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Comprehensive Review of Deep Learning Algorithms for Embedded Healthcare Applications

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Abstract

The integration of deep learning algorithms into embedded healthcare applications has emerged as a promising avenue for revolutionizing medical diagnostics, monitoring, and treatment. This review explores the performance, suitability, and implications of various deep learning algorithms within the context of embedded healthcare systems. Leveraging a diverse range of algorithms including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Transformer Networks, and more. The study presents an overview of embedded systems in healthcare, which leverage Deep learning algorithms to enhance their performance and enable physicians to provide prompt and accurate responses to patients.

Keywords: Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Transformer Networks

1. Introduction

Embedded healthcare applications represent a paradigm shift in the delivery of healthcare services, offering real-time monitoring, diagnostics, and interventions at the point of care. These applications, integrated into wearable devices, medical sensors, and imaging systems, hold the promise of improving patient outcomes, enhancing clinical decision-making, and reducing healthcare costs. At the heart of this transformative landscape lies deep learning, a subset of artificial intelligence (AI) that has demonstrated remarkable capabilities in processing

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and interpreting complex healthcare data. The intersection of deep learning algorithms with embedded healthcare applications presents a fertile ground for innovation, with potential implications spanning from personalized medicine to population health management. However, navigating the plethora of deep learning techniques and selecting the most appropriate algorithm for a given healthcare application remains a daunting task. This necessitates a thorough study to discern the strengths, limitations, and trade-offs associated with various deep learning approaches. In this study, we embark on a journey to evaluate and compare the performance of different deep learning algorithms within the realm of embedded healthcare applications. Through a systematic review of algorithms such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Transformer Networks the study aims to provide insights into their efficacy, robustness, and suitability for addressing the unique challenges posed by healthcare data. Our analysis goes beyond traditional performance metrics to encompass considerations such as hardware compatibility, data requirements, deployment complexities, and scalability. By doing so, we seek to offer a holistic understanding of the implications of employing deep learning algorithms in embedded healthcare settings. Ultimately, our objective is to equip decision-makers, researchers, and practitioners with the knowledge needed to make informed choices in harnessing the power of deep learning for advancing healthcare delivery in embedded systems.

(a)

(b)

Figure 1. (a), (b). Embedded Healthcare Devices

Figure 1 shows a collection of images featuring wearable devices, medical sensors, and examples of devices that collect physiological data, monitor vital signs, or facilitate remote patient monitoring

In recent years, the integration of deep learning techniques into embedded healthcare applications has introduced a transformative era in medical diagnostics, treatment, and patient care. Embedded healthcare applications refer to systems and devices that are seamlessly integrated into the healthcare infrastructure, providing real-time monitoring, analysis, and support at the point of care. These applications range from wearable devices that track vital signs to smart medical imaging systems that assist in diagnosis. Deep learning, a subset of artificial intelligence (AI), has emerged as a powerful tool in healthcare due to its ability to automatically learn intricate patterns and representations from large volumes of data. Unlike traditional machine learning approaches, deep learning algorithms, inspired by the structure and function of the human brain, can automatically extract hierarchical features from raw data, enabling more accurate and robust predictions. Deep learning and embedded healthcare apps together have the potential to completely transform healthcare delivery by providing individualized, effective, and easily accessible solutions. Healthcare advances are being driven by the synergy between deep learning and embedded systems, resulting in early disease identification and remote patient monitoring [7-10].

This introduction lays the groundwork for investigating the interaction of embedded healthcare applications and deep learning. Throughout this study, we will look at the various applications, problems, and achievements in using deep learning algorithms in embedded healthcare systems. We intend to compare the performance, applicability, and consequences of various deep learning technologies in solving today's and tomorrow's complex healthcare needs.

2. Related Study

Yann LeCun et al. [1] provided a comprehensive overview of deep learning techniques, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and autoencoders, and their applications in various domains, including healthcare.

Narges Razavian et al. [2] developed a deep learning-based framework for predicting the onset of multiple diseases from longitudinal electronic health record (EHR) data, demonstrating the potential of deep learning for early disease detection.

Ziad Obermeyer et al. [3] studied the presence of racial bias in a deep learning-based algorithm used for healthcare resource allocation, highlighting the importance of addressing algorithmic fairness in the deployment of deep learning systems in healthcare.

