienced specialist will have no problem with this but some ECG examination can take up to several days. The correct heart rate can be between 60 and even 90 beats at rest. These produce an unimaginably enormous collection to analyse throughout the day. Therefore, automatic classification methods are needed. As a result of the analysis, the doctor receives selected fragments of the signal and proposed types of pathologies [1]. Continuous recording of medical signals is a crucial part of

diagnostics. Monitoring and supervision of the patient's current condition allow to provide a range of information. The signal generated from the sensors during a diagnostic procedure is used in medicine to diagnose heart diseases. ECG measurement obtain the recording of the electrical activity of the heart muscle from the surface of the chest in the form of potential difference (voltage) between the electrodes. The main objective was to produce a solution that would allow the analysis of an electrocardiographic signal with a high classification accuracy. The individual processing steps finally lead to the prediction of each heartbeat. The task of the algorithm is to indicate the type of heartbeat with a high level of certainty about the prediction. Initially, the signal will be decoded and saved in a form more suitable for further processing. This phase also includes steps to discard information less relevant for further processing. The following step is to extract the features. Specifying the properties that differ from certain types will significantly affect the results. The most essential step is to build a classifier. This tool is based on a neural network with a considerable number of hidden layers. An evaluation was carried out by analysing the outcomes and comparing them with the results from work on similar subjects.

It is worth saying a little more about the database that was used. The

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extensive period and its availability meant that this database was often utilised by researchers. Records were documented using the MIT format and contains 48 half-hour fragments of two-channel ambulatory ECG logs. These were obtained from 47 people examined in the Beth Israel Hospital Arrhythmia Laboratory. Twenty-three logs were selected at random from a set of four thousand available ECG records. The remaining twenty-five records were selected but considering less frequent and clinically significant heart condition that would not be well represented using random methods. These 25 logs additionally include cases of complex ventricular, supraventricular arrhythmias and conduction disorders. Such records will be of significant difficulty for arrhythmia detectors due to rhythm characteristics variations in QRS morphology or signal quality. The database has been improved over the years. It contains records of ECG examination of patients with heart arrhythmia.

The problem of classifying heartbeat types is well known in the literature. One approach is to analyze RR intervals (intervals between consecutive R waves in ECG signal) and use a projection matrix, such solutions can be found in [2] and [3]. This is good preprocessing in projects where there are limited computer resources. Usually better results are obtained by processing the ECG signal using wavelet transform as in [4]. However, more computer resources are needed to perform the corresponding calculations. The classifier itself should not be forgotten. Good results can be obtained considering applications based on LSTM recurrent networks as in the solution of [5]. Some of the best results are obtained with classifiers based on deep neural networks which include convolutional layers as in [3] where convolutional neural networks (CNNs) have proven effective in ubiquitous classification tasks, enabling automatic feature extraction during target classification. Deep neural network was also one of the elements of the classification process in the works [4] where a generative adversarial network (GAN) based on a fully automatic electrocardiogram arrhythmia classification system was presented, the discriminator consisted of a CNN that was trained on real as well as generated data. Analyzing ECG sensor readings has been an important diagnostic step for many years and there are numerous standards used worldwide. At each stage, an attempt has been made to follow guidelines or good practice. The main objective was to create a solution to analyze the electrocardiographic signal with a high classification accuracy. The various processing steps ultimately lead to predictions for each heartbeat. The task of the algorithm is to indicate the type of heartbeat with a high level of confidence in the prediction and to focus on groups of heartbeats that may be decisive for the further course of the patient's treatment.

The well-known MIT-BIH database was used in the study so that the results were comparable to as many cases as possible and allowed to assess the quality of the methodology. The specifics of the approach, i.e. the use of deep neural networks, caused the types of heartbeats to be divided in the solution into five main groups in order to make the results of better quality but give sufficient information to the doctor. The entire process of selecting the individual steps that make up the final algorithm was continuously checked against the final results to achieve good performance with a high degree of generalization at the same time. Therefore, measures such as automatic and more optimal selection process of parameters of the deep network model, advanced signal processing or enrichment of a sparse dataset were used. The following sections will introduce the methodology then the results achieved and finally the insights obtained will be discussed in detail.

