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Chapter

Health Risk Measurement and Assessment Technology: Current State and Future Prospect

Sadegh Moradi, Davood Simyar and Mojtaba Safari

Abstract

With accelerated technologies, different kinds of health technology devices have been provided to customers that continuously record bio and vital signals. Some of these products are wearable that can be used all day long and during sleeping time. Due to the wearability feature and continuous recording, a vast amount of data can be achieved and analyzed. The recorded data are usually shared with a cloud to implement comprehensive analysis methods where deep and machine learning algorithms play the main role. Finally, they can assess some health factors of the customer and most likely predict future health risks. This chapter shall review the role of the clinical scanners and their valuable data in risk detection, more portable modalities, home-used commercial devices, and emerging techniques which are so potent for future home-used health risks analysis. In the end, we conclude the state-of-the-art and provide our vision about the future of health risk analysis.

Keywords: artificial intelligence, deep learning, machine learning, CT, PET, MRI, ECG, EEG, NIRS, microwave imaging, bio-impedance, commercial products, disease prediction

1. Introduction

Wellbeing and healthiness are always a crucial concern for human being as the most intelligent specie around the globe. Based on the historical background, people have suffered from different treatment methods which were employed to cure them. The treatment methods are sometimes fruitless, more and less painful, and seldom creates new side effects. By entering 21st century, where biomedical engineering has remarkably developed, the intelligent human has seriously changed his attitude about his wellbeing. Now, his expectance is prediction and prevention, not only treatment! Modern measurement techniques have increased the people’s expectations to predict their health abnormalities and prevent serious health issues. This is achievable by continuous and long-term daily measurement of vital signals of the body and employing novel technologies as well as artificial intelligence (AI) algorithms. In this chapter, the main aim is to review the outstanding studies of the health risk analysis using conventional and novel technologies. Therefore, we firstly introduce machine
learning (ML) and deep learning (DL) in simple words, then review their applications in conventional clinical modalities; Computed Tomography (CT), Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI). Moreover, several selected studies with keywords “AI” and “clinical modalities” are mentioned to explore the state of the art. Later, the most potent portable and home-used modalities for health risk assessment purpose are listed and evaluated here; including electrocardiogram (ECG), electroencephalography (EEG), functional near infra-red spectroscopy (fNIRS), photoplethysmogram (PPG), and digital stethoscope. We definitely choose also some brilliant studies related to the mentioned techniques to discuss. In addition, the chapter also demonstrates the state of the art in commercially-available devices and introduces noteworthy commercial devices which are mostly AI-based to predict or diagnosis of the disease at home. Beside them, there are several products which do not employ AI but provide critical information for remote health analysis. Will finally introduce two attention-deserved modalities, in order to brighten the future prospective; including microwave imaging and bio-impedance measurement.

2. Machine learning and deep learning application in medical devices

Although the details of ML and DL are beyond the scope of this book chapter, this chapter will describe their fundamentals and application in medical imaging. The most interested readers may consult the ML [1] and DL [2] books and explore the seminal papers that will cover here.

The main objective of learning algorithms is to use a priori information to perform a task such as detecting and classifying diseases and abnormalities [3, 4]. They learn from data to perform a task rather than hard-coding.

Let us explain the difference between hard-coding and learning through the dataset itself with an example. Assume we want to know the weather temperature in Celsius (°C) but our measurement device provides it in Fahrenheit (°F). To do that we can write a program to get the temperature in °F with multiplying it by 1.8 and add 32 to it (Figure 1a). Now, let us assume the mathematical relation between the (°C) and (°F) is unknown, and even worst, the user is not able to perform the measurement correctly or the device does not work properly. In this way, the user needs to perform the measurements and employs a linear regression to find the (linear) relation as illustrated in Figure 1b.

![Figure 1.](image)

(a) Hard coding and (b) learning from dataset procedures are illustrated.
Training the ML models itself is composed of three important parts (a) a correct model, (b) an optimizer to find the free parameters of the models to satisfy, and (c) a criterion, which is also called cost function or loss function. Although selecting ML model is a bit tricky, the dataset’s complexity and size guide us to select an appropriate model. The model will over-fit when its complexity is high and the dataset size is small [5]. After selecting the correct model, optimizers like stochastic gradient descent iteratively optimize the cost function to find the model’s free parameters to satisfy a criterion like mean squared error between the predicted and the ground truth values.

The datasets play an essential role in training the ML algorithms. For instance, several a priori features like rate, rhythm, axis, and intervals that are extracted from electrocardiograms were used to classify and localize cardiac diseases [6]. However, it will be naive to discount other kinds of features including morphological and texture feature. Those are indiscernible to the human eye and need to be extracted with engineered algorithms [7].