Alistair E.W. Johnson et al [4] introduced the MIMIC-III dataset, a large-scale, publicly available critical care database, which has been widely used by researchers to develop and evaluate deep learning algorithms for healthcare applications.

Jenna Wiens et al. [5] proposed a framework for the responsible development and deployment of machine learning, including deep learning, in healthcare, addressing ethical considerations, data quality, and model validation.

Brent Mittelstadt et al [6] explored the challenges and limitations of explaining the decision-making process of deep learning models, and discussed strategies to improve the transparency and interpretability of these models in sensitive domains like healthcare.[6]. As shown in Figure 2, this flowchart illustrates the deep learning methodology. Table 1 provides a detailed breakdown of the steps and their descriptions for this methodology.

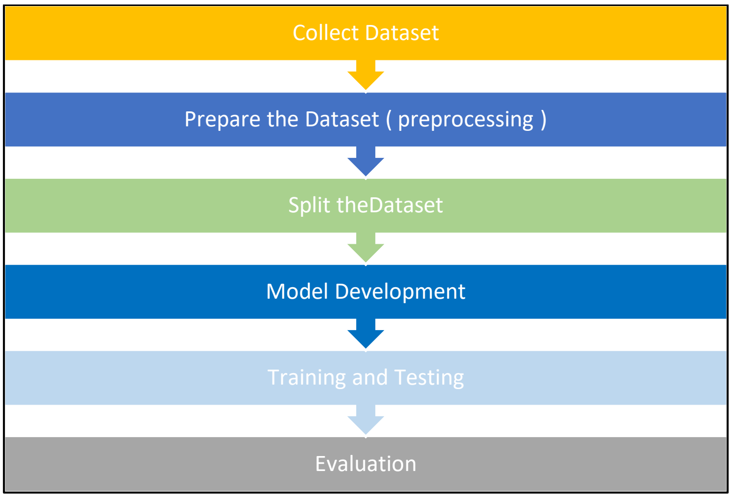

Figure 2. Flowchart of Deep Learning Algorithms Methodology

Table 1. Step and Description of Deep Learning Methodology

Step	General Description
1. Define Objectives	Clearly define the research objectives and goals of the study. Identify the healthcare task or problem to

	be addressed and the performance metrics to be evaluated.
2. Model Selection	Select a range of deep learning architectures based on their suitability for the healthcare task, computational efficiency, and previous performance in similar applications.
3. Data Preparation	Collect and preprocess the data required for training and testing the deep learning models. Apply normalization, augmentation, and feature extraction techniques as needed.
4. Data Splitting	Divide the dataset into training, validation, and testing sets to ensure robust model evaluation. Consider stratified sampling to preserve class distributions in imbalanced datasets.
5. Model Training	Train the selected deep learning models using the training dataset. Apply optimization techniques and hyperparameter tuning to improve model performance and convergence.
6. Evaluation	Evaluate the trained models using the validation and testing datasets. Compute performance metrics such as accuracy, precision, recall, F1 score, and AUC-ROC for comparison.
7. Result Analysis	Interpret and analyze the results of the study to identify trends, strengths, and weaknesses of the deep learning algorithms. Conduct statistical tests if necessary.

3. Importance of Deep Learning Algorithms in Healthcare

Deep learning algorithms play a pivotal role in transforming healthcare by offering sophisticated solutions for analyzing medical data, improving diagnostics, personalizing treatment, and enhancing patient outcomes. The importance of deep learning algorithms in healthcare can be understood through several key aspects:

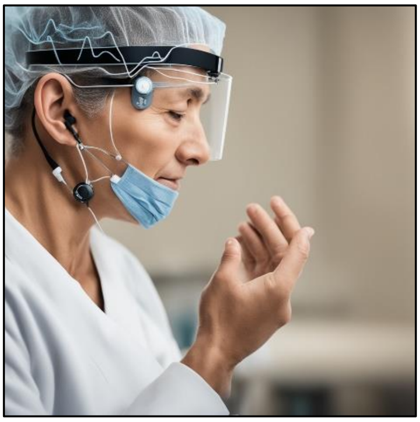

Figure 3. Remote Patient Monitoring

Figure 3. Shows a photograph or illustration of a patient wearing a wearable health monitoring device, with data being transmitted to a deep learning-powered system for real-time analysis and monitoring.

a. Data-driven Insights: Deep learning algorithms excel at learning complex patterns and relationships from large volumes of healthcare data, including electronic health records (EHRs), medical images, genomic data, and sensor data from wearable devices. By analyzing these diverse data sources, deep learning models can extract valuable insights that facilitate better understanding of diseases, risk factors, and treatment responses.

b. Medical Imaging: Deep learning algorithms have revolutionized medical imaging interpretation by enabling automated analysis of radiological images such as X-rays, CT scans, MRI scans, and histopathology slides. Convolutional Neural Networks (CNNs) are particularly adept at tasks such as image classification, segmentation, and anomaly detection, leading to faster and more accurate diagnoses of conditions like cancer, cardiovascular diseases, and neurological disorders.

