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**Automatic Diagnosis of the Short-Duration 12-Lead ECG using a Deep Neural Network: the CODE Study**

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This manuscript was compiled on April 4, 2019

**We present a Deep Neural Network (DNN) model for predicting elec- trocardiogram (ECG) abnormalities in short-duration 12-lead ECG recordings. The analysis of the digital ECG obtained in a clinical setting can provide a full evaluation of the cardiac electrical activity and have not been studied in an end-to-end machine learning sce- nario. Using the database of the Telehealth Network of Minas Gerais, under the scope of the CODE (Clinical Outcomes in Digital Electro- cardiology) study, we built a novel dataset with more than 2 million ECG tracings, orders of magnitude larger than those used in previ- ous studies. Moreover, our dataset is more realistic, as it consists of 12-lead ECGs recorded during standard in-clinic exams. Using this data, we trained a residual neural network with 9 convolutional lay- ers to map ECG signals with a duration of 7 to 10 seconds into 6 different classes of ECG abnormalities. High-performance measures were obtained for all ECG abnormalities, with F1 scores above** 80% **and specificity indexes over** 99%**. We compare the performance with cardiology and emergency resident medical doctors as well as med- ical students and, considering the F1 score, the DNN matches or outperforms the medical residents and students for all abnormali- ties. These results indicate that end-to-end automatic ECG analysis based on DNNs, previously used only in a single-lead setup, gener- alizes well to the 12-lead ECG. This is an important result in that it takes this technology much closer to standard clinical practice.**

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ardiovascular diseases are the leading cause of death world- wide ([1](#_bookmark4)) and the electrocardiogram (ECG) is a major tool

**C**

in their diagnoses. As ECGs transitioned from analog to digital, automated computer analysis of standard 12-lead elec- trocardiograms gained importance in the process of medical diagnosis ([2](#_bookmark5), [3](#_bookmark6)). However, limited performance of classical algorithms ([4](#_bookmark7), [5](#_bookmark8)) precludes its usage as a standalone diagnostic tool and relegates them to an ancillary role ([3](#_bookmark6), [6](#_bookmark9)).

Deep neural networks (DNNs) have recently achieved strik- ing success in tasks such as image classification ([7](#_bookmark10)) and speech recognition ([8](#_bookmark11)), and there are great expectations when it comes to how this technology may improve health care and clinical practice ([9](#_bookmark12)–[11](#_bookmark13)). So far, the most successful applications used a supervised learning setup to automate diagnosis from ex- ams. Supervised learning models, which learn to map an input to an output based on example input-output pairs, have achieved better performance than a human specialist on their routine work-flow in diagnosing breast cancer ([12](#_bookmark14)) and detect- ing retinal diseases from three-dimensional optical coherence tomography scans ([13](#_bookmark15)). While efficient, training DNNs in this setup introduces the need for large quantities of labeled

data which, for medical applications, introduce several chal- lenges, including those related to confidentiality and security of personal health information ([14](#_bookmark16)).

A convincing preliminary study of the use of DNNs in ECG analysis was recently presented in ([15](#_bookmark17)). For single-lead ECGs, DNNs could match state-of-the-art algorithms when trained in openly available datasets (e.g. 2017 PhysioNet Challenge data ([16](#_bookmark18))) and, for a large enough training dataset, present superior performance when compared to practicing cardiologists. However, as pointed out by the authors, it is still an open question if the application of this technology would be useful in a realistic clinical setting, where 12-lead ECGs are the standard technique ([15](#_bookmark17)).

The short-duration, standard, 12-lead ECG (S12L-ECG) is the most commonly used complementary exam for the evalua- tion of the heart, being employed across all clinical settings, from the primary care centers to the intensive care units. While long-term cardiac monitoring, such as in the Holter exam, provides information mostly about cardiac rhythm and repolarization, the S12L-ECG can provide a full evaluation of the cardiac electrical activity. This includes arrhythmias, conduction disturbances, acute coronary syndromes, cardiac chamber hypertrophy and enlargement and even the effects of drugs and electrolyte disturbances. Thus, a deep learning approach that allows for accurate interpretation of S12L-ECGs would have the greatest impact.

S12L-ECGs are often performed in settings, such as in pri- mary care centers and emergency units, where there are no specialists to analyze and interpret the ECG tracings. Primary care and emergency department health professionals have lim- ited diagnostic abilities in interpreting S12-ECGs. ([17](#_bookmark19), [18](#_bookmark20)). The need for an accurate automatic interpretation is most acute in low and middle-income countries, which are respon- sible for more than 75% of deaths related to cardiovascular disease ([19](#_bookmark21)), and where the population, often, do not have

A.H.R., M.H.R., G.P. D.M.O., P.R.G., J.A.C, M.P.S.F and A.L.R were responsible for the study de- sign. A.L.R conceived the project and acted as project leader. A.H.R., M.H.R and C.A. choose the architecture, implemented and tuned the deep neural network. A.H.R did the statistical analysis of the test data and generated the figures and tables. M.H.R., G.M.M.P, J.A.C. were responsi- ble for the preprocessing and annotating the datasets. G.M.M.P was responsible for the error analysis. D.M.O. implemented the semi-supervised methodology to extract the text label. P.R.G. implemented the user interface used to generate the dataset. P.R.G. and M.P.S.F were respon- sible for maintenance and extraction of the database. P.W.M., W.M.Jr., and T.B.S helped in the interpretation of the data. A.H.R., M.H.R, P.W.M., T.B.S. and A.L.R. contributed to the writing and all authors revised it critically for important intellectual content. All authors read and approved the submitted manuscript.

None of the authors have potential conflicts of interest.

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1dAVb | 0*.*893 | 0*.*905 | 0*.*639 | 0*.*605 | 0*.*893 | 0*.*679 | 0*.*821 | 0*.*929 | 0*.*996 | 0*.*997 | 0*.*984 | 0*.*979 | **0.893** | 0*.*776 | 0*.*719 | 0*.*732 |
| RBBB | 0*.*872 | 0*.*868 | 0*.*963 | 0*.*914 | 1*.*000 | 0*.*971 | 0*.*765 | 0*.*941 | 0*.*994 | 0*.*994 | 0*.*999 | 0*.*996 | **0.932** | 0*.*917 | 0*.*852 | 0*.*928 |
| LBBB | 0*.*968 | 1*.*000 | 0*.*963 | 0*.*931 | 1*.*000 | 0*.*900 | 0*.*867 | 0*.*900 | 0*.*999 | 1*.*000 | 0*.*999 | 0*.*997 | **0.984** | 0*.*947 | 0*.*912 | 0*.*915 |
| SB | 0*.*833 | 0*.*833 | 0*.*824 | 0*.*750 | 0*.*938 | 0*.*938 | 0*.*875 | 0*.*750 | 0*.*996 | 0*.*996 | 0*.*996 | 0*.*995 | **0.882** | **0.882** | 0*.*848 | 0*.*750 |
| AF | 0*.*800 | 0*.*769 | 0*.*800 | 0*.*571 | 0*.*923 | 0*.*769 | 0*.*615 | 0*.*923 | 0*.*996 | 0*.*996 | 0*.*998 | 0*.*989 | **0.857** | 0*.*769 | 0*.*696 | 0*.*706 |
| ST | 0*.*897 | 0*.*968 | 0*.*919 | 0*.*882 | 0*.*972 | 0*.*833 | 0*.*944 | 0*.*833 | 0*.*995 | 0*.*999 | 0*.*996 | 0*.*995 | **0.933** | 0*.*896 | 0*.*932 | 0*.*857 |

**Table 1. Performance on the test set. Scores of our DNN are compared with the average performance of: i) 4th year cardiology resident (*cardio.*); ii) 3rd year emergency resident (*emerg.*); and, iii) 5th year medical students (*stud.*). (PPV = positive predictive value)**

1.0

DNN

cardio. emerg. stud.