Although DL is a subset of ML, its architecture is different from ML. for instance, feed-forward DL models are composed of several layers and each layer consists of simple neurons that perform a linear operation. Almost always non-linear transformations like sigmoid functions are added to the neurons’ output to comprehend the dataset’s non-linearity. Figure 2(a) illustrates a neural network (NN) configuration of a input layer and one hidden layer. The deep NN shown in Figure 2b is formed when several hidden layers, which are composed of neurons, are stacked on top of each other. The feed-forward NNs does not consider data continuity that are seen in medical images or electrocardiogram. Thus, the Convolutional Neural Networks (CNNs) that consider the data continuity are more in us [8]. CNNs are composed of the convolution layers that consist of a learnable kernel through error backpropagation (Figure 3).

DL algorithms are different from ML in many aspects like:

1. do not need engineered hand-crafted features;
2. do not need to choose a model for training;

Figure 2.
(a) Input layer with first hidden layer and (b) a complete feed-forward NN are illustrated.
but still we need to design the networks’ architecture.

3. do not need as extensive pre-processing as ML models need;

However, DL typically require a larger dataset compared with ML to train. To improve the generalization of the DL models, the datasets are needed to acquire with different acquisition protocols. While lack of a large medical dataset had limited its applications, nowadays several large databases are available, which push forward the applications of DL in medicine [9, 10].

2.1 Artificial intelligence in clinical modalities

The following chapter will review some DL applications in tomography images. The term tomos (τομος) in Greek means “cut”, however, tomography refers to creating internal images from an imaged object without cutting it open. The tomography images like CT, PET, and MRI can provide anatomical and physiological (functional) information.

The detail of those imaging modalities is beyond the scope of this chapter, the most interested readers refer to the medical imaging books [11, 12] and go through the papers will cover here.

Subsections 2.1.1-2.1.3 will, respectively, review some applications of the DL algorithms in medical images including CT, PET, and MRI to detect and classify lesions, to enhance medical images, and to reconstruct medical images.

2.1.1 Deep Learning in CT

CT modalities with different variations are anatomical images that acquire electron density using x-ray radiations (Figure 4). CTs are widely used in medicine such as diagnosing stroke [13], searching the hemorrhage [14], and planning radiation therapy (RT) [15]. CT images can be acquired after injecting a contrast agent, called CT angiography, that are used to visualize the veins and arteries.

Automatic lesion detection and segmentation will improve (a) hospitals’ throughput, (b) reproducibility of the decision, and (c) accuracy and precision when they are assisted by a user. Segmentation tasks that is time-consuming, on average 56% of the time are preferred by radiologist and oncologists [16]. DL was used to detect and segment cancers including non-small cell lung cancer [16–18] and brain hemorrhage [19] on CT with comparable performances of experienced medical doctors.
CT uses x-ray radiation to acquire the data, so it delivers radiation doses to the patients. However, delivering the radiation doses to the patient should be avoided or should be kept as low as possible. Thus, DL algorithms are used to reconstruct therapeutic CT images from low dose imaging method called low dose CT (LDCT) reconstruction.

Table 1 summarizes the DL application in CT imaging modality.

<table>
<thead>
<tr>
<th>Application</th>
<th>Architecture</th>
<th>Results</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reconstruction</td>
<td>both fully connected and convolutional layers</td>
<td>provide better image quality and higher image contrast.</td>
<td>[20]</td>
</tr>
<tr>
<td></td>
<td>U-net</td>
<td>Outperforms FBP(^1) and POCS-TV(^2)</td>
<td>[21]</td>
</tr>
<tr>
<td></td>
<td>Pix2Pix (GAN)</td>
<td>Outperforms FBP, lower artifact, better generalization</td>
<td>[22]</td>
</tr>
<tr>
<td></td>
<td>both fully connected and convolutional layers</td>
<td>FBP, IR(^3)</td>
<td>[23]</td>
</tr>
<tr>
<td>Quality improvement</td>
<td>CNN</td>
<td>Outperformed ASD-POCS, K-SVD(^4) BM3D(^5) in noise reduction</td>
<td>[24]</td>
</tr>
<tr>
<td></td>
<td>U-net (GAN), CNN</td>
<td>Outperformed in reducing metal artifact FBP(^6)</td>
<td>[25, 26]</td>
</tr>
<tr>
<td></td>
<td>SinoNet</td>
<td>Outperformed in reducing metal artifact FBP(^6)</td>
<td>[27]</td>
</tr>
</tbody>
</table>

\(^1\)Filtered back-projection.\(^2\)Total variation minimization method with projection on convex.\(^3\)Iterative reconstruction sets.\(^4\)Singular value decomposition.\(^5\)Block-matching and 3D filtering.

Table 1. Deep learning applications in CT images.

