AI and Digital Twins Transforming Healthcare IoT

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Abstract: In this age of digital and smart healthcare, cutting-edge technologies are being used to improve operations, patient well-being, life expectancy, and healthcare costs. Digital Twins (DT) have the potential to significantly change these new technologies. DTs could revolutionise digital healthcare delivery with extraordinary creativity. A digital representation of a physical asset that is always its digital twin due to real-time data processing. This paper proposes and builds a DT-based intelligent healthcare system that is aware of its environment. This approach is a great advance for digital healthcare and could improve service delivery. Our most notable contribution is a machine learning-based electrocardiogram (ECG) classifier model for cardiac diagnostics and early problem detection. Our cardiac models predict some situations with exceptional accuracy when applied to different ways. These findings highlight the potential for Digital Twins in healthcare to create intelligent, comprehensive, and scalable Health-Systems that improve patient-physician communication. Our ECG classifier also sets a precedent for using Artificial Intelligence (AI) and Machine Learning (ML) to continually monitor wide range of human body data and identify outliers. ECG data processing has improved significantly using neural network-based algorithms over classic machine learning methods. In conclusion, our work integrates digital twins with cutting-edge AI and machine learning to revolutionise healthcare. Future healthcare will be predictive and improve lives.

Keywords: Digital Twin, Healthcare, Internet of Things (IoT), Artificial Intelligence (AI)

I. Introduction

Technology has had an impact on every sector of the economy, including production, agriculture, education, and healthcare. Smartphones, smart buildings, and healthcare wearables are all revolutionised by the Internet of Things' (IoT) [1] ability to easily connect them [2], [3]. Improvements in data accuracy, data sharing, and pandemic preparedness have all resulted from the widespread adoption of IoT devices in the healthcare industry. The Institute of Medicine in the United States estimates that 400,000 individuals lose their lives each year due to medical errors caused by insufficient data [4], [5]. IoT is a key development because it makes it easier to combine healthcare with consumer gadgets and to gather and share data instantly. This integration helps people live longer and healthier lives. ECG, blood pressure, heart rate, and glucose levels can all be tracked using a combination of app-based tracking and in-device sensors. These devices upload data to the cloud for analysis and comparison in an effort to improve recording accuracy. Alerts are sent out to healthcare providers when abnormalities are detected, dramatically improving both quality and efficiency [5]–[9].

The concept of a "digital twin" for a physical thing is a top technical trend according to the IEEE Computer Society [10]. The digital twin technology in healthcare marketing, monitoring, and administration will have profound effects. Our breakthrough utilises the Internet of Things, data analytics, and AI to create digital twins of actual patients [11]. Healthcare is advanced, professionals are given more agency, and practical examples are used in this new paradigm. We developed an ECG classifier for use in monitoring heart disease patients. This machine learning model, developed in real time using ECG data, outperformed the alternatives [12], [13]. The potential of digital twins in healthcare is discussed, along with relevant studies, framework architecture, system implementation, and results. Problems and potential solutions are discussed [14].

The paper presents the introduction of digital twin (DT) technology in healthcare with AI and different ML models. The rest of the part is organized as follows. The literature review of DT for recent updates is represented in Section 2. Section 3 describes system implementation with MIT-BIH dataset of healthcare and shown result.

II. Related Work

All of these studies demonstrate how DT research has developed through time; the majority of articles published today focus on theoretical framework and models. The problem of the DT in smart healthcare system has been discussed in a number of studies, but no practical solutions or validation have yet been offered. The most pertinent work has been condensed in Table 1.

Table 1
LITERATURE REVIEW

S. No.	Ref.	Technology Used	Limitations
1.	Benedictis et al. [15]	DT, 3D Sensors, AI	• Cannot be implemented in real-time scenarios
2.	Elayan et al. [16]	DT, IoT	• Linking real-time data • Incorporating the models into the suggested framework
3.	Pilati et al. [17]	DT, IoT	• Can't be implemented in real-time • Adoption of the Technology
4.	Esteban et al. [18]	DT, GAN	• Data organization especially images • Discriminator and Generator training time
9.	Erol et al. [19]	DT, IoT, AI	• Limited empirical data • Lack of long-term implementation data
10.	Suzuki et al. [20]	Medical imaging and statistical analysis	• Japanese adults only • Small sample size • Results may not generalise to other groups
11.	Golse et al. [21]	DT	• Small sample size • Specific context • Need for additional confirmation before wider use
13.	Laubenbacher et al. [22]	DT	• Complexity of the immune system • Challenges inaccurate representation of individual variability
14.	Aubert et al. [23]	DT, 3D	• Limited generalizability • A very limited number of cases studied
16.	Grosman et al. [24]	DT	• Limited sample size • Specific to Type 1 diabetes patients • Real-world applicability may vary

