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Pragmatic Evaluation of Health Monitoring & Analysis Models from an Empirical Perspective

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Abstract—Implementing and deploying several linked modules that can conduct real-time analysis and recommendation of patient datasets is necessary for designing health monitoring and analysis models. These databases include, but are not limited to, blood test results, computer tomography (CT) scans, MRI scans, PET scans, and other imaging tests. A combination of signal processing and image processing methods are used to process them. These methods include data collection, pre-processing, feature extraction and selection, classification, and context-specific post-processing. Researchers have put forward a variety of machine learning (ML) and deep learning (DL) techniques to carry out these tasks, which help with the high-accuracy categorization of these datasets. However, the internal operational features and the quantitative and qualitative performance indicators of each of these models differ. These models also demonstrate various functional subtleties, contextual benefits, application-specific constraints, and deployment-specific future research directions. It is difficult for researchers to pinpoint models that perform well for their application-specific use cases because of the vast range of performance. In order to reduce this uncertainty, this paper discusses a review of several Health Monitoring & Analysis Models in terms of their internal operational features & performance measurements. Readers will be able to recognise models that are appropriate for their application-specific use cases based on this discussion. When compared to other models, it was shown that Convolutional Neural Networks (CNNs), Masked Region CNN (MRCNN), Recurrent NN (RNN), Q-Learning, and Reinforcement learning models had greater analytical performance. They are hence suitable for clinical use cases. These models' worse scaling performance is a result of their increased complexity and higher implementation costs. This paper compares evaluated models in terms of accuracy, computational latency, deployment complexity, scalability, and deployment cost metrics to analyse such scenarios. This comparison will help users choose the best models for their performance-specific use cases. In this article, a new Health Monitoring Metric (HMM), which integrates many performance indicators to identify the best-performing models under various real-time patient settings, is reviewed to make the process of model selection even easier for real-time scenarios.

Keywords-Health, Monitoring, Patient, Accuracy, Complexity, Cost, Delay, HMM, RNN, MRCNN, Q-Learning, Reinforcement, Clinical.

I. INTRODUCTION

Design of an efficient Hospital Management deployment is a multidomain task that involves deployment of patient data collection, data pre-processing for noise removal & filtering, data representation in terms of feature vectors, selection of useful features from the extracted set, categorization of these features into one of N classes, and post processing of these class sets via temporal analysis for application-specific use cases. To design such complex models, researchers have proposed a wide variety of techniques that include Convolutional Neural Networks (CNNs), Q-Learning, Masked Region CNN (MRCNN), Reinforcement learning and Recurrent NN (RNN) models, each of which assists in deployment of augmentation-based classification processes. A typical Hospital Management Model that uses multiple interconnected flows can be observed from figure 1, wherein data from multiple information systems is integrated [1] to generate Electronic Healthcare Records (EHRs), which are processed via a multitude of image & signal processing models.

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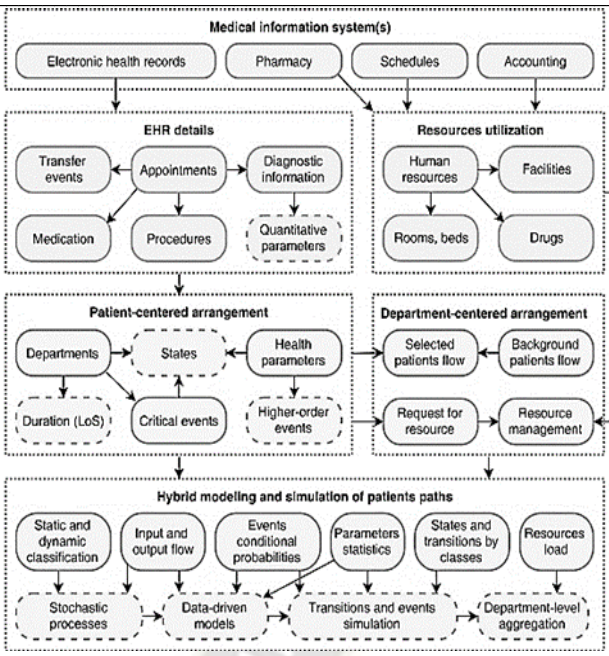

Figure 1. A typical Health Monitoring & Processing Model based on a multilayer interconnected process

The model evaluates transfer events, appointments, diagnostic information, quantitative parameters, event-driven procedures, department states, health parameters, patient flows, resource management processes, classification models, conditional probabilities, load balancing models, etc. for identification of patient conditions. These conditions are processed by various deep learning techniques, which assists in identification of diseases for different patient types. A wide variety of such deep learning models [2, 3, 4, 5, 6] are discussed in the next section of this text, where readers can observe their functional nuances, contextual advantages, application-specific limitations, and deployment-specific future research scopes. Based on this discussion, readers will be able to identify most suited models for their application-specific use cases. This discussion is further extended in section 3, where these models are compared with each other in terms of their accuracy, computational delay, complexity of deployment, scalability and deployment cost measures. This comparative analysis is useful to identify models that are suited for performance-specific use cases. Section 3 also proposes evaluation of a novel Health Monitoring Metric (HMM) that combines various performance measures for estimation of models that can be used for general purpose deployments. Finally, this text concludes with some context-specific & application-specific observations about the reviewed models, and also recommends methods to further optimize this performance.