CT uses x-ray radiation to acquire the data, so it delivers radiation doses to the patients. However, delivering the radiation doses to the patient should be avoided or should be kept as low as possible. Thus, DL algorithms are used to reconstruct therapeutic CT images from low dose imaging method called low dose CT (LDCT) reconstruction. Table 1 summarizes the DL application in CT imaging modality.

2.1.2 Deep learning in PET

PET scanners acquire the metabolic activity images of an organ. Metabolic activity is obtained with a radio-pharmaceutical tracer that is injected to a patient, and, its uptake and washout reveal the function of a target organ (Figure 5). Wash-in and wash-out provide metabolic information of the regions. For instance, the information are used to diagnose neurodegenerative diseases like Alzheimer’s disease, brain mapping, and treatments’ follow-up [28–30].
Clinical diagnostic and prognosis accuracy, precision, and repeatability of PET scans depended significantly on image quality. DL has been used to improve the PET image quality; reduce the PET imaging time; and predict and classify diseases. For instance, DL algorithms were used to reduce noise [31], to reduce the acquisition time [32, 33], and to reduce the motion artifact [34], which deteriorates the image quality. DL algorithms have been showing promising results in predicting and classifying different tumors and neurodegenerative disease types. Table 2 summarizes the DL applications in PET scans including noise reduction, image reconstruction, image motion artifact correction, and disease detection and classification. In reconstruction

<table>
<thead>
<tr>
<th>Applications</th>
<th>Target</th>
<th>Results (Compared with conventional methods)</th>
<th>Ref</th>
</tr>
</thead>
<tbody>
<tr>
<td>Noise reduction</td>
<td>brain</td>
<td>better SNR¹ &amp; SSIM²</td>
<td>[31]</td>
</tr>
<tr>
<td></td>
<td>heart</td>
<td>better SNR &amp; SSIM</td>
<td>[35]</td>
</tr>
<tr>
<td>Reconstruction</td>
<td>brain</td>
<td>better SNR &amp; SSIM</td>
<td>[32]</td>
</tr>
<tr>
<td></td>
<td>brain</td>
<td>better SNR</td>
<td>[33]</td>
</tr>
<tr>
<td>Motion reduction</td>
<td>heart</td>
<td>Reduced</td>
<td>[34]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• mean motion error</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>• maximum motion error</td>
<td></td>
</tr>
<tr>
<td>Diagnosis</td>
<td>head-and-neck cancer</td>
<td>Accuracy 86.60 &amp; AUROC³ 0.87</td>
<td>[36]</td>
</tr>
<tr>
<td>Alzheimer's disease</td>
<td>accuracy &gt;80</td>
<td></td>
<td>[37]</td>
</tr>
<tr>
<td></td>
<td>specificity 75</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>sensitivity 82</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alzheimer's disease</td>
<td>accuracy &gt;84</td>
<td></td>
<td>[38]</td>
</tr>
<tr>
<td></td>
<td>AUROC 0.96</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alzheimer's disease</td>
<td>AUROC 0.98</td>
<td></td>
<td>[39]</td>
</tr>
</tbody>
</table>

¹Signal-to-noise ratio. ²Structural similarity index measure. ³Area under receiver operating characteristic curve.

Table 2.
Wide range of DL applications in PET scans including image enhancement, acquisition acceleration, and diagnosis.
2.1.3 Deep learning in MRI

MRI sequences are obtained without using the radiation doses. In this way, they do not deliver radiation doses to the patients. MRI with different pulse sequences can provide anatomical and physiological information with soft tissue contrast superior to CT and PET images. Figure 6 illustrates a 3D T1 MRI sequence. Soft tissue contrast in MRI is superior to (Figure 4) and PET (Figure 5).

Functional and Anatomical MRI sequences like functional MRI (fMRI) and 3D T1-w sequences have a wide range of applications from diagnosing neurodegenerative diseases such as Parkinson’s disease [40], brain mapping [41], and solid tumor detection and localization [42].

DL algorithms have been investigated intensively for MRI image analysis and processing, because MRI scanners are widely accessible; MRI images are obtained with high spatial and contrast resolutions, and MRI images are obtained without delivering radiation dose. Image processing applications including image reconstructions [43, 44], artifact reduction [45, 46], segmentation [47], and registration [48] have been widely investigated. DL algorithms in MRI are used to detect Parkinson’s disease [49] and Alzheimer’s disease [50]. Moreover, DL has been extensively investigated for brain tumor detection and classification. The list of articles in that domain could be so long, however, interested readers in tumor can check out [51] for brain tumor, for prostate cancer [52], and for breast cancer [53].