III. System Implementation

In this section, Convolutional Neural Networks, Multi-layer Perceptron's, Logistic Regression, Long-Short Term Memory Networks, and Support Vector Classifiers were the techniques used.

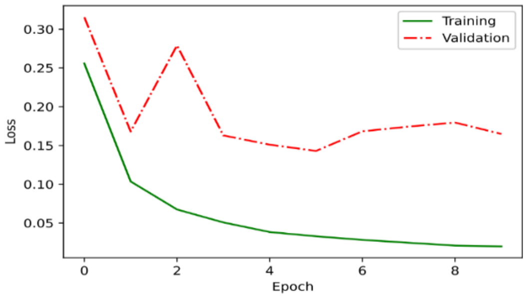
A. Dataset

This research paper's dataset was derived from the MIT-BIH Arrhythmia Database. The BIH Arrhythmia Laboratory collected these 48 half-hour snippets of two-channel ambulatory ECG recordings from 47 patients between 1975 and 1979. The five categories of the dataset are as follows: A for normal, B for supraventricular, C for premature ventricular contraction, D for a combined ventricular and normal rhythm, and E for an irregular heart rate.

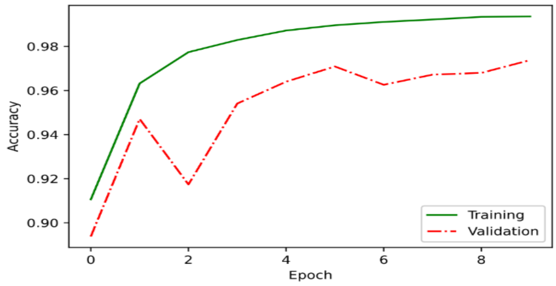
B. Result and Discussion

The best accuracy for the dataset required the construction of five distinct models; this part presents the parameters, performance, collected results, and evaluation for each model that was used. Python, the Sklearn package, Tensorflow, and Keras were used in the experiment. Pandas, Numpy, and Matplotlib were also utilised to aid in data preprocessing and results analysis.

Figure 1 shows the Loss and Accuracy performance of the LSTM sequential model over training epochs, whereas Figure 2 shows the performance of the CNN model. Over multiple epochs, both accuracy and loss improved. This suggests that the models' forecasts are becoming less certain. To that end, the LSTM model with the lowest validation loss was preserved at epoch 5, and the CNN model with the lowest validation loss was saved at epoch 4. LSTM validation accuracy is shown to be higher than CNN validation accuracy, while CNN validation loss is found to be lower. They are so close in performance that the difference between them is nearly negligible.

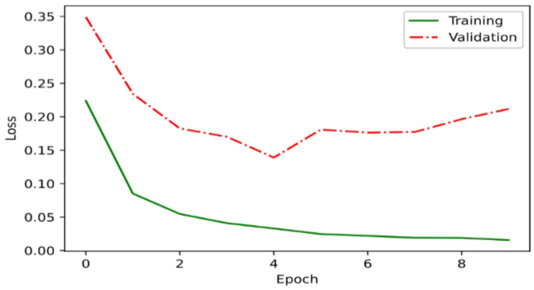


(a) LSTM model Loss performance

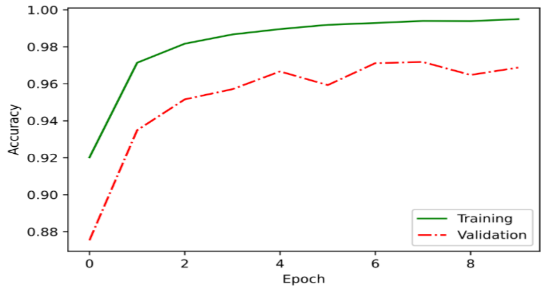


(b) LSTM model Accuracy performance

Fig 1: LSTM model Loss and Accuracy performance



(a) CNN model Loss performance



(b) CNN model Accuracy performance

Fig 2: CNN model Loss and Accuracy performance

C. Evaluation

(1) Accuracy

As indicated in Equation 1, the proportion of True Positives and True Negatives (TP and TN) out of all data samples (TP, TN, FP, and FN) that are correctly predicted can be calculated.