II. LITERATURE REVIEW

Recent spikes in Corona Virus (CoVID-19) activity have resulted in a meteoric rise in diagnostic tools. Researchers have offered a variety of models for use in monitoring and controlling healthcare delivery. New opportunities for covert and distant health regulation are now possible because to wearable and mobile technologies [1]. In order to monitor the emergence of symptoms and take preventative action, medical professionals can now periodically collect samples of a patient's health state. However, when human participation is required, finding the ideal balance between user effort and useful information obtained can be difficult. Hidden Markov models, which are continuous throughout time and clustered for adaptive sampling, have been used by researchers to address problem. The model plans the time for the subsequent sample in accordance with the possibility that the system will change to a "alert" condition. Data on mental health symptoms from the ClinTouch app for schizophrenia patients are used to illustrate the process [1].

Dealing with enormous amounts of physiological data in the intensive care unit (ICU) necessitates novel approaches [2]. IRIS, a platform for physiological monitoring, clinical decision-making, and provider alerting, was created and verified by researchers to solve this. Various patients in the brain ICU had their EEG, ICP, and O2 data effectively analysed using IRIS. EEG electrode issues and other irregularities were found using specialised algorithms, and alarms were provided to medical staff via their API. The real-time technology seeks to improve patient care while lessening the burden of ongoing monitoring [2].

Monitoring data is used in rotating machine prognostics and health management to infer health conditions and stop accidents and monetary losses [3]. Health indices are essential for prognostics and health management because they provide information for prognostic modelling and anomaly detection. The spectral Lp/Lq norm ratio and the spectral Gini index are examined in this work as important health indicators for tracking the condition of rotating machinery. The performance of monitoring is enhanced by the spectral Lp/Lq norm ratio, spectral Gini index, and their ability to characterise impulsivity and identify repeating transients [3].

Applications for smart health can benefit from the Internet of Things (IoT) and intelligent automated diagnostic systems [4]. In order to monitor maternal and foetal signals in high-risk pregnancies, this study suggests combining IoT sensors, data analytics, and a 1-D CNN classifier. The proposed system provides a prediction approach with an F1-score ranging from 0.74 to 0.91 [4] and achieves accurate emergency diagnostic subsystem performance.

Interactions between software and physical systems lead to emergent behaviours in cyber-physical systems (CPSs) [5]. Humans can quickly identify the health monitoring approach described in this paper, which evaluates the likelihood of violations and actual restriction violations. MATLAB/Simulink simulations show its viability and efficacy [5]. It entails probabilistic assessment utilising Bayesian Estimate methodologies.

For the creation and monitoring of public health policies, data analytics and decision-making tools are essential [6]. This work uses model-driven big data analysis to provide an ontology-based public health strategy. Using Hadoop, Spark, and HBASE, the EVOTION research project created a web-based platform [6].

Due to the lack of medical care or vaccination against the COVID-19 pandemic, self-isolation and physical separation are required [7]. Algorithms for IoT and ML are suggested for tracking health systems and spotting illnesses. Virtual zones provide information on environmental risk while a fuzzy Mamdani algorithm assesses users' health conditions and nearby risks [7]. A stacked autoencoder model and multi-objective optimisation are suggested in another study to improve the accuracy of equipment status determination and health indicator monitoring [8].

The coronavirus epidemic has been made worse by the lack of standardised patient diagnostic [9]. The health status of COVID-19-infected patients can be estimated using a correctly calibrated prediction model employing the ARIMA and K-Means algorithms. By contrasting the model with conventional methods, the model's value is established [9]. The technological and systemic use cases for COVID-19 are described in a broader perspective [10]. There are three main approaches noted: telehealth services, unobtrusive sensor systems for illness detection, and wearable gadgets for monitoring at-risk groups [10].

For proactive clinical decision-making, resource management, and personalised treatment, work in [11] emphasises the significance of developing exact projections. Within 24 hours of hospital admission, the authors suggest using machine learning to predict death, ICU admission, and readmission. The method uses a Stack ensemble platform, which outperforms previous platforms in general wards and critical care units [11]. It consists of an unsupervised LSTM Autoencoder and a gradient boosting model.

Communication networks may be down in disaster-prone areas, casting doubt on the efficacy of IoT-based health monitoring systems [12]. To combat this, researchers combine Wireless Body Sensor Networks (WBSNs) with Vehicular Ad-hoc Networks (VANETs) to enable the transmission of health data to hospitals or ambulances for quick medical attention. The weighted geographic routing (W-GeoR) method that has been presented improves post-disaster health monitoring in situations of urban traffic [12].