1.0

1.0

0.8

0.8

0.8

0.6

Precision (PPV)

0.6

0.6

0.4

0.4

0.4

0.2

0.2

0.2

0.0

0.0 0.2 0.4 0.6 0.8 1.0

1. 1dAVb

0.0

0.0 0.2 0.4 0.6 0.8 1.0

1. RBBB

0.0

0.0 0.2 0.4 0.6 0.8 1.0

1. LBBB

1.0

1.0

1.0

0.8

0.8

0.8

0.6

Precision (PPV)

0.6

0.6

0.4

0.4

0.4

0.2

0.2

0.2

0.0

0.0 0.2 0.4 0.6 0.8 1.0

Recall (Sensitivity)

1. SB

0.0

0.0 0.2 0.4 0.6 0.8 1.0

Recall (Sensitivity)

1. AF

0.0

0.0 0.2 0.4 0.6 0.8 1.0

Recall (Sensitivity)

1. ST

**Fig. 1.** Precision-recall curve for our prediction model on the test set with regard to each ECG abnormalities. We also plot the precision-recall points for the DNN with the same threshold used for generating Table [1](#_bookmark0) and for the resident medical doctors and students.

access to cardiologists with full expertise in ECG diagnosis. The use of DNNs for S12L-ECG is still largely unexplored.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | Precision (PPV) |  | Recall (Sensitivity) | Specificity |  | F1 Score |  |
| DNN | cardio. emerg. stud. | DNN | cardio. emerg. stud. | DNN cardio. emerg. | stud. | DNN cardio. emerg. | stud. |

A contributing factor for this is the shortage of full digital S12L-ECG databases, since most recordings are still registered only on paper, archived as images, or stored in PDF format ([20](#_bookmark22)). Most available databases comprise a few hundreds of tracings and no systematic annotation of the full list of ECG diagnoses ([21](#_bookmark23)), limiting their usefulness as training datasets in a supervised learning setting. This lack of systematically annotated data is unfortunate, as training an accurate auto- matic method of diagnosis from S12L-ECG would be greatly beneficial.

In this paper, we demonstrate the effectiveness of DNNs for automatic S12L-ECG classification. We built a large-scale *novel* dataset of labelled S12L-ECG exams for clinical and prog- nostic studies (the CODE - Clinical Outcomes in Digital Elec- trocardiology study) and use it to develop a DNN to classify

6 types of ECG abnormalities: 1st degree AV block (1dAVb), right bundle branch block (RBBB), left bundle branch block (LBBB), sinus bradycardia (SB), atrial fibrillation (AF) and sinus tachycardia (ST). These were considered representative of both rhythmic and morphologic ECG abnormalities.

# Results

We collected a dataset consisting of 2,322,513 ECG records from 1,676,384 different patients of 811 counties in the state of Minas Gerais/Brazil from the Telehealth Network of Minas Gerais (TNMG) ([22](#_bookmark24)). The acquisition and annotation proce- dures of this dataset are described in Methods. We split this dataset into a training set and a validation set. The training set contains 98% of the data. The validation set consists of the remaining 2% (~50,000 exams) of the dataset and it was used for hyperparameter tuning.

We used a DNN architecture known as the residual net-

work ([23](#_bookmark25)), commonly used for images, which we here have adapted to unidimensional signals. A similar architecture has been successfully employed for detecting abnormalities in single-lead ECG signals ([15](#_bookmark17)). The DNN parameters were learned using the training dataset and our design choices were made in order to maximize the performance on the validation dataset. We should highlight that, despite using a significantly larger training dataset, we got the best validation results with an architecture with, roughly, one quarter the number of layers and parameters of the network employed in ([15](#_bookmark17)).

For *testing* the model we employed a dataset consisting

of 827 tracings from distinct patients annotated by 3 differ- ent cardiologists with experience in electrocardiography (see Methods). Table [1](#_bookmark0) shows the performance of the DNN on the test set. High-performance measures were obtained for all ECG abnormalities, with F1 scores above 80% and specificity indexes over 99%. We consider our model to have predicted the abnormality when its output — a number between 0 and 1 — is above a threshold. Figure [1](#_bookmark1) shows the precision-recall curve for our model, for different values of this threshold. For generating the DNN scores presented in Table [1](#_bookmark0) the thresh- old was chosen to maximize the respective F1 score for each abnormality. The precision-recall points corresponding to the DNN with this threshold are plotted in Figure [1](#_bookmark1).

The same dataset was evaluated by: i) two 4th year car- diology residents; ii) two 3rd year emergency residents; and,

iii) two 5th year medical students. Each one annotated half of the exams in the test set. Their average performances are given, together with the DNN results, in the Table [1](#_bookmark0) and their precision-recall scores are plotted on Figure [1](#_bookmark1). Considering the F1 score, the DNN matches or outperforms the medical residents and students for all abnormalities. The confusion matrices and the inter-rater agreement (kappa coefficients) for the DNN, the resident medical doctors and students are provided, respectively, in Tables [5](#_bookmark54) and [6](#_bookmark55) in the supplementary material.

A trained cardiologist reviewed all the mistakes made by the DNN, the medical residents and the students, trying to explain the source of the error. The cardiologist had meetings with the residents and students where they together agreed on which was the source of the error. The results of this analysis are given in Table [2](#_bookmark2).

In order to compare of the performance difference between the DNN and resident medical doctors and students, we com- pute empirical distributions for the precision (PPV), recall (sensitivity), specificity and F1 score using bootstraping ([24](#_bookmark26)). The boxplots corresponding to these bootstrapped distribu- tions are presented in Figure [4](#_bookmark52) in the supplementary material. We have also applied the McNemar test ([25](#_bookmark27)) to compare the misclassification distribution of the DNN, the medical resi- dents and the students. Table [4](#_bookmark53) in the supplementary material show the *p*-values of the statistical test. Both analyses do not indicate a statistically significant difference in performance among the DNN and the medical residents and students for most of the classes.