$$Accuracy = \frac{TP+TN}{TP+NP+FP+FN} \quad (1)$$

(2) Confusion Matrix

Due to the asymmetry of the testing data, the precision reported may not always be reliable. The confusion matrices for each model can be calculated to guarantee optimal performance. The TP, FP, TN, and FN values were obtained after obtaining the Confusion Matrix. After obtaining confusion matrix values, The classification report for each model's overall performance is displayed in Table 2.

Table 2

CLASSIFICATION PRECISION, RECALL, AND F1 SCORE VALUES FOR DIFFERENT ML MODELS

Classes/ Metrics	LSTM			CNN			MLP			SVC			LR		
	Precision	recall	F1-score	Precision	recall	F1-score	Precision	recall	F1-score	Precision	recall	F1-score	precision	recall	F1-score
A	0.99	0.97	0.98	0.99	0.97	0.97	0.99	0.96	0.98	0.97	0.74	0.84	0.97	0.65	0.78
B	0.60	0.83	0.7	0.58	0.86	0.68	0.52	0.8	0.62	0.28	0.65	0.39	0.15	0.67	0.24
C	0.92	0.94	0.92	0.92	0.95	0.92	0.87	0.93	0.8	0.33	0.79	0.47	0.29	0.72	0.42

D	0.60	0.87	0.70	0.57	0.88	0.67	0.6	0.83	0.71	0.1	0.88	0.17	0.08	0.88	0.15
E	0.99	0.99	0.99	0.97	0.99	0.97	0.95	0.98	0.96	0.8	0.91	0.85	0.74	0.91	0.82
Macro avg	0.82	0.92	0.85	0.81	0.93	0.84	0.79	0.9	0.84	0.5	0.79	0.55	0.45	0.76	0.48
Weighted avg	0.98	0.96	0.96	0.97	0.97	0.95	0.95	0.96	0.96	0.89	0.76	0.8	0.88	0.68	0.74

In terms of Precision, Recall, and F1-score, Neural-Network-Based algorithms outperformed other models when the Macro and Weighted average outcomes for each measure were taken into account. The outcomes also showed that the LSTM sequential model had the highest precision, recall, and F1-score scores of all the evaluated models (0.98, 0.96, and 0.96 Weighted Average for Precision, Recall, and F1-score).

D. Emerging Issues with Digital Twins

First, there is a lack of faith in data-transmitting gadgets.

- There is an immediate demand for competent and honest experts in the sector.
- Concerns about the reliability of Machine Learning models.
- Consensus, education, and technological progress are essential for establishing confidence.

Data Security and Privacy

- Safeguarding Your Data from Hackers and Other Online Dangers.
- Managing private information safely.
- Integration of Internet-of-Things devices is a complex process.
- Adherence to data protection laws.

Search for Standardisation

- Security, privacy, and the ability to sync data are all affected.
- Digital twin adoption can be sped up with the use of standardized procedures.

IV. Conclusion

This paper provides a digital twin architecture for health care systems that are aware of their environment. A patient's digital twin employs an ECG-based heart rhythms classifier to monitor health and discover anomalies. The efficiency and precision of five methods were compared. Digital Twins in healthcare improve health, lifespan, and cost while creating intelligent, holistic Health-Ecosystems. It's supposed to fix medical difficulties. ECG classifiers inspire Machine Learning and AI for continuous health monitoring, which increases quality of life. ECG analysis is better with Neural-Network-based methods than with classical ML. Use real-time data, increase use cases to include additional body metrics, and integrate more systems are framework development goals. This study introduces context-aware healthcare using Digital Twins and other cutting-edge technology, which could improve healthcare delivery and patient outcomes.

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