Another study [13] emphasises the significance of thorough inspection and prompt identification of health problems. Recurrent neural networks are used in the proposed monitoring system to classify data and use wearable sensors to link to the hospital database through the Internet of Things. This improves the accuracy of spotting aberrant health data.

[14] presents a scalable healthcare platform with deep-learning algorithms for predicting cardiovascular risk. The platform supports cybersecurity, AI-based analysis, continuous monitoring, and device integration, all of which help with cardiovascular risk intervention planning and epidemiological profiling.

In order to increase compatibility and integration in IoT-enabled at-home healthcare monitoring systems, healthcare device interoperability (HeDI) is researched in [15]. By eliminating the need for physical connectors, the suggested edge device with wireless sensors improves applications for healthcare monitoring.

[16] examines how the autonomic nervous system works together to maintain homeostasis. In order to forecast three blood glucose (BG) ranges—low, moderate, and high—the authors suggest a non-invasive method employing electrocardiograms (ECG), with promising findings for the early detection of diabetes and prediabetes.

Deep learning networks provide end-to-end monitoring for guided wave technique-based structural health monitoring [17]. The work shows a deep transfer learning multi-task monitoring system that outperforms direct training and other deep learning detection methods.

As a technology approach to detecting and preventing frailty, Frail Safe is introduced [18]. Utilising cutting-edge technologies, the system develops composite biomarkers for self-management and preventative measures, showing promise for frailty prediction.

[19] presents a brand-new technique for determining a device's PPG signal strength. The suggested system can be used for real-time monitoring with little energy consumption while effectively reducing false alarms during health monitoring.

Wearable sensor patches for health monitoring utilise Internet of Things (IoT) technologies [20]. The patches monitor electrocardiograms, photoplethysmograms, and body temperature, enabling continuous blood pressure monitoring without the use of extra tools. The study demonstrates the potential of the sensor patch for IoT-connected healthcare applications. The sensor patch is intended for remote health monitoring process.

Work in [21] emphasises the need of treating pain in older people, particularly those who have dementia. Researchers suggest a computer vision-based system that uses deep learning to identify unpleasant facial expressions in the elderly, both with and without dementia, in order to overcome difficulties in pain assessment. The approach performs better than baselines and can help in automatically assessing discomfort.

In [22], researchers offer an unsupervised probabilistic technique for differentiating between gait and non-gait patterns

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in data gathered using accelerometers. Gait analysis is essential in healthcare. Patients with Parkinson's disease can use the approach to forecast medication-induced changes, and it works with sensors located anywhere on the body.

The Internet of Health Things (IoHT) can be used to remotely monitor and analyse gait [23]. The development of a piezoelectric insole locomotion monitoring system enables long-term, accurate real-time gait analysis. The device's 16-hour battery life makes continual monitoring possible.

In [24], a wearable telehealth system is suggested for tracking patients with COVID-19 and other chronic illnesses' vital signs. To forecast lung function and remotely monitor patients, the system fuses sensor fusion, artificial intelligence, and physiological data.

When identifying and categorising dynamic multi-channel temporal data, researchers in [25] develop an adaptive transfer learning technique that produces promising results for event segmentation and feature extraction in health monitoring.

Work in [26] proposes CNN models-based intelligent data retrieval and classification methods for evaluating unstructured medical and health data. Other machine learning techniques are outperformed by the CNN-regular KDD model, which can be utilised in health research to uncover risk factors.

PLS-DA, SVM, RF, and ANN are used to identify changes in knee joint and gait data based on age, BMI, and gender in [27], a telehealth monitoring system for gait evaluation. The system is able to monitor treatment requirements, identify mobility problems, and evaluate health.

[28] introduces a sensor-free frailty assessment (FM) method based on deep learning for image processing. The FM has a good degree of practicality and correlation with sensor-based FM for assessing frailty characteristics in COPD patients.

Various communication technologies are integrated into the cloud convergence health IoT architecture, as detailed in [29], for multimodal information collecting and multi-level service quality assurance. The user experience and connectivity to health IoT apps are improved by this architecture.

[30] makes the suggestion of a fog-based health monitoring system to decrease latency and save network resources. In contrast to cloud-only techniques, a unique Load Balancing Scheme (LBS) is presented to distribute work between fog nodes, resulting in lower latency and network utilisation.

A WRAM model is constructed by researchers in [31], which aims to understand the impact that normal breathing and exercise have on respiratory function. A hybrid hierarchical classification (HHC) approach has been created for the purpose of categorising 15 difficult tasks in an effective manner, attaining high accuracy while simultaneously reducing processing time. For the purposes of health monitoring and precision medicine, the multimodal WRAM system demonstrates to be the most advanced available.

ECG sensors, Arduino, Android phones, Bluetooth, and cloud servers are utilised in the proposed IoT-assisted ECG monitoring system [32], which ensures the transmission of data in a secure manner. The system has the potential to improve the effectiveness, precision, and dependability of unsupervised diagnostic systems for the monitoring of cardiovascular health.

