A Systematic Review on ECG and EMG Biomedical Signal Using Deep-Learning Approaches

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Abstract Biomedical signals play an indispensable role in many medical applications like diagnosis, prognosis, and defining treatment procedures. Recent advancements in artificial intelligence and computation speed have intensified biomedical signal research. This article conducts a systematic and exhaustive overview of the latest research literature on deep-learning methods for the analysis of biomedical signal results, such as electrocardiograms (ECGs) and electromyograms (EMG). ECG and EMG techniques are among some of the most imperative biomedical signals in the diagnosis and activity recognition of the subject. Additionally, the review will explore various well-known databases and discuss numerous contemporary methods with results published between January 2018 and December 2020. We mainly studied the key parameters in the collected paper: deep-learning model and training architecture, medical tasks, dataset sources, and medical application. These are the essential parameters that influence performance. This paper will also discuss and conclude by highlighting critical research gaps and possible future scope to directly build intelligent computational models from biomedical signals.

1 Introduction

Biomedical signals (BS) describe the electrical activity generated by different human body cells like muscular, cardiac, etc. BS evidence in the form of 1D signals are time-domain data, in which sample data points are acquired over time [1]. These signals are constantly changing and reflect the health of the patient's psyche. BS data categories include electromyogram (EMG), data about alterations to skeleton muscle tissue, and electrocardiogram (ECG), data about changes in heartbeat or

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Manju et al. (eds.), *Artificial Intelligence-based Healthcare Systems*,
The Springer Series in Applied Machine Learning,
https://doi.org/10.1007/978-3-031-41925-6_11

rhythm. Some signals are systematic and spontaneous activities of the human psyche, such as electroglottography EEG or ECG. In contrast, others, such as the signal of visual evoked potential, are responses to external stimuli. Additionally, BS analysis practices are often shared. The behavior and essential aspects of generating such signals have to be understood, considering the end objective to retrieve the desired information. However, the form of analysis can alter depending on the analyzed signals and the data to be retrieved. Figures 1 and 2 show the raw EMG sample and raw ECG signal. Deep neural network (DNN) is already increasingly used in various disciplines for prediction and classification. In recent time, DNNs are rapidly developing and significantly impacting generalization ability for a vast range of medical tasks.

We assembled papers via PubMed's search tool with keyword combination: "deep-learning," "deep-learning electromyogram," and "deep-learning electrocardiogram." We found 87 recent research work published between January 2018 and December 2020 inclusive from numerous academic journals and publishers. The predominant objective of this survey is to address a wide range of DLM application in BS research. Next section shows literature review followed by Sect. 3 for the most popular deep training models and training architecture employed in the studied articles. Then, in Sect. 4, we provide a summary of deep-learning deployment in specific signal categories and tabulated representation for quick reference. In tables, we only compare the key parameters within studied paper such as medical application, medical task, variants of different DLM, dataset used, and performance of that paper. The Sect. 5 is for discussion and the final section conclude the key gaps and foreseeing research direction.

2 Related Works

Deep-learning approaches in biomedical signaling application evidence between January 2018 and December 2020 provide two forms of scientific research. The first is oriented toward medical fields, such as a taxonomy focusing on medical activities

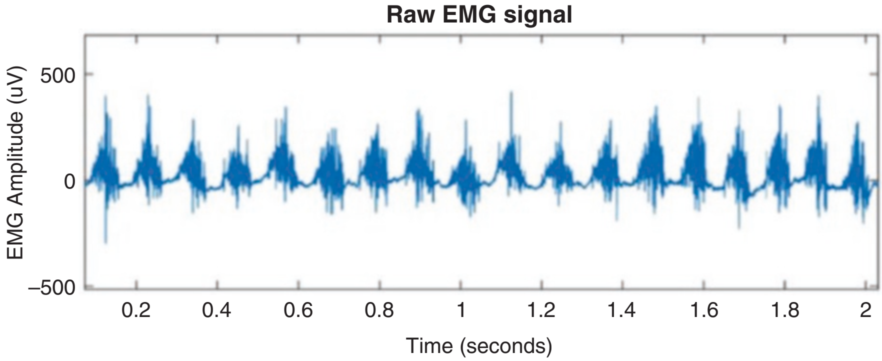

Fig. 1 Raw EMG sample [3]