Figure 4. Medical Imaging Analysis

Figure 4. Shows the image of a radiologist reviewing a CT scan or MRI scan alongside a deep learning algorithm analyzing the same scan, illustrating how deep learning aids in image interpretation and diagnosis.

c. Clinical Decision Support: Deep learning algorithms serve as powerful tools for providing clinical decision support to healthcare providers. By analyzing patient data, including symptoms, medical history, and diagnostic test results, these algorithms can assist clinicians in making more informed decisions regarding diagnosis, treatment planning, and patient management. Deep learning models can also predict patient outcomes, risk factors, and adverse events, thereby improving patient safety and healthcare quality.

d. Drug Discovery and Development: Deep learning algorithms are increasingly being utilized in pharmaceutical research and drug discovery processes. These algorithms can analyze molecular structures, predict drug-target interactions, and identify potential drug candidates with therapeutic efficacy and safety profiles. By accelerating the drug discovery pipeline, deep learning contributes to the development of novel treatments for various diseases, including cancer, infectious diseases, and rare disorders.

e. Personalized Medicine: Deep learning algorithms enable personalized approaches to healthcare by analyzing individual patient data and tailoring treatment plans based on genetic predispositions, lifestyle factors, and disease characteristics. By predicting treatment responses and prognosis on a patient-by-patient basis, deep learning facilitates precision medicine, optimizing therapeutic outcomes and minimizing adverse effects.

f. Remote Patient Monitoring: Deep learning algorithms are integral to remote patient monitoring systems, where wearable devices and mobile applications collect continuous streams of physiological data from patients. These algorithms can analyze the collected data in real-time, detecting anomalies, predicting health deterioration, and alerting healthcare providers to intervene when necessary. Remote patient monitoring empowered by deep learning enables proactive and timely healthcare interventions, particularly for chronic disease management and post-acute care.

g. Healthcare Operational Efficiency: Deep learning algorithms enhance healthcare operational efficiency by automating administrative tasks, optimizing resource allocation, and streamlining workflows. Natural Language Processing (NLP) models can extract information from unstructured clinical notes, automate medical coding, and facilitate clinical documentation. Predictive analytics powered by deep learning can forecast patient admissions, optimize hospital bed utilization, and improve scheduling of medical procedures, leading to cost savings and better resource utilization.

Deep learning algorithms are instrumental in driving innovation across various facets of healthcare, from diagnostics and treatment to personalized medicine and operational efficiency. By harnessing the power of advanced machine learning techniques, deep learning holds the promise of revolutionizing healthcare delivery, improving patient outcomes, and advancing medical research and innovation.

Table 2. Algorithm Comparison Table

Algorithm Name	Description	Input Requirements	Output Type	Complexity (Computational and Memory)	Training Time	Inference Time	Accuracy	Precision	Recall	F1 Score	AUC	Specificity	Sensitivity	Robustness to Noise	Scalability
Convolutional Neural Networks (CNN)	Deep learning model widely used for image analysis.	Images (2D or 3D)	Classification, Detection, Segmentation	High computational, moderate memory	High	Low	High	High	High	High	High	High	High	Moderate	Moderate
Recurrent Neural Networks (RNN)	Suitable for sequential data analysis, such as time series.	Sequential Data (e.g., Time Series)	Classification, Prediction	Moderate computational, low memory	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	High	High
Long Short-Term Memory (LSTM)	A type of RNN known for handling long-range dependencies.	Sequential Data (e.g., Time Series)	Classification, Prediction	Moderate computational, moderate memory	Moderate	Moderate	High	High	High	High	High	High	High	High	High
Gated Recurrent Units (GRU)	Similar to LSTM, but with fewer parameters, making it faster to train.	Sequential Data (e.g., Time Series)	Classification, Prediction	Moderate computational, moderate memory	Moderate	Moderate	Moderate	High	High	High	High	High	High	High	High
Transformer Networks	Introduced for sequence-to-sequence tasks, now widely used in NLP and other domains.	Text, Sequential Data	Classification, Generation	High computational, high memory	High	Moderate	High	High	High	High	High	High	High	High	Moderate
Deep Belief Networks (DBN)	A generative model composed of multiple layers of stochastic, latent variables.	Structured Data (e.g., Feature Vectors)	Classification, Reconstruction	Moderate computational, moderate memory	High	Low	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate
Autoencoders	Unsupervised learning model used for dimensionality reduction and feature learning.	Structured Data, Images	Reconstruction, Feature Extraction	Low to Moderate computational, low memory	Moderate	Low	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	High	High
Generative Adversarial Networks (GANs)	Comprising a generator and a discriminator, used for generating new data instances.	Structured Data, Images	Generation	Moderate to High computational, moderate memory	High	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	High