2. Methodology

The data have been pre-processed to obtain better results. Activities to enhance the differences in the processed information are called feature extraction. In order to correctly classify the types of heartbeats, several stages of analysis are necessary. A signal recording with interference can go through a filtering process. This will get rid of noise and artefacts. The following step is the detection of QRS unit in ECG signal.

This complex is the most dominant in the time course. Unluckily, some types of beats are not characterised by such a structure. Components coming from the measuring apparatus or pacemaker of the examined patient may also occur. This significantly affects the results when comparatively simple algorithms are implemented. Determining a good QRS refraction position is very important when separating time intervals. There are many libraries with a minor error when it comes to detecting the precise parts in the ECG signal. Only the types described in the MIT-BIH database were utilized to train the created model. This approach was also adopted in [6–9] and allow for good evaluation of the neural network model. This means that the signal has been further processed using annotations added by cardiologists to the signal.

Size of the set of heartbeats processed is exceptionally large. Although the information contained therein is selected to consider certain specific and rare conditions, the number of occurrences of several types is small. A grouping method has been chosen to achieve good results and to divide the heartbeat types using reasonable relationships. Table 1 list all beat types and the number of heartbeats after pre-processing. The number may vary slightly because of the exclusion of ranges that occurred at the beginning or ending of the signal and did not have appropriate length for further processing. The table, in addition, contains acronyms used in medical literature.

It is worth mentioning a certain irregularity. The descriptions on the official website [10] from which the MIT-BIH database comes from do not match the markings existing in the waveform files. The numbers, signatures and appearance of the different types have been analysed to select and change the designations accordingly. The names cited are consistent with those presented in the files and will be used in this work. The type with the designation "!" has not been included at all, mainly due to uncertainty about where it should belong. In the works [11, 3, [4] and [5], it is unincluded. The works [12] and [6] grouped this type into a ventricular ectopic beat group. Attention should be paid to the high prevalence of normal heartbeats. Next are bundle branch blocks beat, premature ventricular contraction and paced beat. Although this is reflected in the probability of occurrence, such a distribution may affect the end results of the classifier.

The standard formulated by the "Association for the Advancement of Medical Instrumentation" was used in this work. The AAMI standard "EC38:2007" describes the testing and reporting of heart rate results and algorithms for measuring rhythm and impact events. It recommends categorising the types into five specific groups. Corresponding to the standard, the total MIT-BIH database should be divided according to their physiological origin. It is worth mentioning that a lot of work is not fully compliant with the AAMI standard, because NESC and AESC classes are assigned to the group "N" instead of "S" [11]. This approach has emerged in: [6, 4] and [5]. Incorrect labelling affects 245 strokes in the database, which is 8% of all supraventricular ectopic beats. The exact

Table 1

List of arrhythmia classes and their number.

Heartbeat Type	Acronym	Annotation	Total
Normal Beat	NORMAL	N	74984
Left bundle branch block beat	LBBB	L	8069
Right bundle branch block beat	RBBB	R	7250
Atrial escape beat	AESC	e	16
Nodal (junctional) escape beat	NESC	j	229
Atrial premature beat	APC	A	2544
Aberrated atrial premature beat	ABERR	a	150
Nodal (junctional) premature beat	NPC	J	83
Supraventricular premature beat	SVPCs/SVE	S	2
Premature ventricular contraction	PVC	V	7128
Ventricular escape beat	VESC	E	106
Ventricular flutter wave	FLWAV	!	(472)
Fusion of ventricular and normal beat	FUSION	F	802
Paced beat	PACE	/	7020
Fusion of paced and normal beat	PFUS	f	982
Unclassifiable beat	UNKNOWN	Q	33

grouping can be witnessed in Table 2.