A approach of early screening and real-time monitoring by wearable device-based mHealth is suggested in [33] to manage acute cardiovascular disease (CVD) during pandemics like COVID-19. This strategy can be used to monitor patients in real time. This strategy has the potential to improve treatment while simultaneously lowering the danger of infection.

[34] Pulse signals have the potential to be an informative and helpful source of data for medical professionals. For use in a variety of pulse detection applications in health monitoring, a wearable compound sensing device is being developed. This device will be able to pick up both static pressure and pulse impulses.

The data collected by activity trackers on wearable devices can be utilised to monitor changes in a person's health over time [35]. The data from activity trackers are utilised to train two different classification models, one of which is a hidden Markov model (HMM), which then classifies patient-reported outcomes (PROs) and provides insights into health monitoring in real time.

In [36], there is a discussion of contemporary methods to the circuit design for non-invasive health monitoring devices. These approaches can be useful for detecting infections as well as measuring blood pressure and heart rate.

Wireless body area networks, often known as WBANs, are investigated in [37] as a potential solution for ubiquitous monitoring in the healthcare sector. A change point detection technique based on a Markov chain is proposed as a method for finding WBAN outliers. This method offers excellent detection accuracy while maintaining low false alarm rates.

In [38], a systematic approach to the identification of risk characteristics associated with smart health monitoring wearable devices (SHMWD) is given. It is determined that there are 15 essential engineering factors (EFs) that need to be improved in order to advance SHMWD technology. Important levels of engineering factors (EFs) are analysed.

Researchers in [39] are working on an augmented reality system that will allow for the real-time monitoring of the vital signs of surgical patients. Surgical teams have access to rapid responses as well as a communication system that is easy to use thanks to this system.

The paper [40] proposes a method for estimating respiratory rate during apnea that is based on the merging of multispectral data. This technique increases the accuracy of respiratory activity monitoring that is performed using infrared cameras.

In the world of [41], high levels of stress can lead to mistakes being made on the job, and wearable sensors are employed to

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measure the rate of breathing (f R) as an indicator of the general health of the individual. The wearable system that was built employing fibre Bragg grating (FBG) sensors is capable of tracking f R in both stationary and moving work scenarios. This provides significant data on the psychophysical states and stress levels of employees.

Researchers at [42] developed a gadget that monitors vital signs through the use of visible light sensing (VLS), which does so without directly touching the patient. The VLS-based system is superior to the more traditional contact-based measurements in terms of its ability to reliably determine respiratory and heart rates. This non-contact method may find substantial use in human-computer interaction as well as in the monitoring of sleep apnea.

In [43], a proposal is made for a cloud-based health monitoring service that makes use of SVM classification algorithms. Verifiability of medical judgements made in potentially hazardous conditions caused by cloud-based health monitoring is improved by the reliable SVM classification system (VSSVM). The technology enables the secure and confidential remote monitoring of medical features from a distance for users while respecting their privacy.

The article [44] reviews a health monitoring system for wireless telemedicine that is capable of monitoring multiple vital indicators remotely. These vital signs include temperature, respiration, blood oxygen saturation, pulse, blood pressure, and ECG. In order to gather physiological signals in a precise and dependable manner, the system makes use of fabric electrodes and near-infrared photoplethysmography.

An app for the management of COVID-19 coronavirus infection is reported in [45]. The app is intended to collect information that can be used to prescribe medicine to patients who are unable to leave their homes. Through the use of geolocation technology, the app also detects people who have come into touch with COVID-19 carriers. This paves the way for remote patient monitoring and helps alleviate crowding in hospitals.

IoMT is investigated in [46] for the purpose of remotely monitoring mental and behavioural symptoms based on biosignals. It is proposed that a modified version of the k-medoid data clustering approach be used in order to enable the processing of sensory information received from wearable devices in real time for the purpose of monitoring mental health.

Researchers in [47] propose a wearable sensor device as an alternative to invasive surgical procedures for the purpose of monitoring neonates in NICUs. A calming environment for the care of newborns as well as reliable monitoring of their vital signs can be provided by the smart vest, which makes use of flexible sensors to detect respiratory signals, ECGs, and movement information.

In [48], a new learning from mislabeled training data paradigm for LeMAL (learning from mislabeled training data) is offered as a solution to the problem of faulty machine learning models for home health monitoring caused by mislabeled data. Learning is greatly improved by LeMAL in comparison to more conventional approaches to noise filtering.

In [49], the ballistic cardiogram, also known as the BCG, is investigated for the purpose of ambient remote monitoring of heart failure (HF) patients while they are at home utilising integrated sensors. The Waveform Fluctuation Measure, or WFMR, is used to compare clinical and non-clinical groups. This comparison demonstrates that existing algorithms may be more prone to inaccuracy when applied in a clinical situation for different use cases. To assist readers in selecting the most appropriate models for real-time health monitoring scenarios, the following section evaluates different approaches with regards to their accuracy, operating speed, scalability, deployment costs, and computational complexity levels.