Table 2. provides a comparison of various deep learning algorithms commonly used in embedded healthcare applications based on factors such as input requirements, output type, computational complexity, memory usage, training time, inference time, and performance metrics like accuracy, precision, recall, F1 score, AUC, specificity, sensitivity, robustness to noise, and scalability.

4. Overview of Embedded Systems in Healthcare

Embedded systems have become integral components in modern healthcare, revolutionizing the delivery of medical services, patient monitoring, and treatment interventions. In the context of healthcare, embedded systems refer to specialized computing devices and platforms that are designed to perform specific functions within medical devices, equipment, and systems. These systems are characterized by their compact size, low power consumption, real-time responsiveness, and integration with sensors and actuators, making them well-suited for a wide range of healthcare applications.

Embedded systems play a crucial role in various aspects:

a. Medical Devices and Equipment: Embedded systems power a myriad of medical devices and equipment used in diagnosis, treatment, and monitoring of patients. Examples include infusion pumps, patient monitors, electrocardiography (ECG) machines, insulin pumps, and implantable medical devices such as pacemakers and neurostimulators. These embedded systems collect physiological data, deliver therapeutic interventions, and provide real-time feedback to healthcare providers, enhancing patient care and safety.

b. Wearable Health Technologies: Embedded systems form the foundation of wearable health technologies, including fitness trackers, smartwatches, and biosensors, which monitor vital signs, physical activity, and other health-related parameters. These devices integrate sensors, microcontrollers, and wireless communication capabilities to collect and transmit data to smartphones or cloud-based platforms for analysis and interpretation. Wearable health technologies enable continuous monitoring of health status, early detection of health issues, and support for remote patient monitoring and telehealth services.

c. Telemedicine and Remote Monitoring: Embedded systems facilitate telemedicine and remote monitoring solutions by enabling the transmission of medical data, audiovisual communication, and teleconsultations between patients and healthcare providers. Telemedicine platforms leverage embedded systems to support video conferencing, secure data transmission, and remote access to electronic health records, enabling virtual consultations, remote diagnosis, and management of chronic conditions without the need for in-person visits.

d. Point-of-Care Testing and Diagnostics: Embedded systems are employed in point-of-care testing devices and diagnostic equipment used for rapid and decentralized medical testing. These systems enable healthcare professionals to perform diagnostic tests, analyze biological samples, and obtain immediate results at the patient's bedside or in non-traditional healthcare settings such as clinics, pharmacies, and remote locations. Point-of-care testing devices equipped with embedded systems contribute to timely diagnosis, treatment decisions, and improved patient outcomes.

e. Healthcare Infrastructure and Automation: Embedded systems play a vital role in automating healthcare infrastructure and operations, including hospital management systems, electronic medical records (EMRs), and smart healthcare facilities. These systems support functions such as patient registration, appointment scheduling, inventory management, and workflow optimization, streamlining administrative processes and improving the efficiency of healthcare delivery.

Embedded systems have revolutionized healthcare by enabling the development of innovative medical devices, wearable technologies, telemedicine solutions, point-of-care diagnostics, and healthcare infrastructure automation. Their integration with deep learning algorithms further enhances their capabilities by enabling intelligent data analysis, predictive modeling, and decision support, paving the way for advanced embedded healthcare applications with improved accuracy, efficiency, and patient outcomes.