3. Artificial intelligence in portable and low-cost modalities

The cost of the device and portability could be considered as the most important aspects for home-user costumers who aim to monitor their health condition. Moreover, by producing cost-effective devices, more costumers afford to purchase and use them at home which leads a huge unlimited data from different people. This can provide a priceless condition to apply different DL and ML methods to this big data to extract unexpected information like different disease identification. In the following, we will discuss promising studies which utilize DL and ML.
3.1 Electrocardiography (ECG)

Heart as an autonomous organ is periodically generating electrical stimulus to contract atrias and then ventricles and finally, pump out blood. This phenomenon occurs 60 to 100 times per minute. The mentioned electrical activity can be recorded by an electronic device, named ECG. ECG utilizes sensitive electrodes, attached to the chest, to capture the weak electrical activity of the heart, see Figure 7. ECG signals provide different functional information about the heart that could be analyzed to detect or predict disease and abnormalities of the heart [54].

Here, we mention some notable studies which use AI to diagnose or predict heart diseases using ECG recorded signals. The following studies prove the potential of AI algorithms to apply to ECG signals.

**Heart disease:** as a leading cause of death worldwide, always attracts the attention of scientist to predict and diagnose it. In 2020, Khan et al. [55] developed an IoT framework to assess heart disease more precisely by utilizing a Modified Deep Convolutional Neural Network (MDCNN). The signal was collected by a smartwatch and heart monitoring device that was attached to the patient to monitor the blood pressure and ECG. Based on the results, MDCNN is found to be a more effective method for predicting heart disease than other existing systems. With 98.2% accuracy, the proposed method achieves higher accuracy for the maximum records compared to the existing classifier: hybrid random forest with liner model (HRFLM), neutrosophic multi-criteria decision making (NMCDM), and particle swarm optimizations (PSOs) with support vector machine (SVM).

**Heart disease prediction:** the pattern of heartbeat is an important marker for heart function. The rhythm and rate of the beating can be irregular which is called “Arrhythmia”. Vafaie et al. [56, 57] have used a novel classification method based on dynamical models of ECG signals to classify ECG signals with higher accuracy, leading to more precise arrhythmia detection. The proposed approach uses a fuzzy classifier to segregate ECGs, and simulation results indicate that this classifier is 93.34% accurate. In order to further improve the performance of the classifier, a genetic algorithm is used, which enhances the prediction accuracy to 98.67%.

**Cardiac arrest prediction:** unexpected cardiac arrest in hospitals is always a major burden for the health system. Using ECG and deep learning AI (DLAI). Kwon, J.M. et al. [58] hypothesized that cardiac arrest could be sufficiently predicted and

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**Figure 7.**

ECG device uses several electrodes, attached on the chest, to record electrical activity of heart. Here is also shown a typical ECG signal at left side. EEG also utilizes multiple electrodes placed on the scalp to record brain electrical activity, here we just showed two electrodes to simplify the figure. A regular EEG signal contain different frequency components which individually describes the brain working status. At the right side, an example of different EEG frequency has been pictured.
prevented. During the 24 hours following the ECG, cardiac arrest was observed. Their algorithm could classify some patient as non-event cases who experienced a delay cardiac arrest over 14 days.

**Pulmonary hypertension predication:** pulmonary hypertension (PH) is a mortal condition where the blood pressure in the blood vessels that supply the lungs is high and there is a possibility of damage to the right side of the heart in this condition. Again, Kwon, J.M. et al. [58] in 2020, successfully developed an AI algorithm to predict PH based on ECG signals of patients. ECG signals were acquired by a 12-lead device which enabled them to provide a sensitivity map.

### 3.2 Electroencephalography (EEG)

EEG device is a dedicated modality for brain electrical activity assessment and detects abnormalities in our brain. It has multiple electrodes, dry or wet, placed on the scalp to record the low-level voltage variations. For wet electrodes, it is needed to use conductive gels [59]. EEG signals are primarily amplified by electronic circuits, then processed to extract different frequency components, see Figure 7.

**Cholinergic intervention detection:** it is increasingly important for clinical trials to monitor therapeutic intervention effects on brain function, despite the fact that inter-individual variability and subtle effects make this a difficult task. To meet this goal, Simpraga et al. [60] utilized complementary biomarker algorithms in EEG data processing to figure out the signature of pharmacological intervention as well as ML to improve classification accuracy. A biomarker for muscarinic acetylcholine receptor antagonist (mAChR) that was developed by them, produced higher classification performance than any single EEG biomarker. However, the mAChR index discriminated healthy people from AD patients, an AD-optimized index yielded a better classification. In the end, they concluded that a clinical trial’s accuracy in the detection of disease or drugs can be enhanced if multiple EEG biomarkers are integrated.

**Seizure prediction:** seizure is one of the well-known disorders in the brain. During a seizure, there is an electrical disturbance in the brain that occurs suddenly and uncontrollably. As EEG records the electrical activity, could be a worthy choice to identify or predict seizure. Alshebeili, S.A. et al. [61] proposed a method for predicting seizure activity using EEG signals, by applying statistical analysis, digital filtering, and AI. For the AI part, they used Multi-Layer Perceptron (MLP) networks for seizure prediction. Results of the simulation show that the proposed approaches are highly accurate, have a short prediction time, and have a low false alarm rate.