# Discussion

This paper demonstrates the effectiveness of "end-to-end" au- tomatic S12L-ECG classification. This presents a paradigm shift from the classical ECG automatic analysis methods ([26](#_bookmark28)). These classical methods, such as the University of Glasgow

ECG analysis program ([27](#_bookmark29)), first extract the main features of the ECG signal using traditional signal processing tech- niques and then use these features as inputs to a classifier. End-to-end learning presents an alternative to these two-step approaches, where the raw signal itself is used as an input to the classifier which learns, by itself, to extract the features.

Neural networks have previously been used for classification of ECGs both in a classical — feature-based — setup ([28](#_bookmark30)) and in an end-to-end learn setup ([15](#_bookmark17), [29](#_bookmark31), [30](#_bookmark32)). Hybrid methods combining the two paradigms are also available: the classifi- cation may be done using a combination of handcrafted and learned features ([31](#_bookmark33)) or by using a two-stage training, obtain- ing one neural network to learn the features and another to classify the exam according to these learned features ([32](#_bookmark34)).

The paradigm shift towards end-to-end learning had a sig- nificant impact on the size of the datasets used for training the models. Many results using classical methods ([26](#_bookmark28), [30](#_bookmark32), [32](#_bookmark34)) train their models on datasets with few examples, such as the MIT-BIH arrhythmia database ([33](#_bookmark35)), with only 47 unique patients. The most convincing papers using end-to-end deep learning or mixed approaches, on the other hand, have con- structed large datasets, ranging from 3,000 to 50,000 unique patients, for training their models ([15](#_bookmark17), [16](#_bookmark18), [31](#_bookmark33)).

Large datasets from previous work ([15](#_bookmark17), [16](#_bookmark18), [31](#_bookmark33)), however, were obtained from cardiac monitors and Holter exams, where patients are usually monitored for several hours and the record- ings are restricted to one or two leads. Our dataset with well over 2 million entries, on the other hand, consists of short duration (7 to 10 seconds) S12L-ECG tracings obtained from in-clinic exams and is orders of magnitude larger than those used in previous studies. It encompasses not only rhythm disorders, like AF, SB and ST, as in previous studies ([15](#_bookmark17)), but also conduction disturbances, such as 1dAVb, RBBB and LBBB. Instead of beat to beat classification, as in the MIT- BIH arrhythmia database, our dataset provides annotation for S12L-ECG exams, which are the most common in clinical practice.

The availability of such a large database of S12L-ECG tracings, with annotation for the whole spectrum of ECG abnormalities, opens up the possibility of extending initial results of end-to-end DNN in ECG automatic analysis ([15](#_bookmark17)) to a system with applicability in a wide range of clinical settings. The development of such technologies may yield high-accuracy automatic ECG classification systems that could save clinicians considerable time and prevent wrong diagnoses. Millions of S12L-ECGs are performed every year, many times in places where there is a shortage of qualified medical doctors to interpret them. An accurate classification system could help to detect wrong diagnoses and improve the access of patients from deprived and remote locations to this essential diagnostic tool of cardiovascular diseases.

The error analysis shows that most of the DNN mistakes were related to measurements of ECG intervals. Most of those were borderline cases, where the diagnosis relies on a con- sensus definitions ([34](#_bookmark36)) that can only be ascertained when a measurement is above a sharp cutoff point. The mistakes can be explained by the DNN failing to encode these very sharp thresholds. For example, the DNN wrongly detecting a SB with a heart rate slightly above 50 bpm or a ST with a heart rate slightly below 100 bpm. Figure [5](#_bookmark56) in the supplementary material illustrate this effect. Noise and interference in the

DNN cardio. emerg. stud.

meas. noise unexplain. meas. noise concep. atte. meas. noise concep. atte. meas. noise concep. atte.

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1dAVb | 3 | 2 | 1 | 8 | 3 |  |  | 15 | 3 |  |  | 13 | 3 | 3 |  |
| RBBB | 4 |  | 1 | 4 |  | 2 |  | 1 |  | 8 |  | 3 |  | 2 |  |
| LBBB |  |  | 1 | 1 | 1 | 1 |  |  | 1 | 4 |  |  | 2 | 3 |  |
| SB | 4 |  |  | 4 |  |  |  | 4 |  |  | 1 | 5 |  | 2 | 1 |
| AF |  | 1 | 3 |  | 4 | 2 |  |  | 2 | 5 |  |  | 3 | 7 |  |
| ST | 4 |  | 1 | 1 | 1 |  | 5 | 2 | 1 | 1 | 1 | 2 | 2 | 1 | 5 |

**Table 2. Error analysis of the exams misclassified by the DNN, the cardiology residents, the medical residents and the students, respectively. The errors were classified into the following categories: i) measurements errors (*meas.*) were ECG interval measurements preclude the given diagnosis by its textbook definition ; ii) errors due to *noise*, were we believe that the analyst or the DNN failed due to a lower than usual signal quality; and, iii) other type of errors (*unexplain.*). Those were further divided, for the medical residents and students, into two categories: conceptual errors (*concep.*), where our reviewer suggested that the doctor failed to understand the definitions of each abnormality, and attention errors (*atte.*), where we believe the error could be avoided if the reviewer had been more careful.**

baseline are established causes of error ([35](#_bookmark37)) and affected both automatic and manual diagnosis of ECG abnormalities. Never- theless, the DNN seems to be more robust to noise and it made fewer mistakes of this type compared to the medical residents and students. Conceptual errors (where our reviewer suggested that the doctor failed to understand the definitions of each abnormality) were more frequent for emergency residents and medical students than for cardiology residents. Attention er- rors (where we believe that the error could have been avoided if the manual reviewer were more careful) were present at a similar ratio for cardiology residents, emergency residents and medical students.

Our work is perhaps best understood in the context of its limitations. While we obtained the highest F1 scores for the DNN, the McNemar statistical test and bootstrapping suggest that we do not have confidence enough to assert that the DNN is actually better than the medical residents and students with statistical significance. We attribute this lack of confidence in the comparison to the presence of relatively infrequent classes, where a few erroneous classifications may significantly affect the scores. Furthermore, we did not test the accuracy of the DNN in the diagnosis of other classes of abnormalities, like those related to acute coronary syndromes or cardiac chamber enlargements and we cannot extend our results to these untested clinical situations. Indeed, the real clinical setting is more complex than the experimental situation tested in this study and, in complex and borderline situations, ECG interpretation can be extremely difficult and may demand the input of highly specialized personnel. Thus, even if a DNN is able to recognize typical ECG abnormalities, further analysis by an experienced specialist will continue to be necessary to these complex exams.