5. Application Domains

Table 3. Application Domains

Deep Learning Algorithm	Healthcare Applications	Suitability for Use Cases
	Medical Imaging Analysis (e.g., X-rays, MRI, CT scans)	Highly suitable for image-based tasks such as lesion detection, segmentation, and classification.

Convolutional Neural Networks (CNNs)	Clinical Decision Support Systems	Effective for providing image-based diagnostic assistance and treatment recommendations.
	Remote Patient Monitoring	Useful for analyzing medical images collected from remote monitoring devices.
	Healthcare Robotics and Assistive Technologies	Suitable for vision-based tasks in robotic surgery, patient care, and rehabilitation.
	Physiological Signal Processing (e.g., ECG, EEG)	Ideal for analyzing sequential data and detecting patterns in physiological signals.
	Remote Patient Monitoring	Effective for analyzing time-series data from wearable sensors and remote monitoring devices.
Recurrent Neural Networks (RNNs)	Clinical Decision Support Systems	Suitable for predicting disease progression and treatment outcomes based on longitudinal data.
	Telemedicine and Telehealth Services	Helpful for interpreting continuous monitoring data and providing remote diagnostic assistance.
	Healthcare Robotics and Assistive Technologies	Applicable for analyzing continuous data streams and providing real-time feedback in robotic systems.
	Physiological Signal Processing (e.g., ECG, EEG)	Well-suited for modeling temporal dependencies and detecting long-term patterns in signal data.
	Remote Patient Monitoring	Effective for predicting adverse events and anomalies from continuous monitoring data.
Long Short-Term Memory Networks (LSTMs)	Clinical Decision Support Systems	Suitable for time-series analysis and predicting patient outcomes based on longitudinal data.
	Telemedicine and Telehealth Services	Useful for analyzing streaming physiological data and providing real-time teleconsultation support.
	Public Health Surveillance and Epidemiology	Applicable for monitoring trends in population health data and predicting disease outbreaks.

Table 3. provides insights into the targeted healthcare applications for each deep learning algorithm and highlights their suitability for specific use cases based on their inherent capabilities.

6. Discussion

In recent years, there has been a significant surge in the utilization of artificial intelligence (AI) technologies to enhance medical assistance for vocal disorders. This trend reflects the growing recognition of AI's potential to revolutionize healthcare delivery and improve patient outcomes. AI-enabled medical assistance offers a wide range of capabilities, including accurate diagnosis, personalized treatment planning, remote monitoring, and patient education, all of which are particularly relevant to the management of vocal disorders. Here are some key factors contributing to the rise of AI-enabled medical assistance for vocal disorders:

6.1 Advantages

The over view of the comparative study offered in Table 2 and 3 provides valuable insights for researchers and physicians to make informed decisions regarding the selection and deployment of deep learning models in healthcare systems. This ensures that the chosen algorithm meets the requirements of the intended use case. Additionally, it helps optimize resources by focusing on algorithms that offer high performance while minimizing computational complexity and resource requirements. This allows for efficient utilization of hardware resources in embedded systems. Furthermore, by comparing algorithms across diverse datasets and applications, researchers can assess the generalizability of deep learning models in healthcare settings can provides insights into the robustness and adaptability of algorithms to different healthcare environments, allowing researchers to identify the strengths and weaknesses of each deep learning algorithm and understand their limitations and areas for improvement. This knowledge can guide future research and algorithm development efforts.

6.2 Disadvantages

The performance of deep learning algorithms can be influenced by the characteristics of the datasets used for evaluation. Biases, imbalances, and limitations in the dataset can affect the generalizability of results as well as requires expertise in data science, machine learning, and healthcare domain knowledge. The complexity and variability of healthcare data present challenges in standardizing evaluation methodologies and ensuring fair comparisons. Significant computational resources are required for training and evaluating multiple deep learning models on large-scale datasets. This can present challenges in terms of hardware availability, computational cost, and time constraints. Deep learning models are often characterized by their black-box nature, making it difficult to interpret and explain their decisions, and lack transparency in understanding the underlying mechanisms driving algorithm performance. There is a risk of overfitting and selection bias, where algorithms may perform well on specific datasets or metrics but fail to generalize to real-world healthcare scenarios. Careful validation and cross-validation techniques are necessary to mitigate these risks.