### 3.3 Functional Near Infrared Spectroscopy (fNIRS)

fNIRS is an optics-based technique that uses two or more wavelengths in the near-infrared (NIR) range (650–950 nm) for measuring the haemodynamics in the brain, see Figure 8. As NIR light illuminates the scalp, it will be scattered and absorbed. In the brain cortex, a portion of the incident light reflects and scatters back to the scalp, which can be detected by an ultrasensitive photodetector. In the end, cerebral haemodynamic can be calculated using the modified Beer–Lambert law, if the fNIRS device uses at least two wavelengths around the isosbestic point at ~810 nm, one greater than 810 nm and one less than 810 nm [62].

Let us look at two selected fNIRS studies which are in AI-based studies category.  
**Stress assessment:** stress is well-known to be one of the major threats to human health [63]. According to a promising study, an approach based on CNN is proposed
Epileptic seizure prediction: Epileptic seizure is mostly studied using EEG but a fully different study employed fNIRS to predict it [64]. The fNIRS results were applied to a CNN algorithm due to its ability to model high-dimensional fNIRS as three-dimensional tensors. CNN application to fNIRS recordings demonstrated pretty reliable results to predict epileptic seizure.

3.4 Photoplethysmography (PPG)

PPG is a method to measure blood volume using a light source and detector. PPG could be considered as a simpler version of the NIRS technique, but its aim is only blood volume measurement and heart rate, see Figure 8. PPG devices are low-cost and usually worn on a hand finger. It has recently been used in several studies to predict different diseases or blood components, as described in the following.

Type 2 Diabetes detection: Type 2 Diabetes is a common impairment for people that could be extracted from PPG signals using ML approaches. This study was done by Hettiarachchi, C. et al. [65] based on PPG signals of smart devices and other additional information such as gender, weight, age, and height. They tested several classification models and found that A 79% area under the ROC curve was achieved by the Linear Discriminant Analysis (LDA).

Blood pressure prediction: in 2019, Baek S. et al. [66] proposed a method to predict blood pressure non-invasively using ECG and PPG signals. The method is
based on a deep CNN and the prediction was accurate when both PPG and ECG signals were used for calculation.

**Blood pressure stratification:** One year later, by Wang D. et al. [67] conducted a study to model the relationship between PPG and blood pressure. They employed a multi-information fusion artificial neural network (MIF-ANN). Moreover, this study showed that blood pressure detection accuracy is greatly improved through multi-information fusion based on meticulously designed networks.

**Hemoglobin level prediction:** non-invasively Hemoglobin (Hb) level measurement could be a desirable goal for controlling the disease and its progression [68]. Regularly, it is invasively measured from blood samples. Using the characteristics of the PPG signals and different ML algorithms, a non-invasive method is proposed by Kavsaoğlu, A et al. [68] for the prediction of Hb. They employed different kinds of ML algorithms where notable results were achieved (MSE-0.0027) using the selected features by RELIEFF feature selection (RFS) and support vector regression (SVR).

### 3.5 Digital stethoscopes and sound processing

Digital stethoscope is an electronic device that can capture the voice of the internal part of the body using a microphone and record it continuously. The long-term recorded sound could include an ocean of information about the health of the lungs, heart, and whole respiratory system. In other words, a digital stethoscope provides the opportunity of applying AI algorithms to recorded sounds. In Figure 9, the typical recorded signals of cardiac and pulmonary sound are shown.

**Recognition of pulmonary diseases:** Fraiwan, M et al. [69] conducted a study to figure out the capability of DL in identifying a pulmonary disease from lung sounds. Their DL network structure was built from two CNNs and bidirectional long short-term memory units. Luckily, the performance of the network was promising; the highest average accuracy of 99.62%. They could classify the patients based on type of pulmonary disease with precision of 98.85%.

**Lung disease identification:** the recorded cough sound, similar to lung’s, contains valuable information about the health condition of the respiratory system. Rudraraju, G. et al. [70] could figure out a relationship between cough patterns and respiratory conditions. Including stiff lungs, widened airway, fluid-filled air sacs, and narrowed airway. According to the results, cough sound characteristics are strongly correlated with airflow characteristics which are critical in the identification of the lung disease type.