This proof-of-concept study, showing that a DNN can accu- rately recognize ECG rhythm and morphological abnormalities in clinical S12L-ECG exams, opens a series of perspectives for future research and clinical applications. A next step would be to prove that a DNN can effectively diagnose multiple and complex ECG abnormalities, including myocardial infarction, cardiac chamber enlargement and hypertrophy and less com- mon forms of arrhythmia, and to recognize a normal ECG. Subsequently, the algorithm should be tested in a controlled real-life situation, showing that accurate diagnosis could be achieved in real-time, to be reviewed by clinical specialists with solid experience in ECG diagnosis. This real-time, continuous evaluation of the algorithm, would provide rapid feedback that

could be incorporated as further improvements of the DNN, making it even more reliable.

The TNMG, the large telehealth service from which the dataset used was obtained ([22](#_bookmark24)), is a natural laboratory for these next steps, since it performs more than 2,000 ECGs a day and it is currently expanding its geographical coverage over a large part of a continental country (Brazil). An op- timized system for ECG interpretation, where most of the classification decisions are made automatically would imply that the cardiologists would only be needed for the more com- plex cases. If such a system is made widely available, it could be of striking utility to improve access to health care in low and middle-income countries, where cardiovascular diseases are the leading cause of death and systems of care for cardiac diseases are lacking or not working well ([36](#_bookmark38)).

In conclusion, we developed an end-to-end DNN capable of accurately recognizing six ECG abnormalities in S12L-ECG exams, with a diagnostic performance at least as good as medical residents and students. This is a major advance in relation to the current state-of-the-art in automatic analysis of ECGs and may lead to widespread use of automatic diagnosis by DNNs in clinical practice. Although expert review of complex and borderline cases seems to be necessary even in this future scenario, the development of such automatic interpretation by a DNN algorithm may expand the access of the population to this basic and useful diagnostic exam and improve cardiovascular care worldwide.

# Methods

* 1. **Dataset acquisition.** All S12L-ECGs analyzed in this study were obtained by the Telehealth Network of Minas Gerais (TNMG), a public telehealth system assisting 811 out of the 853 municipalities in the state of Minas Gerais, Brazil ([22](#_bookmark24)). Since September 2017, the TNMG has also provided teledi- agnostic services to other Brazilian states in the Amazonian and Northeast regions. The S12L-ECG exam was performed mostly in primary care facilities using a tele-electrocardiograph manufactured by Tecnologia Eletrônica Brasileira (São Paulo, Brazil) – model TEB ECGPC - or Micromed Biotecnologia (Brasilia, Brazil) - model ErgoPC 13. The duration of the ECG recordings is between 7 and 10 seconds sampled at frequencies ranging from 300 to 600 Hz. A specific software developed in-house was used to capture ECG tracings, to upload the exam together with the patient’s clinical history and to send

it electronically to the TNMG analysis center. Once there, a team of experienced cardiologists analyzes the exam and a report is made available to the health service that requested the exam through an online platform.

We have incorporated the University of Glasgow (Uni-G) ECG analysis program (release 28.5, issued in January 2014) in the in-house software since December 2017. The analysis pro- gram was used to automatically identify waves and to calculate axes, durations, amplitudes and intervals, to perform rhythm analysis and to give diagnostic interpretation ([27](#_bookmark29), [37](#_bookmark39)). The Uni-G analysis program also provides Minnesota codes ([38](#_bookmark40)), a standard ECG classification used in epidemiological stud- ies ([39](#_bookmark41)). Since April 2018 the automatic measurements are being shown to the cardiologists that give the medical report. All clinical information, digital ECGs tracings and the cardi- ologist report were stored in a database. All previously stored data was also analyzed by Uni-G software in order to have measurements and automatic diagnosis for all exams available in the database, since the first recordings. The CODE study was established to standardize and consolidate this database for clinical and epidemiological studies. In the present study, the data (for patients above 16 years old) obtained between 2010 and 2016 was used in the training and validation set and, from April to September 2018, in the test set.

* 1. **Labelling training data from text report.** For the training and validation sets, the cardiologist report is available only as a textual description of the abnormalities in the exam. We extract the label from this textual report using a three- step procedure. First, the text is pre-processed by removing stop-words and generating n-grams from the medical report. Then, the *Lazy Associative Classifier* (LAC) ([40](#_bookmark42)), trained on a 2800-sample dictionary created from real diagnoses text reports, is applied to the n-grams. Finally, the text label is obtained using the LAC result in a rule-based classifier for class disambiguation. The classification model reported above was tested on 4557 medical reports manually labeled. The classification step recovered the true medical label with good results, the macro F1 score achieved were: 0.729 for 1dAVb; 0.849 for RBBB; 0.838 for LBBB; 0.991 for SB; 0.993 for AF; 0.974 for ST.
  2. **Training and validation set annotation.** To annotate the training and validation datasets, we used: i) the Uni-G state- ments and Minnesota codes obtained by the Uni-G automatic analysis (*automatic diagnosis*); ii) automatic measurements provided by the Uni-G software; and, iii) the text labels ex- tracted from the expert text reports using the semi-supervised methodology (*medical diagnosis*). Both the automatic and medical diagnosis are subject to errors: automatic classifica- tion has limited accuracy ([3](#_bookmark6)–[6](#_bookmark9)) and text labels are subject both to errors of the practicing expert cardiologists and the labeling methodology. Hence, we combine the expert anno- tation with the automatic analysis to improve the quality of the dataset. The following procedure is used for obtaining the ground truth annotation:
     1. We:
        1. *Accept a diagnosis* (consider an abnormality to be present) if both the expert *and* either the Uni-G statement or the Minnesota code provided by the automatic analysis indicated the same abnormality.
        2. *Reject a diagnosis* (consider an abnormality to be absent) if only one automatic classifier indicates the abnormality in disagreement with both the doctor and the other automatic classifier.

After this initial step, there are two scenarios where we still need to accept or reject diagnoses. They are: i) both classifiers indicate the abnormality, but the expert does not; or ii) only the expert indicates the abnormality, whereas none of the classifiers indicates anything.

* + 1. We used the following rules *to reject some of the remaining diagnoses*:
       1. Diagnoses of ST where the heart rate was below 100 (8376 medical diagnoses and 2 automatic diagnoses) were *rejected*.
       2. Diagnoses of SB where the heart rate was above 50 (7361 medical diagnoses and 16427 automatic diagnosis) were *rejected*.
       3. Diagnoses of LBBB or RBBB where the duration of the QRS interval was below 115 ms (9313 medi- cal diagnoses for RBBB and 8260 for LBBB) were *rejected*.
       4. Diagnoses of 1dAVb where the duration of the PR interval was below 190 ms (3987 automatic diagnoses) were *rejected*.
    2. Then, using the sensitivity analysis of 100 manually re- viewed exams per abnormality, we came up with the following rules *to accept some of the remaining diagnoses*:
       1. For RBBB, d1AVb, SB and ST, we *accepted* all medical diagnoses. 26033, 13645, 12200 and 14604 diagnoses were *accepted* in this fashion, respectively.
       2. For AF, we required not only that the exam was classified by the doctors as true, but also that the standard deviation of the NN intervals was higher than 646. 14604 diagnoses were *accepted* using this rule.