III. PRAGMATIC ANALYSIS

The literature analysis reveals that Machine Learning Models (MLMs), such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their equivalents, exhibit superior accuracy and scalability performance in comparison to linear monitoring strategies. However, these models need increased latency and exhibit more intricacy, rendering them ineffective for distant monitoring applications. In order to assess their performance, this section conducts a comparative analysis of these models with respect to accuracy (A), speed of operation (S), scalability (Sc), deployment cost (DC), and computational complexity (CC) metrics. The evaluation of these measurements was conducted by considering the internal operational features of the underlying models. Subsequently, they were categorised into four levels: Low Level (LL=1), Medium Level (ML=2), High Level (HL=3), and Very High Level (VHP=4). This facilitates the comparison of different models using a standardised scale, enabling readers to choose the most suitable models for their unique performance requirements. The similarity may be noted from Table 1, shown as follows,

Table 1. Pragmatic analysis of different models

Method	A	CC	DC	S	Sc
Gini Index [3]	HL	LL	LL	HL	ML
1D CNN [4]	VHL	HL	HL	HL	HL
BE [5]	ML	ML	HL	HL	ML
PHP DM [6]	ML	ML	HL	ML	HL
Fuzzy [7]	HL	LL	ML	ML	HL
NSGA [8]	HL	ML	ML	HL	VHL

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ARIMA [9]	HL	HL	HL	ML	HL
LSTM AE [11]	VHL	HL	VHL	VHL	HL
WGeo R [12]	HL	ML	HL	HL	HL
DEV DAN [13]	VHL	LL	LL	VHL	VHL
DB SCAN CNN [16]	VHL	ML	VHL	HL	VHL
GW CNN [17]	VHL	HL	HL	HL	VHL
Frail Safe [18]	LL	ML	LL	ML	LL
SQA PC [19]	ML	HL	HL	HL	LL
PAT [20]	LL	ML	ML	ML	LL
Gait [22]	ML	HL	HL	ML	LL
CoP GAIT [23]	ML	HL	HL	LL	ML
HMM FLDA [25]	HL	ML	HL	ML	HL
PCC CNN [26]	VHL	HL	VHL	HL	HL
PLS-DA [27]	HL	ML	HL	ML	VHL
SVM [27]	HL	ML	ML	ML	HL
RF [27]	ML	LL	HL	HL	HL
ANN [27]	HL	HL	HL	ML	HL
FM [28]	ML	ML	ML	LL	ML
FNPA [30]	ML	HL	HL	ML	LL
HHC [31]	LL	ML	ML	ML	LL
HMM [35]	HL	HL	HL	LL	HL
Markov Chain [37]	HL	HL	HL	ML	HL
PCA [38]	HL	ML	HL	HL	HL
FBG [41]	HL	HL	HL	ML	ML
VS SVM [43]	HL	HL	HL	ML	HL
ALM [44]	ML	HL	ML	HL	ML
CNN [46]	VHL	HL	HL	HL	HL
PDMS [47]	HL	ML	HL	ML	ML
LeMAL [48]	VHL	HL	VHL	ML	HL
BCG WFMR [49]	HL	HL	HL	HL	ML

Based on this evaluation in figure 2, it can be observed that 1D CNN [4], LSTM AE [11], DEV DAN [13], DB SCAN CNN [16], GW CNN [17], PCC CNN [26], CNN [46], and LeMAL [48] showcased better accuracy, thus can be used for high-performance health monitoring scenarios.