The normal heartbeat group is the largest. This is a significantly big disproportion, especially as these are not the rare types of heartbeat that a specialist should focus on when analysing the results.

Signals were loaded and processed using the Python programming language. Each of two signals is loaded using WFDB library. The name of database indicates the format of its storage. Three essential files are responsible for storing recordings of ECG signals. The header document includes text in ASCII format concerning the title of the record, number and name of channels. In addition, contain information regarding the sampling rate of the signal, recording length and binary format. It may also contain details regarding the age and gender of the person being examined and includes information about the doctor's diagnosis and the medication patient is taking. Next file is the original signal record in binary format. Last document of the MIT format obtains a file with time annotations. Each record is encoded in 16 bits. The six most important ones are responsible for encoding the type of morphology of the beat or heart rate changes. The remaining bits express the distance from the previous annotation. Each of the separate files is named with a number derived from the name of the study.

Annotations allow to place the R wave in the signal. This can be used to keep important compartments and only these are processed further. A continuous digitally recorded signal was processed to isolate relevant information, a fixed distance was used for this purpose. Interval covers 260 signal points with 360 Hz sampling. The annotation place, i.e. the position of the R wave, has been shifted by a distance equal to 40% of the entire range from the first vector point. This value has been selected because of the unique nature of the heartbeat characteristic. At this stage, the information about the specific patient's affiliation is also lost. An insignificant number of papers use two signals, one of them is [3]. This approach allows to get better results.

The recording of the ECG signal is affected by several disturbances. The time course of the signal can be influenced by the way the measuring equipment is powered, characteristics of the electrode connection point and patient movements during the test. A standard problem is isoelectric line level fluctuation, which may be caused by chest breathing movements [13].

Data augmentation is frequently used in real applications. Deep neural networks need much information to learn specific features of a class. Reproduction by modification allows you to easily increase the number of resources in the collection. It is important to remember that data after modification should not lose relevant information. The fusion beat group contains very few examples. In the majority of works, it achieves the worst result during classification. Because there is only one type of heartbeat in this collection, it is easier to process and verify how the modification will affect the result. Data in the amount of 80% of the whole group were duplicated four times. The process started after the rejection of the data for the test set. The signal points have been multiplied, and heartbeat intervals have been shortened using a small factor. The modifications described here allow to generate some differences without significantly disturbing the signal characteristics. Test and validation set differs significantly in the number of samples for group F due to the generation of additional data samples that could not be included in the test set. Adding such samples would affect final result. Test set is intended to be representative.

Table 2
Grouping of heartbeat types according to AAMI standard.

AAMI Classes	Symbol	MIT-BIH heartbeat types	Total
Normal beat	N	NORMAL, LBBB, RBBB	90303
Supraventricular ectopic beat	S	APC, NPC, ABERR, SVPCs/SVE, NESC, AESC	3024
Ventricular ectopic beat	V	PVC, VESC	7234
Fusion beat	F	FUSION	802
Unknown beat	Q	PACE, PFUS, UNKNOWN	8035

One of the frequently used steps when pre-processing an ECG signal is to create a spectrogram. This is a time spectrum analysis that shows in the time and frequency domains the energy distribution of the studied waveform. It is determined by dividing the signal into shorter periods for which the amplitudes of harmonic components are calculated. The application of this method in subsequent stages of the signal processing allows to bypass many steps that would occur in the initial phase. To proceed, a linear interpolation was needed because record of one heartbeat is actually a set of points. The spectrogram is created using a moving Fourier transform, illustrating frequency changes.

The process of creating the spectrogram applies to both signals. The resulting RGB colour image represent the product of two processes. An example is shown in Fig. 1.