According to the sensitivity analysis, the number of false positives that would be introduced by this procedure was smaller than 3% of the total number of exams.

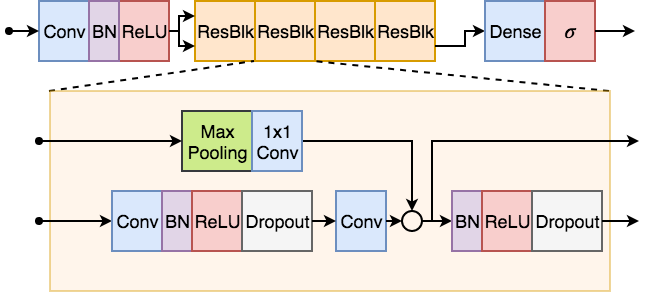
* + 1. After this process, we were still left with 34512 exams where the corresponding diagnoses could neither be ac- cepted nor rejected. These were *manually reviewed* by medical students using the Telehealth ECG diagnostic system, under the supervision of a certified cardiologist with experience in ECG interpretation. The process of manually reviewing these ECGs took several months.

It should be stressed that information from previous medi- cal reports and automatic measurements were used only for obtaining the ground truth for training and validation sets and not on later stages of the DNN training.

* 1. **Test set annotation.** The dataset used for testing the DNN was also obtained from TNMG’s ECG system. It was indepen- dently annotated by two certified cardiologists with experience in electrocardiography. The kappa coefficients ([41](#_bookmark43)) indicate the inter-rater agreement for the two cardiologist and are: 0.741 for 1dAVb; 0.955 for RBBB; 0.964 for LBBB; 0.844 for SB; 0.831 for AF; 0.902 for ST. When they agreed, the com- mon diagnosis was considered as ground truth. In cases where there was *any* disagreement, a third senior specialist, aware of the annotations from the other two, decided the diagnosis. The American Heart Association standardization ([42](#_bookmark44)) was used as the guideline for the classification.

It should be highlighted that the annotation was performed in an upgraded version of the TNMG software, in which the automatic measurements obtained by the Uni-G program are presented to the specialist, that has to choose the ECG diag- nosis among a number of pre-specified classes of abnormalities. Thus, the diagnosis was codified directly into our classes and there was no need to extract the label from a textual report, as it was done for the training and validation sets.

* 1. **Neural network architecture and training.** We used a con- volutional neural network similar to the residual network ([23](#_bookmark25)), but adapted to unidimensional signals. This architecture al- lows deep neural networks to be efficiently trained by including skip connections. We have adopted the modification in the residual block proposed in ([43](#_bookmark45)), which place the skip connec- tion in the position displayed in Figure [2](#_bookmark3).



**Fig. 2.** The uni-dimensional residual neural network architecture used for ECG classification.

All ECG recordings are re-sampled to a 400 Hz sampling rate. The ECG recordings, which have between 7 and 10 sec- onds, are zero-padded resulting in a signal with 4096 samples for each lead. This signal is the input for the neural network. The network consists of a convolutional layer (Conv) fol- lowed by 4 residual blocks with two convolutional layers per block. The output of the last block is fed into a fully connected layer (Dense) with a sigmoid activation function, *σ*, which was used because the classes are not mutually exclusive (i.e. two or more classes may occur in the same exam). The output of each convolutional layer is rescaled using batch normalization, (BN), ([44](#_bookmark46)) and fed into a rectified linear activation unit (ReLU).

Dropout ([45](#_bookmark47)) is applied after the nonlinearity.

The convolutional layers have filter length 16, starting with 4096 samples and 64 filters for the first layer and residual block and increasing the number of filters by 64 every second residual block and subsampling by a factor of 4 every residual block. Max Pooling ([46](#_bookmark48)) and convolutional layers with filter length 1 (1x1 Conv) are included in the skip connections to

make the dimensions match those from the signals in the main branch.

The average cross-entropy is minimized using the Adam optimizer ([47](#_bookmark49)) with default parameters and learning rate lr =

0*.*001. The learning rate is reduced by a factor of 10 whenever the validation loss does not present any improvement for 7 consecutive epochs. The neural network weights was initialized as in ([48](#_bookmark50)) and the bias were initialized with zeros. The training runs for 50 epochs with the final model being the one with the best validation results during the optimization process.

* 1. **Statistical and empirical analysis of test results.** We com- puted the precision-recall curve to assess the model discrimi- nation of each rhythm class. This curve shows the relationship between precision (PPV) and recall (sensitivity), calculated using binary decision thresholds for each rhythm class. For imbalanced classes, such as our test set, this plot is more infor- mative than the ROC plot ([49](#_bookmark51)). For the remaining analyses we fixed the DNN threshold to the value that maximized the F1 score, which is the harmonic mean between precision and recall. The F1 score was chosen here due to its robustness to class imbalance ([49](#_bookmark51)).

For the DNN with a fixed threshold, and for the medical residents and students, we computed the precision, the recall, the specificity, the F1 score and, also, the confusion matrix. This was done for each class. Bootstrapping ([24](#_bookmark26)) was used to analyze the empirical distribution of each of the scores: we generated 1000 different sets by sampling with replacement from the test set, each set with the same number samples as in the test set, and computed the precision, the recall, the speci- ficity and the F1 score for each. The resulting distributions are presented as a boxplot. We used the McNemar test ([25](#_bookmark27)) to compare the misclassification distribution of the DNN and the medical residents and students on the test set and the kappa coefficient ([41](#_bookmark43)) to compare the inter-rater agreement.

All the misclassified exams were reviewed by an experienced cardiologist and, after an interview with the ECG reviewers, the errors were classified into: measurement errors, noise errors and unexplained errors (for the DNN only) and conceptual and attention errors (for medical residents and students only). This study was approved by the Research Ethics Commit- tee of the Universidade Federal de Minas Gerais, protocol

68496317.7.0000.5149.

* 1. **Code Availability.** Upon publication, code for the model training, evaluation and statistical analysis will be made avail- able on Github as open source code with no use restriction.
  2. **Data availability.** Upon publication, the test data used to support the findings of this study will be made publicly avail- able without restrictions. The DNN model parameters that give the results presented in this paper will also be made available without restrictions. Restrictions apply to the avail- ability of the training set, for which requests to access the training data will be considered on an individual basis by the Telehealth Network of Minas Gerais. Any data use will be restricted to non-commercial research purposes, and the data will only be made available on execution of appropriate data use agreements.

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IATS, MASWeb, INCT-Cyber and Atmosphere, and by the *Wal- lenberg AI, Autonomous Systems and Software Program (WASP)* funded by Knut and Alice Wallenberg Foundation. We also thank NVIDIA for awarding our project with a Titan V GPU. ALR and WMJr are recipients of unrestricted research scholarships from CNPq; AHR receives a Split-PhD scholarship from CNPq and MHR receives a Google Latin America Research Award scholarship. None of the funding agencies had any role in the design, analysis or interpretation of the study.