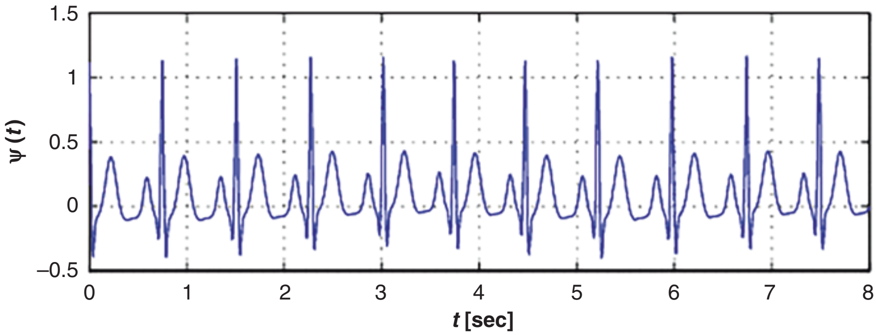

Fig. 2 Raw ECG sample [4]

such as computer-aided detection, illness detection, etc. or a taxonomy focusing on anatomy implementation areas such as the heart, chest, abdomen, eyes, and liver, among others.

The author [5] has accumulated 53 scientific publications on deep-learning strategies for BS processing conducted from 2012 to 2017. This research initially used DLM techniques such as RNN, auto-encoder (AE), DBN, RBM, and GAN. The papers are then categorized according to the BS data modalities. Each segment contains information about the clinical applications, the deep-learning algorithm, the dataset, and the results. The second section discusses deep-learning strategies such as taxonomy centered toward deep-learning architectures such as RNN, AE, DBN, GAN, CNN, and U-Net [2]. A comprehensive systematic study is conducted on one-dimensional BS (base station) data, with a specific emphasis on developing a taxonomy. This study collected 71 articles, mostly ECG publications from 2010 to 2017. The survey's primary objective was to analyze a variety of DLM for the BS study. It then classified DLMs according to their data source, application purpose, input BS class, dataset volume, and neural network training aspect. The author of [6] listed a few biomedical domain factors in deep-learning intervention studies for healthcare complex challenges. It defined the use of DLM in medicine by categorizing it as biological systems, e-health records, medical images, and BS. It concluded by presenting research directions for optimizing health management through the use of BS applications.

3 Deep-Learning Techniques and Training Architecture

3.1 Deep-Learning Techniques

Deep learning concerns research on the extraction of information, predictions, sensible decision, or the recognition of complex patterns employing a collection of data. DNNs are far more adaptable compared to traditional learning approaches since higher accuracy is ideally achieved by increasing the network's size or the training set's scale. For certain modern implementations, shallow teaching strategies such as random forest and support vector machines (SVMs) are insufficient, requiring a large number of generalization experiments and significant manual skilled effort to specify a prior pattern to model [6, 7]. Several DLMs, such as the feed forward network (FFN), convolutional neural network (CNN), recurrent neural network (RNN) and restricted Boltzmann machine (RBM), and vision transformer, have been proposed recently to enhance the accuracy of various learning tasks. The contrastive learning and vision transformer network has recently been applied in learning theory which tremendously improves the DLM [8, 9]. There are also assemble learning technique which combines multiple neural networks [10] and recent approach like transfer learning which transfers the knowledge from one task to another task.

The diversity of training architecture was studied according to the range of data modality. The first type of architecture exploits the traditional MLM as a feature extractor and DLM as a classifier. For instance, mean absolute value divided the raw EMG sample into N levels then, feed into CNN to discriminate sample. The feature extractor and classifier design is shown in Fig. 3.