7. Future Directions and Recommendations

federated learning techniques to enable real-time data processing and model inference directly on embedded healthcare devices. This will reduce reliance on centralized infrastructure and enhance privacy and security by keeping sensitive patient data locally. Design embedded healthcare applications that adapt to individual patient needs and contextual factors such as environmental conditions, activity levels, and social determinants of health. Personalized interventions can improve patient engagement and outcomes while reducing healthcare disparities.

Implement continuous monitoring solutions integrated with predictive analytics algorithms to detect early signs of deterioration, predict adverse events, and facilitate timely interventions. This proactive approach can prevent hospital readmissions and improve patient outcomes. Prioritize human-centered design principles to create intuitive, user-friendly interfaces for embedded healthcare devices and applications. Engaging end-users, including patients, caregivers, and healthcare providers, in the design process ensures that solutions meet their needs and preferences.

8. Conclusion

Selecting the right deep learning algorithm for embedded healthcare applications is a pivotal decision with far-reaching implications for patient care, system performance, and resource utilization. Throughout the study of deep learning algorithms for embedded healthcare applications, it becomes evident that no single algorithm reigns supreme in all scenarios. Instead, the choice of algorithm must be guided by the specific requirements of the healthcare task, the characteristics of the data, and the constraints of the embedded system. The review has shed light on the strengths and weaknesses of various deep learning algorithms across different healthcare domains. The study revealed that Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image-based tasks such as medical imaging analysis, making them well-suited for tasks like lesion detection and segmentation. Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs) excel in processing sequential data, making them ideal for tasks involving physiological signal processing and time-series analysis.

However, the decision-making process extends beyond mere algorithmic performance. Factors such as computational efficiency, resource constraints, interpretability, and regulatory considerations play pivotal roles in selecting the most appropriate algorithm for embedded healthcare applications. Furthermore, the dynamic nature of healthcare demands continuous evaluation and adaptation of algorithms to evolving clinical needs, patient populations, and technological advancements.

References

[1] LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." nature 521, no. 7553 (2015): 436-444.

[2] Razavian, Narges, Jake Marcus, and David Sontag. "Multi-task prediction of disease onsets from longitudinal laboratory tests." In Machine learning for healthcare conference, pp. 73-100. PMLR, 2016.

[3] Obermeyer, Ziad, Brian Powers, Christine Vogeli, and Sendhil Mullainathan. "Dissecting racial bias in an algorithm used to manage the health of populations." Science 366, no. 6464 (2019): 447-453.

[4] Johnson, Alistair EW, Tom J. Pollard, Lu Shen, Li-wei H. Lehman, Mengling Feng, Mohammad Ghassemi, Benjamin Moody, Peter Szolovits, Leo Anthony Celi, and

Roger G. Mark. "MIMIC-III, a freely accessible critical care database." Scientific data 3, no. 1 (2016): 1-9.

[5] Wiens, Jenna, Suchi Saria, Mark Sendak, Marzyeh Ghassemi, Vincent X. Liu, Finale Doshi-Velez, Kenneth Jung et al. "Do no harm: a roadmap for responsible machine learning for health care." Nature medicine 25, no. 9 (2019): 1337-1340.

[6] Mittelstadt, Brent, Chris Russell, and Sandra Wachter. "Explaining explanations in AI." In Proceedings of the conference on fairness, accountability, and transparency, pp. 279-288. 2019.

[7] Yao, Shuochao, Shaohan Hu, Yiran Zhao, Aston Zhang, and Tarek Abdelzaher. "Deepsense: A unified deep learning framework for time-series mobile sensing data processing." In Proceedings of the 26th international conference on world wide web, pp. 351-360. 2017.

[8] Gope, Prosanta, and Tzonelih Hwang. "BSN-Care: A secure IoT-based modern healthcare system using body sensor network." IEEE sensors journal 16, no. 5 (2015): 1368-1376.

[9] Jiang, Fei, Yong Jiang, Hui Zhi, Yi Dong, Hao Li, Sufeng Ma, Yilong Wang, Qiang Dong, Haipeng Shen, and Yongjun Wang. "Artificial intelligence in healthcare: past, present and future." Stroke and vascular neurology 2, no. 4 (2017).

[10] Esteva, Andre, Brett Kuprel, Roberto A. Novoa, Justin Ko, Susan M. Swetter, Helen M. Blau, and Sebastian Thrun. "Dermatologist-level classification of skin cancer with deep neural networks." nature 542, no. 7639 (2017): 115-118.