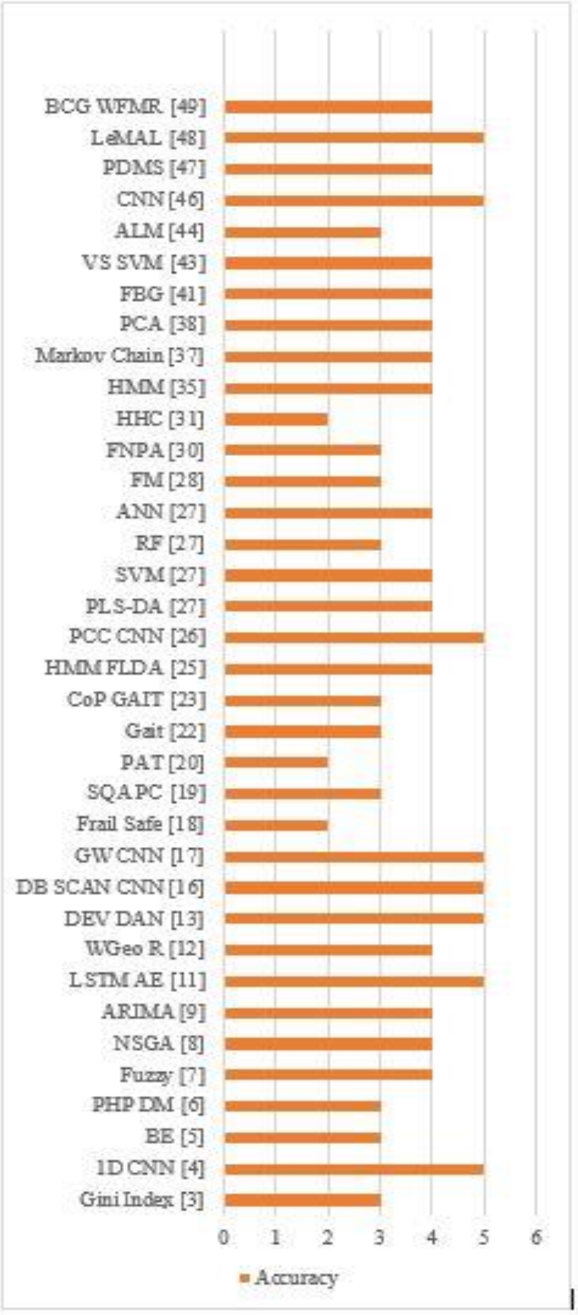

Figure 2. Accuracy of different models

Similarly, based on the evaluation in table 1 and figure 3, it can be observed that Gini Index [3], Fuzzy [7], DEV DAN [13], and RF [27] showcased lower complexity, which makes them highly useful for small scale applications.

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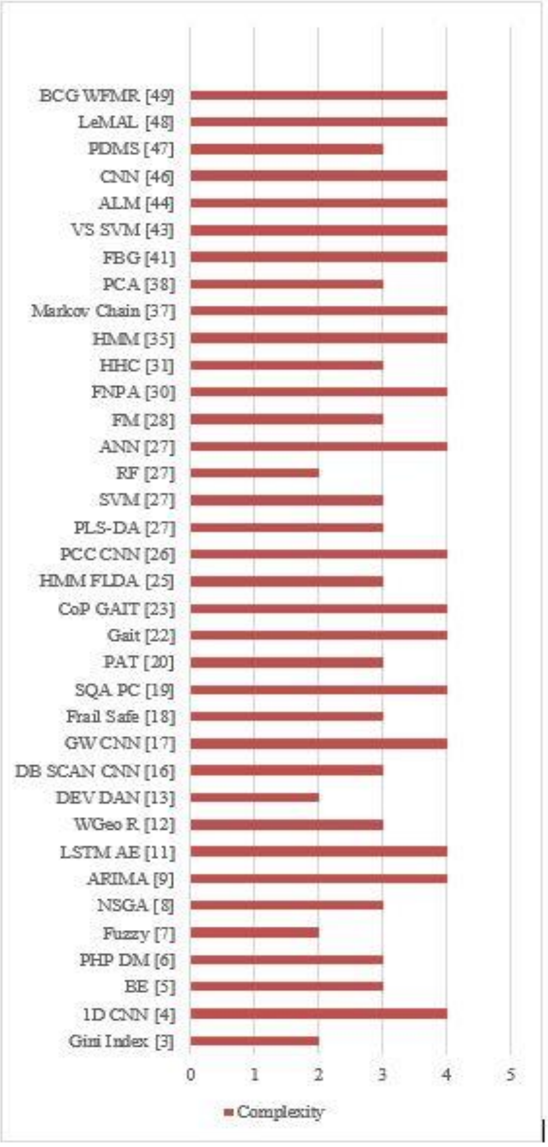

Figure 3. Computational complexity of different models

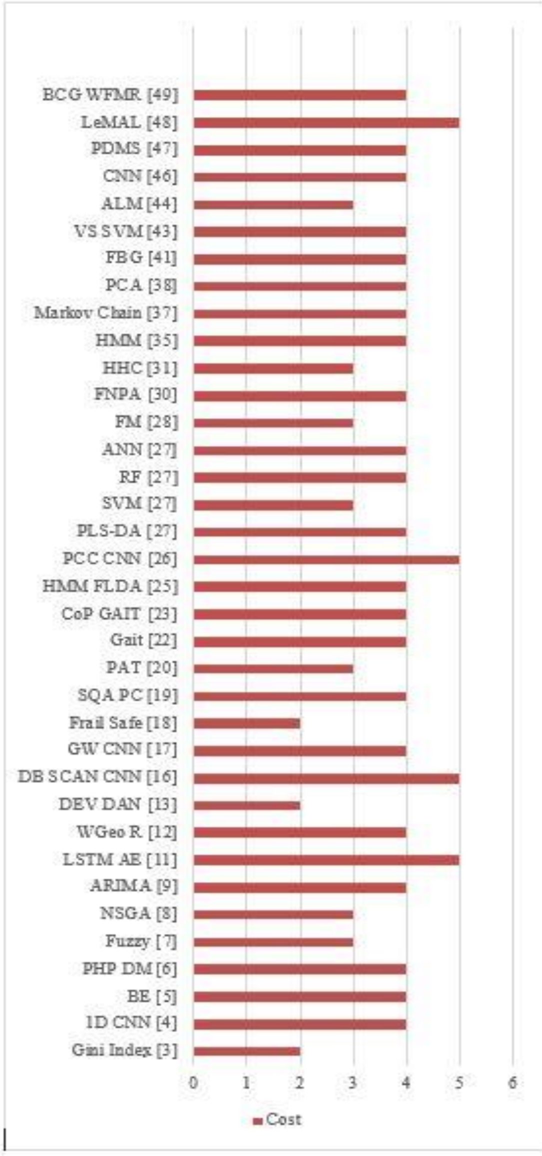

Figure 4. Deployment costs of different models

While, based on the evaluation in figure 4, it can be observed that Gini Index [3], DEV DAN [13], Frail Safe [18] showcased lower deployment costs, thus can be used for low-cost monitoring scenarios.