In contrast, the second architectural type utilizes the DLM as an extractor and the traditional MLM as a classifier. The deep-learning extraction process uses unlabeled data to train the raw sample. The training architecture depicted in Fig. 4 employs deep learning as a feature extractor and conventional machine learning as a classifier. For instance, SAE is used to divide the raw EEG sample into N levels, and then SVM classifies the emotion state based on the featured data.

The third architecture type uses only a DLM to train the raw sample and achieve the final output. The training architecture depicted in Fig. 5 demonstrates the use of only deep-learning approaches to acquire raw data, perform classification, and produce the outcome. For instance, the ECG sample is fed into LSTM to discriminate the patient's cardiac condition.

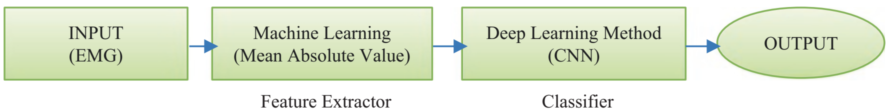

Fig. 3 Training architecture with machine learning acts as feature extractor and deep learning acts as a classifier

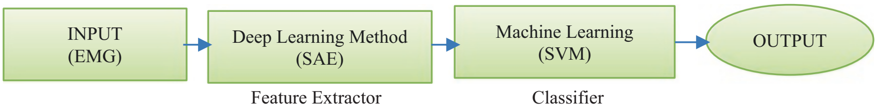

Fig. 4 Deep learning is used to derive features and machine learning is used to classify

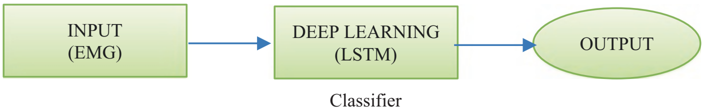

Fig. 5 End-to-end deep-learning training architecture

4 Biomedical Signal Analysis

BS analysis is research that estimates a physical phenomenon for human health. In order to record biomedical parameters, three strategies are practiced: reports (RP), reading (RD), and behavior (BH) [11]. The RP is a manual evaluation of the subject by the specialist. The RD consists of data that are collected by a computer for reading the condition of the patient body, including muscle strength, pulse, etc. The measuring of BH records a range of behavioral patterns like human eye response. This article emphasizes only the RD and BH measurement technique in which the outcomes of the response are given in an ECG, EMG, signal modality.

The EMG signal's muscle tension pattern gives recognition to the movement of the muscles. The rhythm of the heart or pulse version includes a range of cardiovascular diseases, sleep, sentimentality, and gender. This section includes categorization of BS modality in relation to various deep learning models. We compare the DLM quantitatively and qualitatively. The list of DLM used in medical application is depicted for quantitative comparison. Since the performance metric is not given universally for qualitative comparison, we presume an accuracy value as a base criterion for an overall performance comparative analysis.

4.1 Deep Learning with Electrocardiogram (ECG)

As shown in Tables 1, 2, and 3, we identified 56 research papers that used DLM to evaluate ECG signal datasets from the public, private, and hybrid dataset sources. Their important contributions include recognition of cardiac diseases, classification of heartbeat signals, classification of sleep stages, gender-age estimation, and emotion recognition. In a public dataset, the CNN model achieves an overall accuracy of more than 83% for heart disease classification. The LSTM model gives an average accuracy of greater than 90%. The CNN + LSTM model achieves an average accuracy of more than 98%. In the private dataset's heart disease identification, the CNN model achieves an average accuracy of greater than 97%, while the CNN + LSTM model achieves an accuracy of greater than 83%. Therefore, the CNN model outperforms the CNN + LSTM model. As a result, the CNN + LSTM model outperforms the others. For heartbeat signal classification in a publicly available dataset, the CNN model achieves an overall accuracy of greater than 95%. The LSTM model achieves an overall accuracy of greater than 98%, and the hybrid of CNN and LSTM achieves an overall accuracy of greater than 87%. In heartbeat signal classification of the private dataset, only the CNN model is employed and the model performs with an overall