* + 1. Roth GA, et al. (2018) Global, regional, and national age-sex-specific mortality for 282 causes of death in 195 countries and territories, 1980–2017: A systematic analysis for the Global Burden of Disease Study 2017. *The Lancet* 392(10159):1736–1788.
    2. Willems JL, et al. (1987) Testing the performance of ECG computer programs: The CSE diagnostic pilot study. *Journal of Electrocardiology* 20 Suppl:73–77.
    3. Schläpfer J, Wellens HJ (2017) Computer-Interpreted Electrocardiograms: Benefits and Lim- itations. *Journal of the American College of Cardiology* 70(9):1183.
    4. Willems JL, et al. (1991) The diagnostic performance of computer programs for the interpre- tation of electrocardiograms. *The New England Journal of Medicine* 325(25):1767–1773.
    5. Shah AP, Rubin SA (2007 Sep-Oct) Errors in the computerized electrocardiogram interpreta- tion of cardiac rhythm. *Journal of Electrocardiology* 40(5):385–390.
    6. Estes NAM (2013) Computerized interpretation of ECGs: Supplement not a substitute. *Cir-* *culation. Arrhythmia and Electrophysiology* 6(1):2–4.
    7. Krizhevsky A, Sutskever I, Hinton GE (2012) Imagenet classification with deep convolutional neural networks in *Advances in Neural Information Processing Systems*. pp. 1097–1105.
    8. Hinton G, et al. (2012) Deep Neural Networks for Acoustic Modeling in Speech Recognition: The Shared Views of Four Research Groups. *IEEE Signal Processing Magazine* 29(6):82– 97.
    9. Stead WW (2018) Clinical implications and challenges of artificial intelligence and deep learn- ing. *JAMA* 320(11):1107–1108.
    10. Naylor C (2018) On the prospects for a (deep) learning health care system. *JAMA*

320(11):1099–1100.

* + 1. Hinton G (2018) Deep learning—a technology with the potential to transform health care.

*JAMA* 320(11):1101–1102.

* + 1. Bejnordi BE, et al. (2017) Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer. *JAMA* 318(22):2199.
    2. De Fauw J, et al. (2018) Clinically applicable deep learning for diagnosis and referral in retinal disease. *Nature Medicine* 24(9):1342–1350.
    3. Beck EJ, Gill W, De Lay PR (2016) Protecting the confidentiality and security of personal health information in low- and middle-income countries in the era of SDGs and Big Data. *Global Health Action* 9:32089.
    4. Hannun AY, et al. (2019) Cardiologist-level arrhythmia detection and classification in ambula- tory electrocardiograms using a deep neural network. *Nature Medicine* 25(1):65–69.
    5. Clifford GD, et al. (2017) AF Classification from a Short Single Lead ECG Recording: The PhysioNet/Computing in Cardiology Challenge 2017. *Computing in Cardiology* 44.
    6. Mant J, et al. (2007) Accuracy of diagnosing atrial fibrillation on electrocardiogram by primary care practitioners and interpretative diagnostic software: Analysis of data from screening for atrial fibrillation in the elderly (SAFE) trial. *BMJ (Clinical research ed.)* 335(7616):380.
    7. Veronese G, et al. (2016) Emergency physician accuracy in interpreting electrocardiograms with potential ST-segment elevation myocardial infarction: Is it enough? *Acute Cardiac Care* 18(1):7–10.
    8. World Health Organization (2014) *Global Status Report on Noncommunicable Diseases 2014: Attaining the Nine Global Noncommunicable Diseases Targets; a Shared Responsi-* *bility.* (World Health Organization, Geneva). OCLC: 907517003.
    9. Sassi R, et al. (2017 Nov - Dec) PDF-ECG in clinical practice: A model for long-term preser- vation of digital 12-lead ECG data. *Journal of Electrocardiology* 50(6):776–780.
    10. Lyon A, Mincholé A, Martínez JP, Laguna P, Rodriguez B (2018) Computational techniques for ECG analysis and interpretation in light of their contribution to medical advances. *Journal* *of the Royal Society Interface* 15(138).
    11. Alkmim MB, et al. (2012) Improving patient access to specialized health care: The Telehealth Network of Minas Gerais, Brazil. *Bulletin of the World Health Organization* 90(5):373–378.
    12. He K, Zhang X, Ren S, Sun J (2016) Deep Residual Learning for Image Recognition in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. pp. 770–778.
    13. Efron B, Tibshirani RJ (1994) *An Introduction to the Bootstrap*. (CRC press).
    14. McNemar Q (1947) Note on the sampling error of the difference between correlated propor- tions or percentages. *Psychometrika* 12(2):153–157.
    15. Jambukia SH, Dabhi VK, Prajapati HB (2015) Classification of ECG signals using machine learning techniques: A survey in *Proceedings of the International Conference on Advances* *in Computer Engineering and Applications (ICACEA)*. (IEEE), pp. 714–721.
    16. Macfarlane PW, Devine B, Clark E (2005) The university of glasgow (Uni-G) ECG analysis program in *Computers in Cardiology*. pp. 451–454.
    17. CUBANSKI D, CYGANSKI D, ANTMAN EM, FELDMAN CL (1994) A Neural Network System for Detection of Atrial Fibrillation in Ambulatory Electrocardiograms. *Journal of Cardiovascu-* *lar Electrophysiology* 5(7):602–608.
    18. Rubin J, Parvaneh S, Rahman A, Conroy B, Babaeizadeh S (2017) Densely Connected Con- volutional Networks and Signal Quality Analysis to Detect Atrial Fibrillation Using Short Single- Lead ECG Recordings. *arXiv:1710.05817*.
    19. Acharya UR, et al. (2017) Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals. *Information Sciences* 415-416:190– 198.
    20. Shashikumar SP, Shah AJ, Clifford GD, Nemati S (2018) Detection of Paroxysmal Atrial Fibril- lation Using Attention-based Bidirectional Recurrent Neural Networks in *Proceedings of the*

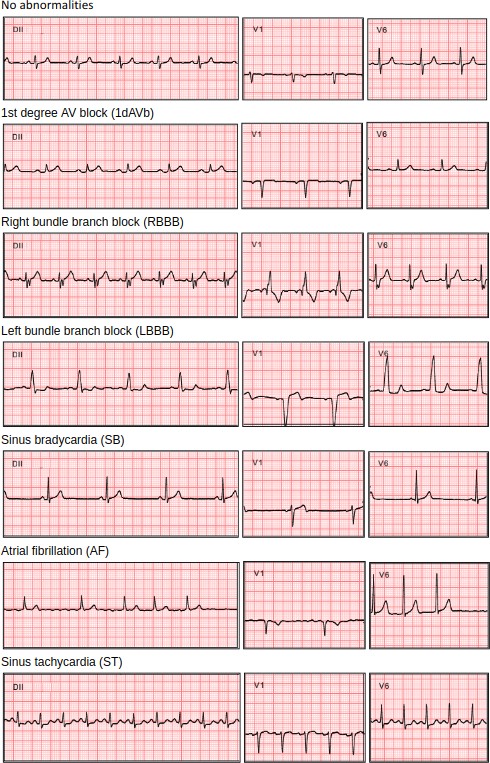
*24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, KDD ’18. (ACM, New York, NY, USA), pp. 715–723.

