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Survey on Univariate and Multivariate Electrocardiography Signal Classification using Machine Learning

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ABSTRACT: Heart ailments are fundamentally analyzed by the electrocardiogram (ECG) or (EKG). The correct characterization of ECG signals helps in diagnosing heart sicknesses. This paper contemplates and examines the univariate and multivariate ECG signal order issues to locate the ideal classifier for ECG signals from existing cutting-edge time arrangement characterization models.

KEYWORDS: multivariate, convolution ECG, neural network, deep learning, time series

I. INTRODUCTION

The heart is one of the fundamental organs liable for keeping the body's life for humans and vertebrates. The heart is a solid organ that siphons blood through the veins of the human and vertebrate bodies [1]. Furthermore, the most usually utilized system to monitor heart signal is a non-obtrusive clinical technique called electrocardiogram (ECG) or (EKG) component.The ordinary ECG is the 12-lead ECG, where the heart signal is recorded by putting ten cathodes on the patient's chest surface and appendages[2]. These terminals recognize the heart muscle's electrophysiologic design during every heartbeat. Therefore, ECG contains essential information about the heart's usefulness. Understanding (arranging) the ECG signal helps make the correct determination and quick treatment for a patient, particularly in the crisis units where the time is an essential factor to spare a patient's life.The vast majority of the cardiologists can make a proper investigation and arrangement of the ECG recording because of their experience. In any case, in the crisis units and ambulances, the doctors also, crisis clinical experts, now and again, do not have a similar encounter to comprehend and arrange the ECG signal correctly, which could influence patients, particularly the individuals who have complex conclusions [3]. To take care of this issue, a computational strategy could assist with helping the doctors. Also, crisis clinical professionals to investigate the ECG signal quicker and support their examination choice for the ECG signal incredibly when the cardiologist authority does not make access to support the patient.

Moreover, understanding and group the behavior of the ECG sign could assist with constructing human contemplations. For instance, the polygraph machine goes about as a lie detector test. Its system is dependent on recording a few signs from people to set up a physiological indicators map.There are a few computational techniques that endeavor to characterize the ECG signal. Nonetheless, the vast majority of these strategies require information about the execution of subtleties[4]. Therefore, they do not give any information that assists with approving their proposed precision.

Additionally, the theoretical clarification of such models is not clear. Thus, in this paper, we center on the believed cutting edge time arrangement grouping models with settled writing or potentially free usage. The majority of these models are effectively focusing on the time arrangement characterization from various source-got information such as sensor, picture, Spectro, and traffic datasets.

II. ELECTROCARDIOGRAPHY(ECG)

Electrocardiography (ECG) or (EKG) is the cycle of recording the electrical sign of the heart movement[5]. The ECG assists with acquiring information about the capacity of the heart all through a specific period. The ECG is recorded by setting cathodes over the skin to recognize the skin's little electrical changes. The ECG signal also depolarizes,

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repolarizes during every heartbeat. The ECG is one of the most straightforward non-intrusive techniques to distinguish heart issues. The ECG signal consists of three principal components the P-wave, QRS-complex, and T-wave. The P-wave represents the atrial depolarization. The QRS-complex represents the depolarization of the ventricles.

The T-wave representsthe repolarization of the ventricles [6]. The ECG signal is likewise portrayed as the sign, which consists of S-T segments. Figure 1 shows the S-T segment outline, which was planned by ED Burns [6]. Every S-T segment consists of similar intervals PR interval, RR interval, TP interval, and QT interval. P, Q, R, S, T, and U are alluding to the ECG segment peaks.

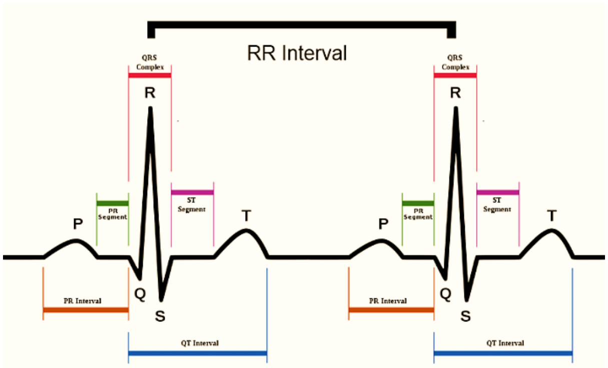

Fig 1: The S-T segment of the ECG signal

The segments, intervals, and peaks are known as the features of the ECG signal. The estimations of these features depict either the cardiovascular cycle is normal or abnormal. Therefore, ECG could be utilized to detect a few cardiovascular problems. However, perusing and understanding the ECG signal is not a simple task.