![Figure 9.](image-url)

*Figure 9.* Recording of heart and pulmonary sounds could provide plenty of information which contain buried hints to evaluate the healthiness of corresponding organs. Using a microphone and an electronic circuit, this goal could be easily achieved. Then, sound processing and AI algorithms take the role of interpreter to illustrates the behind mysteries.
Respiratory anomalies prediction: respiratory sound is also investigated by researchers to detect respiratory disease or any abnormality in the sound [70]. In 2020, Pham, L et al. [71] firstly presented an extensive analysis of how different factors like respiratory cycle length and time resolution affect the prediction accuracy. Finally, they proposed a novel DL-based framework for respiratory disease detection which performed truly well compared to available methods.

Respiratory anomalies prediction: one year later, Pham, L et al. [72] again utilized respiratory sound as input for an inception-based deep NN to detect lung disease. In a process called front-end feature extraction, recorded sounds from patients are firstly converted to spectrograms that represent both spectral and temporal information. Then, in another process called back-end classification, the spectrograms are fed into the introduced network to detect lung diseases in patients. Finally, the result of the experiment was definitely competitive in lung disease detection.

Detection of chronic heart failure: there are several papers that they have utilized heart sounds to detect the disease and we mention one here. Gjoreski, M. et al. [73] presented a method to detect chronic heart failure (CHF) based on heart sounds. In their method, traditional ML and end-to-end DL are combined. The proposed method showed bright results in discriminating healthy subjects from patients as well as in the detection of different CHF phases.

4. Commercially available portable and home-used devices

Home-used health technology devices have recently emerged as critical tools for monitoring people’s vital signs and health status in the modern world. The fast-growing field of home-used and mobile health has covered the monitoring of numerous human organs. They could provide massive data by continuous, recuring, or occasional measurements that provide a wider playground for ML and DL algorithms. That is why novel home-used devices day by day present new clues about costumers’ healthiness which were unknown and unexpected before. Moreover, most of these devices are designed for personal and private use that can enable the company to provide personalized results for each person, based on his/her lifestyle, medical background, and other individual information.

Here, we introduce some noteworthy commercially available products and classify them based on their provided results into two categories: the first group is AI-beneficiary products that provide additional information besides vital signs and the second is raw data products that only vital signs or basic parameters. To have a glance at our desired products to be introduced, see Figure 10.

4.1 AI-beneficiary products

basic vital signs, using different methods which have been already mentioned by us. The duration of the measurement could be non-stop, even during sleeping, periodically, several times per day, and occasionally. Clearly, the continuous measuring devices could record more data and have a better estimation of the health situation. Moreover, they can share the recorded big data with a cloud to analyze it utilizing AI and provide admirable information, including health warnings, disease prediction, and diagnosis. Here we mention some brilliant AI-based devices and their application.
The first device to review is Oura ring [74], a 100 percent wearable device to measure heart rate (HR), blood oxygenation (SpO2), and temperature. The ring contains a long-duration battery and internal memory and is able to measure continuously for a whole week and transfer it to the mobile application. Moreover, it can provide some information about daily activities, workouts, sleep quality as well as the possibility of limited disease, like flu, prediction. Oura ring is a talented device to use AI, due to continuous daily and nightly measurement.

The second device is Nukute [75], which consists of two wireless wearable sensors, a tablet computer, and a cloud application for remote sleep apnea screening and diagnosis. The sensors record bio-signals such as breathing, blood oxygen saturation, heart rate, and sleeping position to be algorithmically analyzed in the cloud. Using an intuitive online user interface, the physician can view results and confirm the diagnosis.

The next popular product is BPM Core [76], a multimodal device that measures the systolic and diastolic blood pressures in a medically accurate manner. Blood pressure measurement at home can also help to avoid white-coat syndrome, detect masked hypertension, and manage nocturnal hypertension. BPM Core also includes medical-grade ECG thanks to 3 electrodes. The data is presented lively on the device and transferred to the mobile application, to receive instant feedback on atrial fibrillation diagnosis. In addition, it contains a digital stethoscope beside ECG and blood pressure meter. By placing next to the chest during a measurement, the digital stethoscope detects the specific heart sound frequencies that correspond to the opening and closing of the heart valves. Using these sounds as well as AI, BPM Core can detect potential disturbances.

Muse S [77] is an innovative brain-sensing headband that monitors brain activity during the day and provides real-time biofeedback to help refocus. It consists of EEG sensors, an accelerometer, a gyroscope, and PPG. This smart device could provide a kind of meditation for customer, as feedback on brain and heart activities is recorded by EEG, PPG, and other sensors. Using the app generates sounds of weather to help customer stay calm and focused.
Nowadays, cardiac arrhythmias could be detected at home using long-term data recording by commercial low-cost products. A wearable, mobile, and waterproof ECG recording with intelligent arrhythmia detection is an ideal solution presented by Bittium Faros [78].

IBreastExam [79] is a radiation and painless device to assess women’s breast condition. This device utilizes capacitive sensing technology to detect breast lesions earlier. It could be a talented replacement for mammography which is radiation based. The device is fully portable but relatively expensive for home users.