Table 1 Medical task in ECG analysis using public dataset sources

Medical task	No. of subjects	Dataset	DLM	Results
Anomaly class identification [12]	43	MIT-BIH Arrhythmia	LSTM + MLP, LSTM + SVM	LSTM + MLP = 50.0% LSTM + SVM = 42.86%.
Atrial fibrillation detection [13]	23	MIT-BIH Arrhythmia	STFT + CNN	Acc. = 98.29%, Sens. = 98.34%, Spec. = 98.24%
ECG signal detection [14]	47	PhysioNet	LSTM + CNN	Acc. = 99.86%
Heart failure detection [15]	15	BIDMC-CHF	LSTM	Acc. = 99.23%
	18	MIT-BIH NSR		Acc. = 98.84%
	40	Fantasia		Acc. = 98.93%
Dofetilide plasma prediction [16]	42	PhysioNet	CNN	Correlation = 0.85
ECG characteristic detection [17]	23	QT database (ST-T + MIT-BIH Arrhythmia + other)	CNN + RA	QRS-on = −0.70 ± 10.9 QRS-off = −04.80 ± 13.10, T-peak = −0.30 ± 10.50 T-off = −0.30 ± 18.5 P-on = 0.40 ± 14.4, P-peak = −0.40 ± 10.10 P-off = −02.00 ± 12.70
ECG signal compression [18]	48	MIT-BIH Arrhythmia	AE	RMS = 8.00%, comp ratio = 106.50
Electrocardiogram diagnosis [19]	19,000	Chinese Cardiovascular Disease	CNN + RNN	Acc. = 87.69%
Heartbeat classification [20]	N/A	MIT-BIH Arrhythmia	LSTM	F1 = 95.5%, acc. = 99.2% Sens. = 93.0%, spec. = 99.8%
Heartbeat classification [21]	48	MIT-BIH Arrhythmia	CNN	F1 = 90%, acc. = 96%
Heartbeat classification [22]	47	MIT-BIH Arrhythmia	CNN + RBM	AUC = 0.999
Heartbeat classification [23]	48	MIT-BIH Arrhythmia	CNN	Acc. = 98.6%

Medical task	No. of subjects	Dataset	DLM	Results
Multilead ECG classification [24]	48	MIT-BIH Arrhythmia	DLCCA Net	Acc. = 95.3%
	78	INCART Database	TLCCA Net	Acc. = 95.5%
Classification of premature ventricular contraction [25]	119	MIT-BIH Arrhythmia	EBR	Acc. = 100%, prec. and recall = 100%
Ventricular/supraventricular heartbeat identification [26]	44	MIT-BIH Arrhythmia	RBM + DBM	Acc. = 95.57% (supraventricular) Acc. = 93.63% (ventricular)
Arrhythmia classification [33]	47	MIT-BIH Arrhythmia	AE + LSTM	Acc. = 99.0%
Arrhythmia diagnosis [34]	47	MIT-BIH Arrhythmia	CNN + LSTM	Spec. = 98.70%, sens. = 97.50%, acc. = 98.10%
Arrhythmias detection [35]	48	MIT-BIH Arrhythmia	CNN	Acc. = 99.30%
Atrial fibrillation prediction [36]	139	MIT-BIH	CNN	Spec. = 98.7%, sens. = 98.6%, acc. = 98.7%
Beat-wise arrhythmia detection [37]	74	MIT-BIH NSRDB + MIT- BIH AFDB + PAFDB	U-Net + AE	Sens. = 98.7%, spec. = 98.6%, acc. = 98.7%
Cardiac arrhythmia classification [13]	208	PhysioBank	MLP, CNN	Acc. = 88.6%
Heart failure detection [44]	128	Heart Failure Database	CNN	AUC = 84.01%
	208	Kaggle		Acc. = 83.50%
Cardiac arrhythmia classification [38]	45	MIT-BIH Arrhythmia	1D CNN	Acc. = 91.30%
Cardiologist-level arrhythmia classification [39]	53,877	Ziomonitor (iRhythm Technologies)	CNN	F1 = 0.837, AUC = 0.97%
Detection of myocardial ischemia [40]	N/A	PhysioNet	CNN	F1-score = 89.2%, sens. = 84.4%, spec. = 84.9%, AUC = 89.6%
Heart disease classification [41]	47	MIT-BIH	Faster RCNN	Acc. = 99.21%