In this work the supervised learning method was implemented. All possible heart evolutions from the MIT-BIH database were used. The exceptions are the heart evolutions that ended and started a given signal recording. The reason was insufficient signal length. In order to utilise these parts, additional processing would have to be carried out. The data were divided in a ratio of 60% into test set and 20% validation data. The test set also contained 20% of the initial data. After this process, modified information was included. The training set represents all heartbeat classes, their exact number is shown in a Table 3. The test set represents the distribution of individual groups of entire database. The other two sets acquire additional modified units coming from the fusion group.

Among the various scientific studies, the most frequently used classification methods are the decision tree, the support vector machine (SVM), artificial neural networks or dynamic Bayesian networks [7]. A complex neural net based on convolutional layers will be used in this work. Networks of the Inception family (developed by the "Google" Company) are based on functional modules whose inputs are processed by several parallel convolutional branches [2]. In later steps, these inputs are combined. The network consists of a stack of modules. Each of the self-contained modules has three or four branches. The feature of such a construction is to facilitate learning of channels and spatial dependencies. Each of the branches differs in order to learn different features. An additional system which significantly influenced the achievements turned out to be a technique allowing to include residual

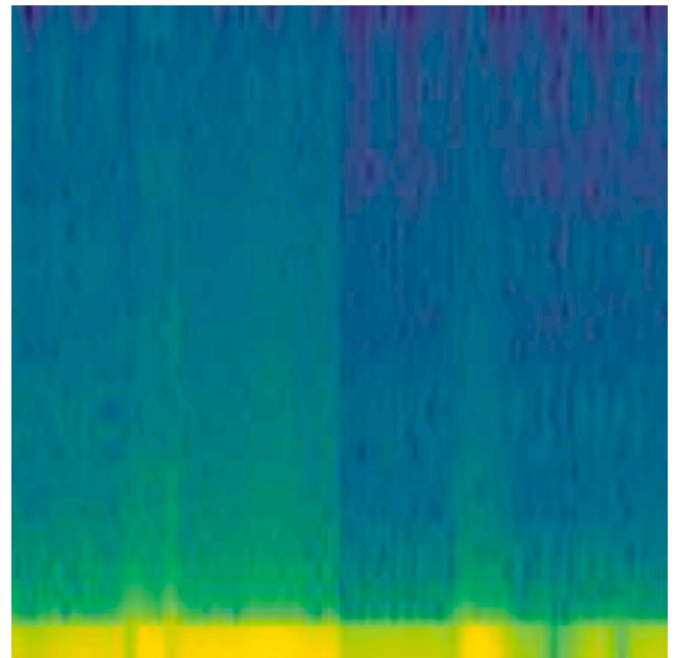


Fig. 1. The final photo, consisting of two spectrograms, comes from the ventricular ectopic group.

Table 3

The number of each class in the training, validation and test set.

Set	Number of heartbeat units of a group				
	Normal	Supraventricular ectopic	Ventricular ectopic	Fusion	Unknown
Training	54181	1814	4340	2472	4821
Validation	18060	604	1446	898	1607
Test	18062	606	1448	160	1607

connections to the model. The networks of this group are called ResNet and were developed by Microsoft.

Both architectures presented above are remarkably efficient and have low calculation costs. Many solutions have been tested during the creation of this work. The own idea based on generally known diagrams produced good results, but they were not enough. Therefore, it was decided to use the existing architecture. The model based on the construction of Inception-ResNet v2 proved to be the best solution which is available in the Keras library. The schematic diagram of this solution is shown in Fig. 2.