III. UNIVARIATE ECG SIGNAL CLASSIFICATION

Datasets Description

The univariate ECG dataset comprises of one perception according to which the characterization of the ECG is applied. Simultaneously, the multivariate time arrangement is more unpredictable and complex than the univariate time arrangement since it has different fluctuating conditions after some time[7]. For the univariate ECG datasets, we utilized the 6 ECG datasets from the UCR benchmark as the most remarkable time arrangement order benchmark with the full portrayal. The UCR benchmark datasets are separated into preparing and testing datasets, which helps build up a reasonable examination among various classifiers.

Models and Descriptions

We contemplated eight diverse cutting edge time arrangement grouping strategies to locate the ideal univariant ECG signal classifier[7]. These models are the entire convolution network (FCN), long short-term memory and utterly convolutional network (LSTM-FCN) and its consideration based LSTM model (ALSTM-FCN), the profound gated repetitive and convolutional network half and half model (GRU-FCN), the lingering network mode (ResNet), multilayered perceptrons model (MLP), dynamic time warping model (DTW), also, the clamor decrease based model (BOSS).

Results

Our experiments on univariate time arrangement classification results appear in Table I. We got the aftereffect of GRUFCN, FCN, LSTM-FCN, ALSTM-FCN, MLP, and ResNet by recovering their models from their source codes accessible on the web. The other models' outcomes were obtained from their unique distributed writing. As indicated by the outcomes that appeared in Table I, we found that GRU-FCN outperforms the cutting edge classification models

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in 5 out of 6 univariate ECG datasets. Likewise, the GRU-FCN has the smallest Mean Per-Class Error (MPCE) esteem contrasted with the cutting edge models.

Table I:CLASSIFICATION ACCURACY RANK FOR 6 UNIVARIATE ECG DATASETS FROM THE UCR BENCHMARK

Dataset	**Classification Method and Testing Accuracy**							
	GRU-FCN	FCN	LSTMFCN	ALSTMFCN	ResNet	MLP	DTW	BOSS
ECG200	0.922	0.911	0.900	0.912	0.871	0.792	0.771	0.871
ECG5000	0.950	0.942	0.948	0.948	0.932	0.936	0.751	0.945
ECGFiveDays	0.994	0.991	0.9870	0.987	0.954	0.971	0.769	1.1
NonInvThor1	0.995	0.962	0.965	0.962	0.949	0.943	0.792	0.840
NonInvThor2	0.964	0.956	0.955	0.951	0.950	0.946	0.864	0.838
Two Lead ECG	1.0	1.0	1	0.987	0.951	0.854	1.0	0.897
No. best	4	2	1	2	1.1	0	1	1
MPCE	0.0091	0.0105	0.0114	0.0105	0.0173	0.0241	0.0481	0.0151

The normal arithmetic position of every classification technique over the 6 univariate ECG datasets is appeared in Figure 2. The GRU-FCN additionally shows the smallest arithmetic normal contrasted with the cutting edge models in univariate ECG datasets classification.

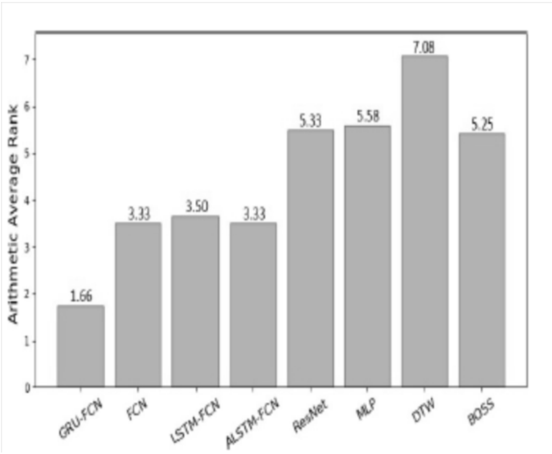

Fig 2: The average arithmetic rank of each classification method over the 6 UCR benchmark univariate ECG datasets.

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The fundamental contrast outline dependent on applying the Nemenyi or Bonferroni-Dunn test on the arithmetic mean of model positions. Figure 3 shows that the GRU-FCN outperforms the cutting edge classification strategies in univariate ECG datasets classification.

IV. MULTIVARIATE ECG SIGNAL CLASSIFICATION

Dataset Description

For the multivariate ECG datasets, we utilized the ECG multivariate dataset in CMU datasets benchmark. This dataset contains the ECG sign of the supraventricular untimely beat issue. The untimely supraventricular beat is a sort of arrhythmia where the heart issue is allowed with the heartbeat rate (mood). It means the heartbeat rate could be exceptionally snappy, slow, or with a sporadic example. This dataset portrays an ECG sign of supraventricular untimely beat signal with two classes: typical sign class and anomalous sign class.

It additionally contains missing qualities. The full depiction of the CMU datasets [8] benchmark for the supraventricular untimely beat classification issue dataset we utilized in our experiments appears in Table II.