Similarly, based on the evaluation in figure 5, it was observed that LSTM AE [11], and DEV DAN [13] showcased higher speed, thus can be used for low delay monitoring applications.

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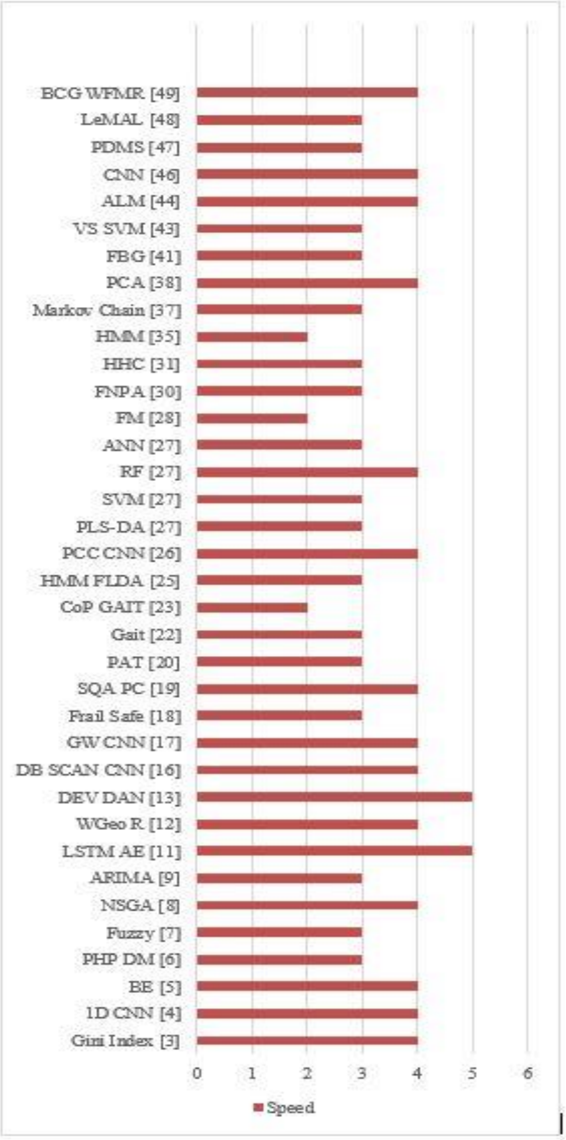

Figure 5. Speed of operation for different models

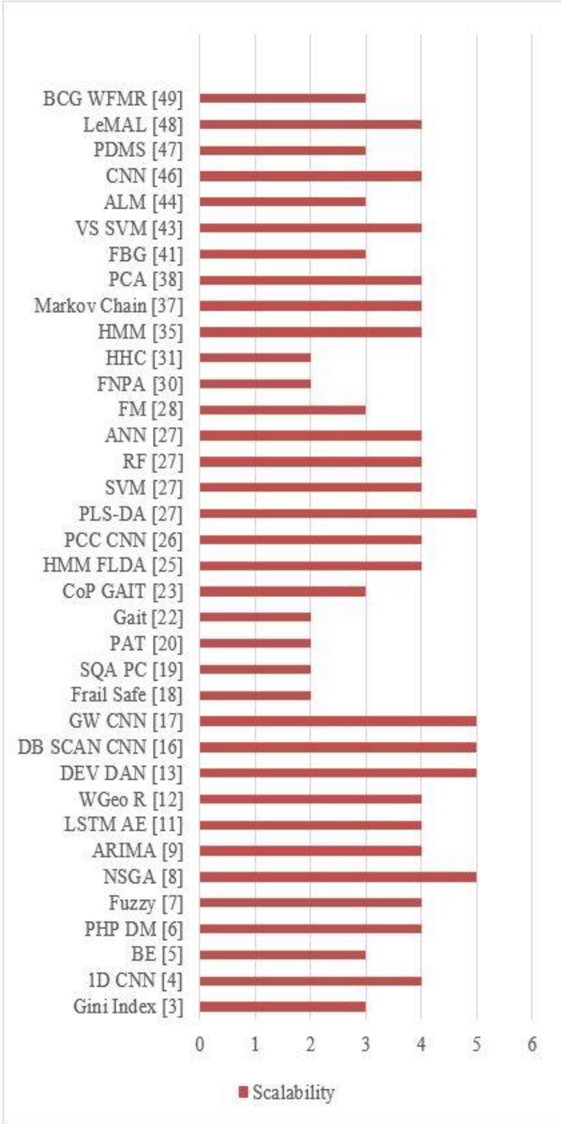

Figure 6. Scalability for different models

While, based on the evaluation in figure 6, it was observed that NSGA [8], DEV DAN [13], DB SCAN CNN [16], GW CNN [17], and PLS-DA [27] showcased higher scalability, thus can be used for analysis of larger number of diseases with high performance.