(continued)

Table 1 (continued)

Medical task	No. of subjects	Dataset	DLM	Results
Heart disease classification [42]	N/A	PhysioNet	LSTM	Acc. = 98.4%
Cardiac arrest detection [43]	35 + 22	Malignant Ventricular Arrhythmia + Creighton University Ventricular Tachyarrhythmia	CNN	Sens. = 97.07%, spec. = 99.44%, acc. = 99.26%
Heart failure detection [44]	128	Heart Failure Database	CNN	AUC = 84.01%
Mental stress recognition [45]	18	Zephyr BioHarness 3	CNN + LSTM	F1 = 0.81%, AUC = 0.92%, acc. = 83.9%,
Apnea detection [46]	35	PhysioNet	CNN	Sens. = 93.0%, spec. = 94.9%, acc. = 94.4%
Sleep position classification with signal quality [47]	12	MIT-BIH Arrhythmia	CNN	Recall and prec. = 0.99%
Sleep apnea detection [48]	70 + 25	University College Dublin + PhysioNet Apnea	CNN	AUC = 0.950, sens. = 83.1%, spec. = 90.3%, acc. = 87.6%
Sleep apnea detection [49]	86	SA Dataset	1D-CNN, GRU	Recall = 99.0%, acc. = 99.0%
	9	KU Leuven University, Belgium		Acc. = 73.95%
Stressful state classification [50]	13	Kwangwoon University, Korea	RNN + CNN	Acc. = 87.38%
Gender-age prediction [50]	275,056	Mayo Clinic Digital Data Vault	CNN	AUC = 0.97%, acc. = 90.4%
Arrhythmia triage in the ED [51]	142,040	University Medical Center Utrecht	Residual CNN	ROC (concordance statistic) = 93.
Atrial fibrillation [52]	75,778	UK Biobank	CNN	F1 = 87.22%, Sens. = 88.55%, Spec.= 85.95%

Medical task	No. of subjects	Dataset	DLM	Results
Atrial fibrillation [53]	11,994	Chinese PLA General Hospital, wearable ECGs, CPSC2018	CNN	Acc. = 99.35 ± 0.26%
Left ventricular hypertrophy [54]	21,286	Sejong General Hospital, Mediplex Sejong Hospital, Korea	CNN	AUC = 0.880
Racial bias [55]	97,829	Mayo Clinic	CNN	AUC = 0.930
Mortality [56]	422,311	Geisinger Hospital System	CNN	AUC = 0.88
Mitral regurgitation [57]	38,241	Sejong General Hospital, Mediplex Sejong Hospital, Korea	CNN + RNN	Area under the ROC = 0.859
Aortic stenosis [58]	39,371	Sejong General Hospital, Mediplex Sejong Hospital, Korea	CNN	Areas under the ROC = 0.884