Data Set	Train Size	Test Size	Classes	Length	Attributes	Instances	Type
ECG	100	100	2	454	281	453	Supraventricular premature beat

Models and Descriptions

In multivariate ECG signal classification, we analyzed and broke down various nine multivariate time arrangement classifiers. We got the consequences of these state-of-the-art models from their distributed writing, and we recovered the FCN [9] model outcomes. The state-of-the-art classification models that we examined are the FCN [10], MLSTMFCN,WEASEL+ MUSE classifier (MUSE),summed up random shapelet woodlands classifier (gRSF),dynamic time traveling (DTWi),symbolic representation-based classifier (SMTS),neighborhood auto patterns-based classifier (LPS),autoregressive woodlands classifier mvARF, and autoregressive bits classifier (ARKernel).

Results

The classification exactness of this experiment has appeared in Table III. Both the MUSE and gRSF [11] have a similar classification precision for the ECG multivariate.

TABLE IV: Classification Accuracy Rank For One Multivariate Ecg Dataset Obtained From Cmu Datasets.

Data Set	Classification Method and Testing Accuracy								
	FCN	*MLSTMFCN*	*MUSE*	*gRSF*	*DTWi*	*SMTS*	*LPS*	*mvARF*	*ARKernel*
ECG	0.840	0.871	0.881	0.882	0.792	0.820	0.823	0.786	0.821

Supraventricular untimely beat signal (88%) is trailed by the MLSTMFCN model, which depends on long transient memory and a completely convolutional network. Plus, both MUSE and gRSF effectively handle the missing qualities in the multivariate ECG dataset.

V. CONCLUSION

This paper contemplates the univariate and multivariate ECG signal datasets classification issue, supporting the doctors in cardiovascular issues diagnosing. This paper gives ECG signal classification scientists and researchers succinct direction to the to-date existing state-of-the-art classification models concerning both univariate and multivariate ECG signal classification undertakings. We attempted to locate the most proper and ideal classification strategy to-date for ECG datasets classification from the current state-of-the-art classification strategies. We found that the GRU-FCN

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model, which depends on deep learning calculations, has the highest classification exactness over the other state-of-the-art classification strategies in the univariate ECG signal datasets. We then found that the MUSE and gRSF, non-deep learning-based calculations, have the highest exactness over the supraventricular untimely beat multivariate ECG signal dataset.

REFERENCES

[1] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in IEEE Conf. Comput. Vis. Pattern Recognit. IEEE, 2016, pp. 770–778. [Online]. Available: https://doi.org/10.1109/CVPR.2016.90
[2] Ankit Narendrakumar Soni (2018). Image Segmentation Using Simultaneous Localization and Mapping Algorithm. International Journal of Scientific Research and Engineering Development, 1(2), 279-282.
[3] Vishal Dineshkumar Soni. (2018). ROLE OF AI IN INDUSTRY IN EMERGENCY SERVICES. International Engineering Journal For Research & Development, 3(2), 6. https://doi.org/10.17605/OSF.IO/C67BM
[4] Ketulkumar Govindbhai Chaudhari. (2018). Analysis on Transport Layer Protocols and Its Developments. International Journal of Innovative Research in Computer and Communication Engineering, 6(9), 7707-7712. DOI: 10.15680/IJIRCCE.2018. 0609046.
[5] Ankit Narendrakumar Soni (2018). Data Center Monitoring using an Improved Faster Regional Convolutional Neural Network. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 7(4), 1849-1853. doi:10.15662/IJAREEIE.2018.0704058.
[6] Karunakar Pothuganti, Aredo Haile, Swathi Pothuganti,(2016)" A Comparative Study of Real Time Operating Systems for Embedded Systems" International Journal of Innovative Research in Computer and Communication Engineering, Vol. 4, Issue 6, June 2016.
[7] Ketulkumar Govindbhai Chaudhari. (2018). Comparitive Analysis of CNN Models To Diagnose Breast Cancer. International Journal of Innovative Research in Science, Engineering and Technology, 7(10), 8180-8187. DOI:10.15680/IJIRSET.2018.0710074.
[8] Vishal Dineshkumar Soni (2018). Prediction of Stock Market Values using Artificial Intelligence. International Journal of Advanced Research in Electrical Electronics and Instrumentation Engineering, 7(4), 1844-1848. doi:10.15662/IJAREEIE.2018.0704057.
[9] Ankit Narendrakumar Soni (2018). Application and Analysis of Transfer Learning-Survey. International Journal of Scientific Research and Engineering Development, 1(2), 272-278.
[10] Vishal Dineshkumar Soni .(2018). Internet of Things based Energy Efficient Home Automation System. International Journal of Innovative Research in Science Engineering and Technology, 7(3), 2924-2929. doi:10.15680/IJIRSET.2018.0703148.
[11] Ketulkumar Govindbhai Chaudhari. (2018). E-voting System using Proof of Voting (PoV) Consensus Algorithm using Block Chain Technology. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 7(11), 4051-4055. DOI:10.15662/IJAREEIE.2018.0711019