All these measures were combined to form a novel Health Monitoring Metric (HMM), which was evaluated via equation 1,

$$HMM = \frac{A}{5} + \frac{S}{5} + \frac{Sc}{5} + \frac{1}{CC} + \frac{1}{DC} \ldots (1)$$

Based on this evaluation and figure 7, it was observed that DEV DAN [13], DB SCAN CNN [16], GW CNN [17], NSGA [8], LSTM AE [11], 1D CNN [4], CNN [46], PCC CNN [26], and Fuzzy [7] showcased better overall performance, thus can be used for high-accuracy, high-speed, high scalability, low complexity, and low-cost applications.

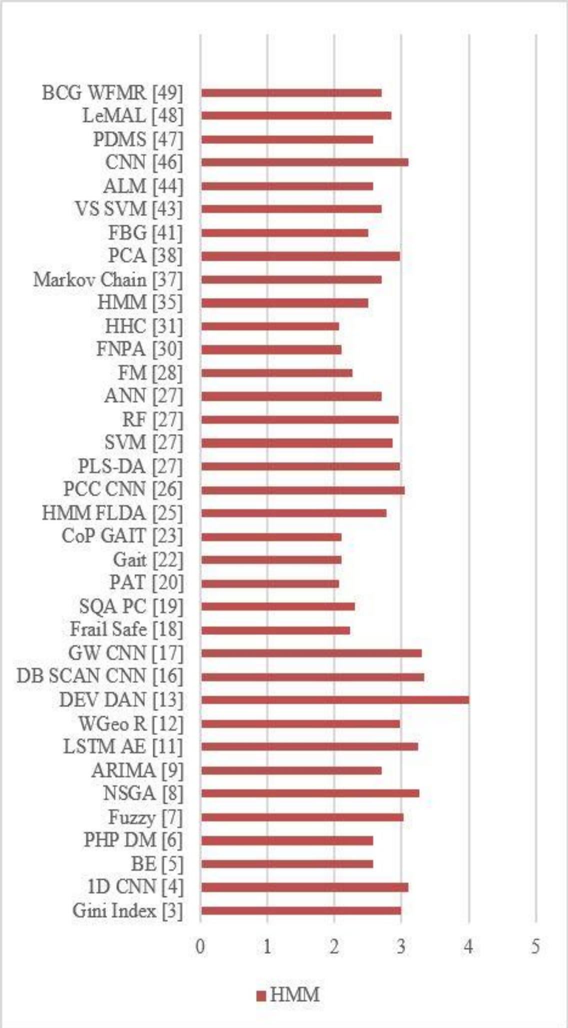

Figure 7. Health Monitoring Metric for different models

Based on this evaluation, researchers can select which models are useful for their performance-specific applications.

IV. CONCLUSION

This paper critically assessed a diverse range of health monitoring models and conducted a comparative analysis of their performance using several assessment measures. The observation indicates that current models using deep learning and machine learning algorithms exhibit superior performance in comparison to linear processing methods. This phenomenon may be attributed to the fact that these models possess the ability to enhance characteristics with a high level of efficiency, while maintaining satisfactory performance in terms of evaluation delay. Based on an evaluation, it was determined that 1D CNN, LSTM AE, DEV DAN, DB SCAN CNN, GW CNN, PCC CNN, CNN, and LeMAL shown higher accuracy, but Gini Index, Fuzzy, DEV DAN, and RF exhibited lesser complexity. Additionally, it was noted that the Gini Index, DEV DAN, and Frail Safe algorithms exhibited reduced deployment costs, whilst the LSTM AE and DEV DAN algorithms had greater speeds. In relation to scalability, NSGA, DEV DAN, DB SCAN CNN, GW CNN, and PLS-DA demonstrated superior performance, making them valuable for deployments on a broad scale. The models were integrated, and a novel Health Monitoring Metric was assessed, revealing that DEV DAN, DB SCAN CNN, GW CNN, NSGA, LSTM AE, D CNN, CNN, PCC CNN, and Fuzzy exhibited superior overall performance. Consequently, these models can be employed for applications requiring high accuracy, high speed, high scalability, low complexity, and low cost. In the future, researchers have the potential to integrate these models in order to develop hybrid approaches that can demonstrate improved accuracy and reduced complexity via the use of model fusion techniques. It is essential to verify these models on bigger datasets in order to enhance their deployment capabilities in large-scale situations. Furthermore, it is essential to investigate the use of Deep Q Networks (DQNs) in conjunction with incremental and continuous learning techniques in order to enhance the overall monitoring capabilities across diverse application situations.

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