Table 2 Medical task in ECG analysis using a private dataset sources

Medical task	No. of subjects	Dataset	DLM	Results
ECG anomaly detection [27]	155,8415	Telehealth Network of Minas Gerais	CNN	Spec. = 99%, F1-score = 80%
Veritas detection and cardiologs [28]	1500	ECGs of HCMC	CNN	Acc. = 92.2%, spec. = 94.0%, sens. = 88.7%
Detection of dysfunction of left ventricular systolic [29]	16,056	Mayo Clinic ECG	CNN	Acc. = 86.5%, spec. = 86.8%, sens. = 82.5%
Noise detection with screening model [30]	165, 142, 920	Trauma intensive-care unit	CNN	F1 = 0.80%, AUC = 0.93%, sens. = 0.88%, spec. = 0.89%
ECG classification (scalogram) [31]	290	Physikalisch-Technische Bundesanstalt	ResNet (CNN)	Acc. = 0.730%
	100	Chosun University-ECG		Acc. = 0.940%

Table 3 Medical task in ECG analysis using hybrid dataset sources

Medical task	No. of subjects	Dataset	DLM	Results
Ventricular fibrillation detection [32]	N/A	Creighton Uni. Ventricular Tachyarrhythmia PhysioNet MIT-BIHMVA	1D-CNN + LSTM	Spec. = 98.9%, sens. = 99.7%, BAC = 99.3%
	N/A	OHCA Sujects		Spec. = 96.7%, sens. = 99.2%, BAC = 98.0%

accuracy above 78%. Therefore, the LSTM model outperforms CNN and a hybrid of CNN and LSTM models for heartbeat signal classification. Only the CNN model is used to detect and classify sleep stages in the public dataset, with an accuracy level greater than 87%. The private dataset's sleep-stage classification was performed with 99% accuracy using the CNN-GRU model. We only found gender-age prediction and emotion analysis from the private dataset source. In gender-age prediction, the CNN model performs with an accuracy of more than 90%. CNNs along with RNN models provide an accuracy of more than 73% in classifying emotions. The CNN model performs well in terms of gender-age estimation, with an accuracy of more than 90%.

Deep Learning with Electromyogram

Electromyographic signals (EMG) are biomedical signals that depict the electric charge produced by skeletal muscle fibers. EMG detectors acquire signals from multiple motor units simultaneously, resulting in signal interaction. Since distinct muscle knowledge is characterized by distinct movement, it is capable of discriminating between patterns of action such as an open or closed hand. To classify certain motion patterns based on EMG signal knowledge, 26 research works were performed using DLM, as shown in Table 2. There are two kinds of significant contributions within these study works. One is devoted to hand gesture detection, and the other is devoted to muscle movement recognition in general. In publicly available datasets for hand motion recognition, CNN and CNN + RNN models are the widely used model. The CNN model achieves an average accuracy of more than 68%. However, the CNN + RNN model outperforms the CNN model with a score of more than 82%. In private dataset, the DBN model outperforms other model with an average 88% accuracy. For muscle activity recognition in public dataset, the CNN is most favored. The CNN model has NMSE of 0.034 ± 0.017, while RNN-LSTM model has NMSE of 0.096 ± 0.014. As a result, the CNN is better option than LSTM model in this medical challenge as shown in Table 4.

Table 4 Medical task in EMG analysis using a public dataset, private dataset, and hybrid dataset sources

Medical task	No. of subjects	Dataset	Sources	DLM	Results
Gesture recognition [59]	27	NinaProDB1	Public	CNN + RNN	Acc. = 87.0%
	40	NinaProDB2			Acc. = 82.2%
	17	BioPatRec			Acc. = 94.1%
	18	CapgMyo			Acc. = 99.7%
	5	CSL-HDEMG			Acc. = 94.51%
Gesture recognition [60]	128	NinaPro		CNN	Acc. = 85.78%
	53	BioPatRec			Acc. = 94.0%
Gesture signal classification [61]	17	MYO		CNN	Acc. = 98.31%
	10	NinaPro			Acc. = 68.9%
Hand gesture classification [62]	10	NinaPro		GFM	Acc. = 63.8 ± 05.12%
Hand movement classification [63]	78	Ninapro		CNN + RNN	Acc. = 87.31 ± 04.9%
Sign language recognition [64]	8	6D inertial sensor	Private	DBM	Acc. = 95.1%
Hand-grasping classification [65]	15	MYO		SAE	Acc. = 95%
Hand motion classification [66]	7	MYO		CNN	MCE ± SD = 09.79 ± 04.61
Limb movement estimation [67]	8	NCC Medical Co., LTD		CNN + RNN	Mean_R2 = 90.30 ± 04.50%