A deep neural network very often consists of many different types of layers. One of these is the layer which creates a spatial transformation by looking for patterns. It is called convolutional layer will determine the output of neurons of which are connected to local regions of the input through the calculation of the scalar product between their weights and the region connected to the input volume [15]. One of the basic layers of deep networks is called fully connected. In a model with convolutional layers, the features generated by the final convolutional layer correspond to a portion of the input image as its receptive field does not cover the entire spatial dimension of the image [16]. Therefore, a good network also needs several fully connected layers. Pooling layers are applied the output of convolution layers. To summarize the activation maps, prevent overfitting and reduce the number of computational nodes, pooling operation is used by sliding a window on the image [17]. These are the main layers of which a convolutional neural network is composed. However, methods are often used which only show their importance during the learning process. Dropout is one of the useful approaches for preventing overfitting, some selected activations are set to zero during the training, and selected neurons are changed in each iteration [17]. It is possible to load model weights from the learning process on the "ImageNet" collection. This option was unused because it did not produce good results. Even when a significant part of the layers was unblocked for teaching on the training set. The neural network had to be taught from scratch. At this stage, the weights of specific classes have also been set to balance their numerical diversity. The values selected correspond to the natural logarithm from the numerical ratios of the specific classes. This approach allows for much better

generalisation. One of the other advantages is it makes it easier to track losses when classes have different amounts of data. The assigned values influence the losses, informing in a considerably more effective way during each run about the generalisation of the network at a given stage. Most of the hyperparameters were selected based on the results from the use of the Hyperopt and Hyperas library. Both allow to optimise selected hyperparameters. Their main task is to process the model for previously optional hyperparameters and return the ones which after several runs allowed to achieve the best result.

3. Results

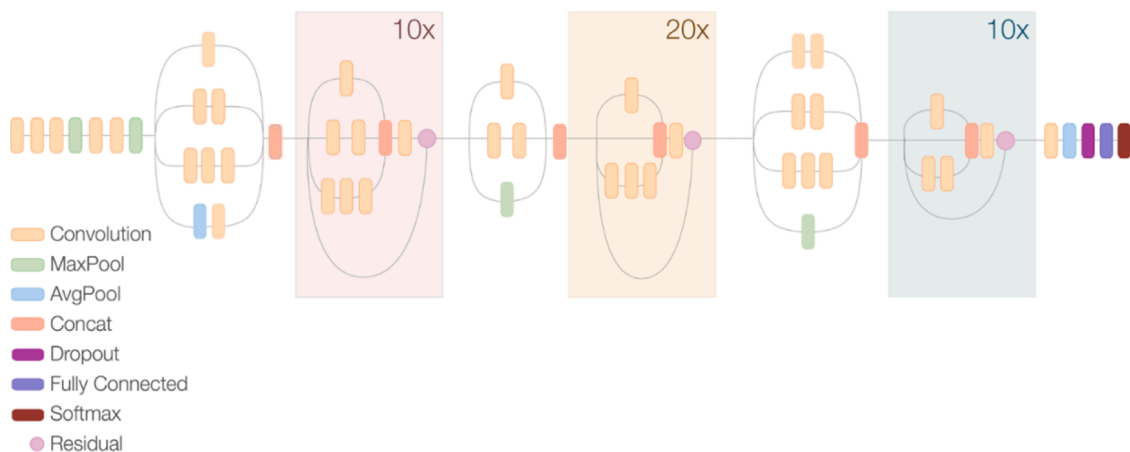
Analysing the results remains a troublesome task, especially when the classes you own to having various levels of significance. There are problems where it is better to get a poorer overall score but the most beneficial possible outcome from several specific classes. Table 4 presents the exact results of the classification. Specialised metrics are needed to make a subjective evaluation of a complex algorithm. Testing the correctness of the result alone usually does not provide sufficient information. Confusion matrix is a technique for summarizing the performance of a classification. Accuracy alone may not be enough. Therefore, the percentage score of true positives in relation to all results considered positive was also used. The next measure is sensitivity, which is the percentage of true positives in relation to all the positives in the set. Finally, the percentage of true negative score in relation to all negative score in the set, in other words specificity.