* + 1. Rahhal MA, et al. (2016) Deep learning approach for active classification of electrocardiogram signals. *Information Sciences* 345:340–354.
    2. Goldberger AL, et al. (2000) PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. *Circulation* 101(23).
    3. Rautaharju PM, Surawicz B, Gettes LS (2009) AHA/ACCF/HRS Recommendations for the Standardization and Interpretation of the Electrocardiogram: Part IV: The ST Segment, T and U Waves, and the QT Interval A Scientific Statement From the American Heart Asso- ciation Electrocardiography and Arrhythmias Committee, Council on Clinical Cardiology; the American College of Cardiology Foundation; and the Heart Rhythm Society Endorsed by the International Society for Computerized Electrocardiology. *Journal of the American College of* *Cardiology* 53(11):982–991.
    4. Luo S, Johnston P (2010) A review of electrocardiogram filtering. *Journal of Electrocardiology*

43(6):486–496.

* + 1. Nascimento BR, Brant LCC, Marino BCA, Passaglia LG, Ribeiro ALP (2019) Implementing myocardial infarction systems of care in low/middle-income countries. *Heart* 105(1):20.
    2. Macfarlane P, et al. (1990) Methodology of ECG interpretation in the Glasgow program. *Meth-* *ods of information in medicine* 29(04):354–361.
    3. Macfarlane PW, Latif S (1996) Automated serial ECG comparison based on the Minnesota code. *Journal of Electrocardiology* 29:29–34.
    4. Prineas RJ, Crow RS, Zhang ZM (2009) *The Minnesota Code Manual of Electrocardiographic* *Findings*. (Springer Science & Business Media).
    5. Veloso A, Meira Jr W, Zaki MJ (2006) Lazy Associative Classification in *Proceedingsof the* *6th International Conference on Data Mining (ICDM)*. pp. 645–654.
    6. Cohen J (1960) A Coefficient of Agreement for Nominal Scales. *Educational and Psycholog-* *ical Measurement* 20(1):37–46.
    7. Kligfield P, et al. (2007) Recommendations for the Standardization and Interpretation of the Electrocardiogram. *Journal of the American College of Cardiology* 49(10):1109.
    8. He K, Zhang X, Ren S, Sun J (2016) Identity Mappings in Deep Residual Networks in *Com- puter Vision – ECCV 2016*, eds. Leibe B, Matas J, Sebe N, Welling M. (Springer International Publishing), pp. 630–645.
    9. Ioffe S, Szegedy C (2015) Batch Normalization: Accelerating Deep Network Training by Re- ducing Internal Covariate Shift in *Proceedings of the 32nd International Conference on Ma-* *chine Learning*. (PMLR), pp. 448–456.
    10. Srivastava N, Hinton GE, Krizhevsky A, Sutskever I, Salakhutdinov R (2014) Dropout: A sim- ple way to prevent neural networks from overfitting. *Journal of Machine Learning Research* 15(1):1929–1958.
    11. Hutchison D, et al. (2010) Evaluation of Pooling Operations in Convolutional Architectures for Object Recognition in *Artificial Neural Networks – ICANN 2010*, eds. Diamantaras K, Duch W, Iliadis LS. (Springer Berlin Heidelberg), Vol. 6354, pp. 92–101.
    12. Kingma DP, Ba J (2014) Adam: A Method for Stochastic Optimization in *Proceedings of the* *3rd International Conference for Learning Representations (ICLR)*.
    13. He K, Zhang X, Ren S, Sun J (2015) Delving deep into rectifiers: Surpassing human-level performance on imagenet classification in *Proceedings of the IEEE International Conference* *on Computer Vision*. pp. 1026–1034.
    14. Saito T, Rehmsmeier M (2015) The Precision-Recall Plot Is More Informative than the ROC Plot When Evaluating Binary Classifiers on Imbalanced Datasets. *PLOS ONE* 10(3):e0118432.

# Supplementary Material



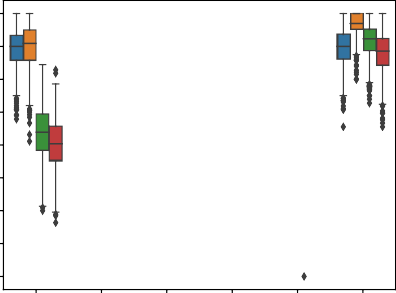
**Fig. 3.** A list of all the abnormalities the model classifies. We show only 3 representative leads (DII, V1 and V6).

|  |  |  |
| --- | --- | --- |
| Abnormality | Train+Val (n = 2,322,513) | Test (n = 827) |
| 1dAVb | 35,759 (1.5 %) | 28 (3.4 % ) |
| RBBB | 63,528 (2.7% ) | 34 (4.1 %) |
| LBBB | 39,842 (1.7%) | 30 (3.6 %) |
| SB | 37,949 (1.6%) | 16 (1.9 %) |
| AF | 41,862 (1.8%) | 13 (1.6 %) |
| ST | 49,872 (2.1%) | 36 (4.4 %) |
| Age group |  |  |
| 16-25 | 155,531 (6.7 %) | 43 (5.2 % ) |
| 26-40 | 406,239 (17.5 %) | 122 (14.8 % ) |
| 41-60 | 901.456 (38.8 %) | 340 (41.1 % ) |
| 61-80 | 729,300 (31.4 %) | 278 (33.6 % ) |
| *≥*81 | 129,987 (5.6 %) | 44 (5.3 % ) |
| Male | 922,780 (39.7 %) | 321 (38.8 % ) |
| Female | 1,399,733 (60.3 %) | 506 (61.2 % ) |

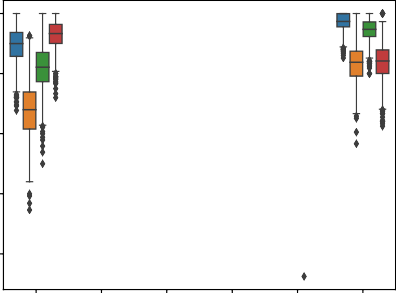
**Table 3. Patient characteristcs and abnormalities prevalence, n (%).)**