Ava bracelet [80] is a dedicated device for women that tracks five physiological signals such as breathing rate, resting pulse rate, temperature, etc. In this device, ML algorithms are used to determine the five most fertile days of the menstrual cycle based on this data. Luckily, women only need to wear it during sleep.

mouthLAB [81] is a device from Aidar. It is a hand-held and rapid health assessment device for home users. It is capable of measuring multiple vital health parameters in under 1 minute. It utilizes clouding AI algorithms to identify and predict health status and disease progression early.

The last device in this part is PulseOn [82]. Another multimodal product that measures heart rate optically using an optical sensor as well as ECG to screen atrial fibrillation, a heart arrhythmia.

4.2 Raw data products

The vital sign, including heart rate, blood pressure and etc., are always essential to know for sake of health assessment. There are plenty of commercial products whose task is just measuring and informing results to the customer, not any more linking to cloud computing for further interpretation. They cannot predict disease or more abnormalities but they are worthy to have at home to track health situations. The aim of introducing raw data product is the topic of the chapter; “Health Risk Measurement”. The result of these devices could be considered as a warning for customer to follow his/her own health condition. In the following, several of the commercial products are mentioned and described as their purpose.

Butterfly [83] network is a battery-powered, compact, and portable ultrasound product, no similar to conventional clinical sonography systems. This device is relatively light and can be carried by hand, then connected to a smartphone to show the ultrasound images. This device could be definitely beneficial in different applications such as critical care, ambulance services, primary care and etc.

However, the novel non-invasive techniques are rapidly growing, still, urine analyzers are mostly photoelectric-based, including different strip sensors for specific urine components. FL401 urine analyzer [84] is a home-used portable urine analyzer that measures glucose, bilirubin, specific gravity, ketones, protein, urobilinogen, nitrates, leukocyte, intravascular contraction, PH, malonic acidemia, creatinine, and urinary calcium. Each of these results could be considered as a warning alarm for the customer to visit health centers. Moreover, the device could transfer the data to smartphone via Bluetooth.

Lumen [85] is the first light, hand-held and portable device, presented for accurate measurement of body metabolism which is a critical measure to evaluate and assess overall health status. Lumen measures CO\textsubscript{2} concentration in a single breath using a CO\textsubscript{2} sensor and flow meter, then the type of fuel your (fat or carb) body uses to produce energy is clearly indicated. The Lumen’s results are clear indicators for losing weight and getting healthier.
5. Emerging techniques

In recent decades, newborn medical applications have been grown and developed by researchers to non-invasively discover impairments in our body. These new techniques are still in progress but provide a bright future for disease diagnosis with help of the current fast technology growth rate. In this part, we introduce the most talented methods which have a high capacity to provide new opportunities in close future.

5.1 Microwave imaging

The term “microwave imaging” refers to applications that utilize electromagnetic radiation between several hundred megahertz and several gigahertz. Many optically semi-opaque media, like the human body, can be penetrated by this radiation, depending on its frequency. Microwave imaging can be used in non-invasive diagnosis to inspect body impairments [86].

In the past, this technology was a favorite choice in a variety of applications for decades such as flight radars, marine, remote sensing, and target tracking but nowadays, worldwide research is devoted to imaging body parts and tissues. There are several wise reasons to use this technique in biomedical applications: 1- microwave sensing is a non-invasive modality. 2- Due to the advent of radio-on-a-chip (RoC) and single-chip radars operating in the GHz band, microwave imaging hardware can be manufactured at low prices and in compact sizes. Now, Due to these advancements, microwave sensors are available in large arrays and are also affordable. In exciting and optimistic words, microwave imaging has reached a point where is possible to be home-used, portable, and low-cost (Figure 11) [86].

Classification and detection of brain abnormalities: In microwave brain imaging, an automated method for classifying and detecting brain abnormalities like tumors is vital to medical investigation and disease monitoring. Hossain et al. [87] have presented a DL-based method to classify and detection of brain abnormalities. The method has been used in a portable microwave brain imaging system. The result of this algorithm is reliable and could be used in real-time monitoring applications.

**Breast tumor classification:** Breast cancer diagnosis and staging depend heavily on the size and shape of breast tumors. In 2020, Conceição, Raquel C., et al. [88] classified breast tumors based on their size and shape of them. Their microwave...

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**Figure 11.**
In microwave imaging, several antennas surround the organ (here brain). Microwaves are transmitted by an antenna and receive by others. On the right side, the typical curves of scattering parameters are shown. Based on the scattering parameters, the image of the organ is reconstructed.
imaging prototype collected the signals using a monostatic ultra-wideband radar (1–6 GHz) and ML algorithms were applied to the signals later.