Feature extraction allowed to obtain results with a low error rate. Some classes have done worse than others. Class F obtained the worst performance of all before including the modified data to the training sets. The results indicate the biggest mistake is to classify the supraventricular ectopic beat as normal beat. Class Q has the best results. Only a few data samples were recognised as other classes. It can be concluded that the characteristics of this group are very strong and define the affiliation well. A considerable number of errors between the S and N classes can be observed. Such a correlation is also observed in other papers. This means that both groups are similar. In the diagnosis of ECG signals, the most crucial task is to separate the group of supraventricular

Table 4

Results of the heartbeat group classifier

AAMI Class	Accuracy [%]	Precision [%]	Sensitivity [%]	Specificity [%]
N	98.45	98.70	99.41	94.07
S	98.93	90.59	75.62	99.73
V	99.67	96.75	98.25	99.77
F	99.73	94.38	75.50	99.96
Q	99.95	99.38	100	99.95

**Fig. 2.** Compressed view of Inception-ResNetv2 [14].

ectopic and ventricular ectopic. The number of these errors was very low. Fusion class can be described as a phenomenon of overlap between the ventricular ectopic and normal type. It is therefore not surprising that there were errors in this group concerning the classification of several samples into N and V classes. No errors in other groups related to this class can mean a relatively considerable learning of the group's characteristics by the tested model.

In order to require a more appropriate comparison, Table 5 was created, which shows the percentage results of many researches works. Ventricular ectopic class came out fine in comparison with other works. The supraventricular ectopic group performed a little less well but does not differ significantly from other results.

The work cited above has different processing and classification processes. This also applies to the number of data transferred to the learning process and test set. A change of proportions may have an impact on the results and accuracy of the presented final relations.

Although the analysis concerns the last model with the best results, it is important to mention a few changes that have made a noticeable contribution improve evaluation. In the beginning, the picture after the extraction of the features contained only one signal. Adding the second one increased the effectiveness by two percentage points on average. The amount of data for S class is small, which is mapped in the results. Initially, the statistical measurement values of class F were the worst of all. Modified data significantly increased the amount of information in the training sets. The attempt to simply duplicate the data of this group did not produce positive results. In the beginning, because of the lack of implementation of generators, less content was used. The results were not satisfactory, the model responded much better to an unbalanced training set, but with a lot more learning data. Probably more data would have allowed to produce better results. Hyperparameters for a model are chosen according to the problem being solved. Sometimes it is better to have less weight to learn, because the network can remember a certain modest number of variables and therefore focus on the most important ones. During the analysis of the model, a positive impact on the result could be observed when increasing the number of weights. The results obtained are satisfactory compared to other work and previous initial assumptions.

4. Discussion

Good solutions should have significant resistance to errors and interference. Each measurement of signals coming from the patient is dependent on the quality of the performed process. This is influenced by the person examined and the specialist responsible for the course of the examination. The patient may have involuntary muscle spasms, which occur in many diseases or other ailments changing the parameters of body composition. It is good if the model responsible for the classification has learned only such features that differ in the types of heartbeats.

Managing such tools, the diagnostician must make his own judgement. He should not have utmost confidence in the tools used, especially as he apparently does not know the details of the algorithm. It may be unappropriated to have unlimited confidence in the results if specialist is

dealing with the health and life of another person. ECG signal analysis has been an important diagnostic step for many years, thanks to which there are many standards used worldwide.

At each stage, guidelines or good practices were followed. The use of a validation set allowed for better separation of test data. Therefore, training on the training set, selecting hyperparameters on the validation set, and conducting trials on the test set allows for greater generalisation and better representation of real-world conditions. An even worthier solution could be to apply data to the test phase that comes from a completely different distribution. Simplistic, resource-efficient solutions are being sought. The presented classifier does not belong to them, although one cannot say too much before implementation and practical use. It is likely that the time required for processing may turn out to be low enough, and the results are correct sufficiently for a solution based on an extensive neural network model to be implemented. The solution, although it may need a lot of processing power to operate, is still relatively simple compared to solutions with good results in this area.