Sex

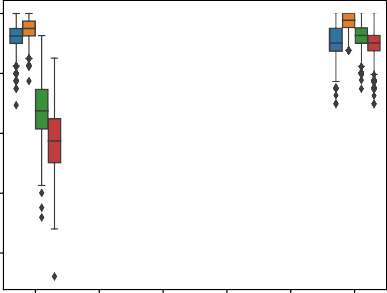
1.0



1.0



1.00



0.9

0.8

0.8

0.99

0.7

0.6

0.6

0.98

0.5

0.4

0.4

0.97

0.3

0.2

0.2

0.96

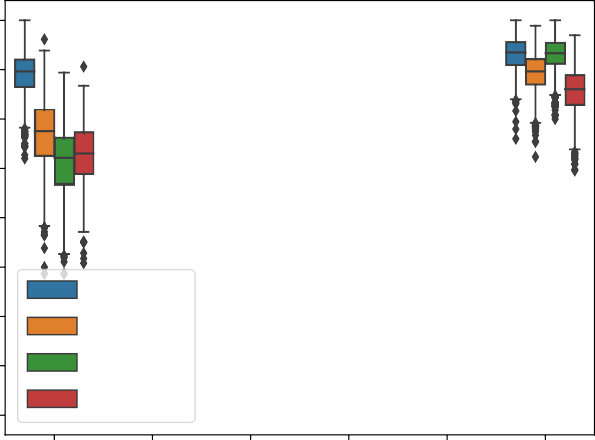
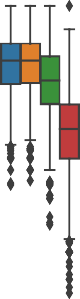
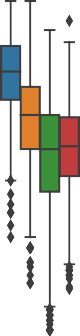
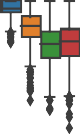
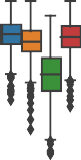
1dAVb RBBB LBBB SB AF ST

1dAVb RBBB LBBB SB AF ST

1dAVb RBBB LBBB SB AF ST

* + - 1. Precision (PPV)
      2. Recall (Sensitivity)
      3. Specificity

1.0



DNN

cardio. emerg. stud.

0.9

0.8

0.7

0.6

0.5

0.4

0.3

0.2

1dAVb RBBB LBBB SB AF ST

* + - 1. F1 score

**Fig. 4.** Boxplots for the bootstrapped scores. Sampling with replacement (i.e. bootstrapping) was used to generate the empirical distribution of precision, recall, specificity and F1 score on the test set for the DNN and the medical residents and students.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 1dAVb | RBBB | LBBB | SB | AF | ST |
| DNN vs cardio. | 0*.*225 | 0*.*655 | 0*.*317 | 1*.*000 | 0*.*414 | 0*.*480 |
| DNN vs emerg. | **0.011** | 0*.*285 | 0*.*102 | 0*.*705 | 0*.*366 | 1*.*000 |
| DNN vs stud. | **0.009** | 1*.*000 | 0*.*102 | 0*.*157 | 0*.*058 | 0*.*096 |
| cardio. vs emerg. | 0*.*108 | 0*.*366 | 0*.*317 | 0*.*564 | 0*.*763 | 0*.*527 |
| cardio. vs stud. | 0*.*102 | 0*.*739 | 0*.*414 | **0.046** | 0*.*206 | 0*.*405 |
| emerg. vs stud. | 0*.*853 | 0*.*248 | 1*.*000 | 0*.*083 | 0*.*439 | 0*.*059 |

**Table 4. *p*-values for McNemar test comparing the misclassification on the test set. The DNN, the medical residents and the students were compared two at a time. Entries with statistical significance (with 0.05 significance level) are displayed in boldface.**

predicted label

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | DNN | cardio. | emerg. | stud. |
| true label | not present present | not present present | not present present | not present present |

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1dAVb | not present | 796 | 3 | 797 | 2 | 786 | 13 | 782 | 17 |
| present | 3 | 25 | 9 | 19 | 5 | 23 | 2 | 26 |
| RBBB | not present | 788 | 5 | 788 | 5 | 792 | 1 | 790 | 3 |
| present | 0 | 34 | 1 | 33 | 8 | 26 | 2 | 32 |
| LBBB | not present | 796 | 1 | 797 | 0 | 796 | 1 | 795 | 2 |
| present | 0 | 30 | 3 | 27 | 4 | 26 | 3 | 27 |
| SB | not present | 808 | 3 | 808 | 3 | 808 | 3 | 807 | 4 |
| present | 1 | 15 | 1 | 15 | 2 | 14 | 4 | 12 |
| AF | not present | 811 | 3 | 811 | 3 | 812 | 2 | 805 | 9 |
| present | 1 | 12 | 3 | 10 | 5 | 8 | 1 | 12 |
| ST | not present | 787 | 4 | 790 | 1 | 788 | 3 | 787 | 4 |
| present | | 1 | 35 | 6 | 30 | 2 | 34 | 6 | 30 |

**Table 5. Confusion matrices. Show the absolute number of: i) false posives; ii) false negatives; iii) true positives; and, iv) true negatives, for each abnormality on the test set.**

1dAVb RBBB LBBB SB AF ST

|  |  |  |
| --- | --- | --- |
| DNN vs cardio. 0*.*643 | 0*.*932 | 0*.*929 0*.*830 0*.*782 0*.*881 |
| DNN vs emerg. 0*.*643 | 0*.*779 | 0*.*893 0*.*796 0*.*554 0*.*945 |
| DNN vs stud. 0*.*633 | 0*.*915 | 0*.*896 0*.*760 0*.*716 0*.*871 |
| cardio. vs emerg. 0*.*656 | 0*.*824 | 0*.*923 0*.*912 0*.*515 0*.*847 |
| cardio. vs stud. 0*.*612 | 0*.*871 | 0*.*889 0*.*880 0*.*700 0*.*792 |
| emerg. vs stud. 0*.*615 | 0*.*799 | 0*.*852 0*.*907 0*.*508 0*.*897 |

**Table 6. Kappa coefficient measuring the inter-rater agreement on the test set. The DNN, the medical residents and the students were compared two at a time. If the raters are in complete agreement then it is equal to 1. If there is no agreement among the raters other than what would be expected by chance it is equal to 0.**

200 200



correct prediction

False True



correct prediction

False True

175 175

150 150

125 125

heart rate

heart rate

100 100

75 75

50 50

25 25

0 0

False True

SB

**(a)**

False True

ST

**(b)**

**Fig. 5.** Distribution of heart rate measured by the Uni-G software for signals in the testset. The color indicates if the *DNN* make the correct prediction or not. The x-axis separates the dataset accordingly to the presence of: SB in (a); and, ST in (b). A horizontal line show the threshold of 50 bpm for SB (a) and of 100 bpm for ST (b), which delimit the consensus definition of SB and ST. Notice that most exams for which the neural network fails to get the correct result are very close to this threshold line and are the borderline cases we mentioned in the discussion. It should be highlighted that this automatic measurement system is not perfect, and measurements that may indicate some of the conditions do not necessarily agree with our board of cardiologist (e.g. there are exams with heart rate above 100 acording to Uni-G that are not classified by our cardiologist as ST).

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