(continued)

Table 4 (continued)

Medical task	No. of subjects	Dataset	Sources	DLM	Results
Movement multi-labeled info. extraction [68]	14	ELSCH064NM3		CNN	Mean matchRate = 78.7%.
Muscle activity detection [69]	N/A	Vastus Lateralis		RNN	SNR < 5
Musculoskeletal force prediction [70]	156	TrignoWireless EMG system		CNN	Std. = 0.13, RMSE = 0.25
Prosthetic limb control [71]	2	Grapevine NIP system		CNN	NMSE = 0.032 ± 0.018
Wave form identification [72]	83	Tokushima University Hospital		CNN	Acc. = 86%
Gesture recognition [73]	137 182	NinaPro	Public	CNN	Acc. = 98.15%
Gesture recognition [74]	18+5	CapgMyo (DB-a) + CSL-HDEMG		3D CNN	Acc. = 90.7%
Sleep staging classifier [75]	5213	Sleep Heart Health Study		CNN + LSTM	F1 = 0.87, K = 0.82
Neuromuscular disorder detection [76]	25	EMGLAB database		CNN + kNN	Mean acc. = 100%
Multi-stroke handwriting character [77]	3	MYO		CNN + LSTM	Acc. = 94.85%

5 Discussion

All the performance of the studied architecture is investigated by using seven popular metrics. They are accuracy (acc.), sensitivity (sen.), specificity (spe.), precision (pre.), false positive rate (FPR), F1 score, and Cohen's kappa index.

For the deep-learning task in medical application, we observed that the majority of the contributions were made for the detection, feature retrieval, and data compression tasks. The detection task emphasizes whether or not the instance exists. Arrhythmia diagnosis [35], for example, determines whether a cardiovascular pattern is natural or arrhythmic. The classification activity often concentrates on a grouping or even leveling the instance types. For instance, the classification of emotions analyzes emotion into the depressed, pleasant, normal, or fear categories. The objective of the extraction of features [41] focuses on improving the training dataset to escape an added stress of manually labeled data, using unsupervised learning techniques. Data compression [28] minimizes data size while ensuring high data quality for processing and transfer.

The studied paper has three basic training architecture from using traditional MLM as feature extractor and classifying using DLM to DLM as feature extractor and traditional MLM as the classifier. However, this type of architecture consumes more time and needs extra human labor in selecting the suitable parameter or model. The third architecture takes direct raw input and only needs a DLM to reach the final output. This architecture's goal is to strengthen the algorithm of the DLM without focusing on the input type, which eases the implementation stage. Our survey concludes that each of them has its limitation and benefit, but the third architecture has a much better future scope as dataset size increases by time, and so computation power.

6 Conclusion

This survey conveyed an analysis of deep-learning systems implemented in biomedical 1D signal over the past 3 years. We found 87 papers using the DLM in EMG and ECG biosignal. By examining these works, we present to identify critical parameters used to predict age, gender, sleep analysis, emotion, heart signal analysis, and hand motion.

Additionally, we exhibit that the CNNs outperform the BS at the ultramodern level. We also have determined that there is still no well-defined standardized hyperparameter setting. These nonuniform parameters make it problematic to compare actual performance. The comparison we made should acquaint other researchers to make quick decisions on choosing input data, deep-learning architecture for achieving their desired MA, and obtaining more reliable outcomes. As a lesson learned from these reviews, our discussion can also help fellow researchers make suitable decisions for future work. The parameter we studied has a significant weight on the system performance. In conclusion, a DLM has confirmed promising for bringing those modern contributions to the up to the minute BS analysis for medical treatment.

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