Several interferences occurring have not been removed from the waveforms due to their prevalence in all signals. It can be assumed that due to their nature they do not have much influence on the learned traits. And finally, waveform results from external databases that most likely do not have these distortions. At the very beginning, because of an error, a spectrogram was created over the entire interval. The Fourier transform covered the entire length of each heartbeat. The results obtained were surprisingly impressive. It can be assumed that many of the key features that decide about belonging to a particular group were found using the ordinary Fourier transform.

When data is randomly divided into sets, there is a risk that the network will adapt to the characteristics of the patient record. This is a complex problem to verify. It is important to consider the steps of processing and extraction of the features, which have minimised the possibility of this problem by the disappearance of certain signal information. While working on the neural network, there was an idea to use part of the scales of the finished model, which was taught on a well-known image database. Allowing only a few final layers to be changed in order to leave the learned transformations and shorten the learning process significantly. Unfortunately, the results were considerably worse than during the learning process of the whole model, starting with randomised scales.

Generating one image from two signals increases the calculation effort only minimally. This does not extend the number of pixels of the image, so the time to train the network should not increase. Obtaining good results for groups "V" and "S" is very important. One way to achieve this is to set more weight during the learning process so that errors in these classes deliver higher values of loss. The algorithm would focus more on these problems to minimise the overall value. This approach has been implemented and has produced positive results. The applied processing steps allow for the quick process and incorporate data from other sources into the training set.

Table 5
Comparative classification results for AAMI grouping using MIT-BIH database.

Publication	ACC	TPR	SPC	TPR(N)	(N)	ACC(S)	TPR(S)	(S)	ACC(V)	TPR(V)	(V)
[9] 2004	81.9	-	-	86.9	99.2	94.6	75.9	38.5	97.4	77.7	81.9
[7] 2012	86.4	-	-	88.5	97.5	-	60.8	52.3	-	81.5	63.1
[18] 2014	86.7	-	-	88.9	99.0	-	79.1	36.0	-	85.5	92.8
[19] 2016	96.40	68.80	99.50	-	-	-	-	-	-	-	-
[6] 2017	93.1	-	-	98.4	95.4	-	29.5	38.4	-	70.8	85.1
[20] 2018	98.63	98.79	97.87	-	-	-	-	-	-	-	-
[21] 2018	-	-	-	-	-	93.78	88.39	33.63	96.63	77.74	69.20
[22] 2018	98.6	96.5	99.1	97.3	-	98.4	96.1	-	99.1	96.8	-
[5] 2020	98.17	97.78	98.57	99.24	-	98.99	70.04	-	98.77	89.28	-
created sol.	98.37	98.54	95.08	99.41	98.70	98.93	75.62	90.59	99.67	98.25	96.75

5. Conclusion

During the development of this solution, the use of a waveform transformer was tested instead of the continuous Fourier transformer used in the end. The results obtained were much better. This approach was not implemented because the time needed to extract the features increased several times, making it impossible to analyse the solution more sensibly.

One of the ideas for modifying the work is to use two images of the spectrograms without combining the signals into one picture. In this case, the model should have two input layers, which would connect after several blocks of the neural network. Presumably the results would be better because in the used base the signals do not always come from the same sensors. Much better results can typically be achieved by using model assemblies. Blocks should vary greatly and at the same time achieve good results. The variety of models allows to provide information not available for one type of neural network. The combination of such models should be done using an appropriate weighted average. The weights shall be determined by the results of the network type. Research work shows that good results can be obtained using recurring networks. Only higher computing power requirements may remain a negative factor in this case. Manual tuning of the model hyperparameters does not make sense if there are automatic methods. It is worthier to use automated techniques, which allows for faster and more reliable optimisation in this area. An interesting solution is to use additional information about RR intervals, which would be processed during the same learning action. This could be performed by creating a second data input, which would take a tensor with this information. It is likely that any new data could provide additional information to help improve this classifier. This includes information about the patient such as his age, medical history and gender.

Declaration of Competing Interest

None declared

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