5.2 Bio-impedance measurement

Bioelectrical impedance measurement is a low-cost, non-invasive, and portable technique that could be used for the determination of tissue’s electrical properties at different frequencies. In simple words to describe the principle, a tiny current in the range of microamperes is passed through tissue, between two electrodes, and the difference voltage of electrodes is simultaneously measured, see Figure 12. Then, impedance and the phase can be calculated based on the current value, measured voltage, and phase difference [89].

**Breast cancer risk factor:** impedance techniques are currently used in mammography, known as electro-impedance mammography, to obtain more information about the breast tumor. Coripuna, Rosario Lissiet Romero, et al. [90] evaluated the importance of the electrical-conductivity index of the mammary gland for earlier detection of breast cancer. They studied different algorithms where SVM achieved better results. According to this study, the conductivity index plays a crucial role in assessing local risk factors.

**Classification of breast tumors:** Biopsy is always a painful and invasive part of the treatment procedure for patients who suffer from breast cancer. Al Amin et al. [91] studied the feasibility of tumors characterization using electrical impedance measurement and ML techniques. Basically, it is expected that the impedance of malignant and benign tumors will change at a constant frequency due to changes in cell morphology. They used four electrodes around the region of tumor to measure the impedance at specific frequencies, then fed them into the ML procedure. The result was encouraging to conduct more studies to improve the idea.

**Apnea detection:** one of the most common sleep-related breathing disorders is sleep apnea which can be diagnosed at a specialized sleep clinic through a nightly sleep study. In 2020, Van Steenkiste, et al. [92] presented a portable sleep monitoring device that was based on the bio-impedance of the chest. In this way, they could continuously monitor the respiration rate and utilized a two-phase Long Short-Term Memory (LSTM) DLA for automated event detection. By using this bio-impedance-based device there is no need for in-hospital apnea detection.
6. Pitfalls

Although DL algorithms show many promising results like disease detection or prediction. The DL algorithms generalization, however, is still questionable. A DL model with promising results in a specific task might not perform as expected on the unseen data acquired under different protocols. Also, data with similar acquisition protocols but with different noise levels might adverse the performance of the DL algorithms. In addition, DL algorithms need large datasets for training that are not always accessible. Also due to the data sharing policies, datasets most of the time cannot be shared even after anonymization [93, 94].

7. Conclusion

By reviewing the past roadmap of science and technology to reach the current point in health risk assessment, we can proudly observe the efforts of researchers and scientists to develop new devices and algorithms which provide us vital information about our body health and could prevent further impairments in our body. The other fruit of these efforts is the decrement in hospitalization and a huge load drop in the different countries’ health systems. Definitely, the role of AI can be never neglected as the complementary element in this puzzle.

In today’s stage, despite the previous noteworthy efforts, there are still lots of opportunities to improve the past results or introduce a new generation of techniques. For example, portable modalities like fNIRS, ECG, and EEG are technically well-grown but there is no end to applying new algorithms and hypotheses to explore more abnormalities or diseases. As the commercial aspect of portable products has been reviewed in the current chapter, we can hear a loud message about the powerful demand in the market which could encourage to produce novel devices.

Same clinical modalities like CT, MRI, and PET are mature from a technical point of view, but there is a wide playground for researchers to investigate images more and apply more DL and ML approaches. Of course, this procedure is strongly ongoing by research groups. DL and ML approaches attempt to speed up clinical imaging to increase the throughput of the clinical imaging centers. Therefore, clinical imaging will be more accessible and affordable. Also, DL and ML attempt to reduce the effect of a given imaging technique like CT on a patient’s health by sacrificing close to zero image quality.

Multimodal measurements, using several measurement techniques at the same time, could provide more additional information which is impossible to obtain via individual methods. In other words, researchers could utilize the results of the different techniques to extract new information and discover hidden phenomena. Of course, multimodal measurements have been already realized by researchers around the world but normally at hospitals and health centers using too complicated and costly setups. Today, there is the time to implement it in portable sizes and low-prices, as sensor and electronic technologies are luckily enough-grown. For example fNIRS-EEG systems are currently developed and available in market, but other different combinations of sensors are still in progressing that can prove the role of multimodal measurements in future of health analysis. Please refer to our “Commercially available portable and home-used devices” section in current chapter where we mentioned few of multimodal devices like Muse S and BPM core. We consider multimodal measurement as a mid and continuous long-term goal for future of the home-used devices.
But about the newly emerged modalities like microwave imaging and bio-impedance measurement, technical progress must be considered as well as algorithms, as they have already proven their ability to disease diagnosis and prediction. At the moment, there is a long way to have fully portable, home-used, and cost-effective microwave imager and bio-impedance meter products.

Thanks

We would like to appreciate Dr. Teemu Myllylä, the head of Myllylä group at University of Oulu for his warmly supporting and guidance.

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