A Comparative Study on Cloud-based and Edge-Based Digital Twin Frameworks for Prediction of Cardiovascular Disease

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Abstract: Digital Twins that can integrate with related technologies such as Artificial intelligence, optimization, mobile communication systems, edge computing, fog computing, cloud computing, etc. are virtual representations of physical objects and reflect the real time status through streaming data. In this study, we provide two Digital Twin frameworks both cloud-based and edge-based and compare them in terms of scalability, flexibility, latency and security. We represented those frameworks by developing a case study to predict cardiac patient, continuously monitor the risks related to heart disease, and reporting the risks to both healthcare professionals and users in real time. We extracted features over electrocardiogram signals and performed popular machine learning algorithms. We employed feature binning and feature selection methods to increase the robustness of the prediction model and, in total, we built 20 models. We presented empirical analysis on a publicly available dataset based on PTB Diagnostic ECG Database and evaluated the results in terms of accuracy, precision, recall and F-score. When predicting cardiac patients, Linear Regression outperformed the other classifiers with accuracy and F-score rates of 86% and 92%, respectively. This model has also the highest recall rate (98%), which is vital in predicting diseases. Meanwhile, Gradient Boosted Tree applied binning, mRMR feature selection method and random oversampling achieve high precision (91%).

1 INTRODUCTION

Industry 4.0 is one of the key initiatives of utilizing a wide range of advanced technologies, such as cloud computing, big data, Digital Twin (DT), Machine Learning (ML), Deep Learning (DL) and virtual reality. The Internet of Things (IoT), which is another aspect of Industry 4.0, has a significant role in the digitalization of data for contributing value to many sectors including health, energy, education, industry, etc.-. Also, IoT and digitalization represent a novel paradigm by enabling the creation of DTs through the capability to collect and communicate data.

DT was introduced as a concept underlying product lifecycle management by Grieves (2002) and offered with different names such as mirrored spaces model (Grieves, 2005), information mirroring model, and virtual twin (Githens, 2007). In 2010, NASA used DT for the Apollo project in which two identical space vehicles were created to simulate space status during flight training. Thus, John Vickers first coined ”DT” name for the model in 2010 NASA Roadmap Report (Piascik et al., 2012). In this context, DT concept is a model that can separate information about a physical system from the system itself and subsequently mirror or twin that system (Grieves, 2019).

Industry 4.0 also elevates healthcare to novel and advanced levels on the basis of digitization, IoT, AI, cloud/fog/edge computing and 5G networks. Furthermore, those technologies make possible the collection and analysis of data from anyone, anywhere and anytime and dramatically impact the healthcare systems by connecting them to patients' personal devices to capture data and to notify patients, doctors, or patient relatives in real time Ge et al. (2019). Moreover, the emergence of smart healthcare services, through digitalization, has grown rapidly the body of research and implementation of several methods focus on improving the quality of healthcare services and human welfare while reducing healthcare costs and the death rate

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(Huang. et al., 2021; Dritsas. et al., 2022). In this context, DT promises a new era for healthcare by changing the smart health concept and taking medicine to an unprecedented level.

In recent years, researchers from both academia and industry have expressed considerable interest in the improvement of DT technologies. Therefore, research studies on DTs and their applications have been prominent in a wide range of domains including healthcare. DTs, which can combine other core technologies including AI, big data, 5G/6G, cloud computing and edge computing, are virtual representations of physical assets and can express the real time situation through streaming data (Fuller et al., 2020). Moreover, edge computing and cloud computing, through supplementary capabilities, offer new aspects when implementing DTs on the different levels where they have several requirements such as scalability, latency, reliability, centralization, etc. to process, analyse and transmit data. There exist many studies investigating edge-based DT and cloud-based DT, separately. However, there is a gap in studies implementing both cloud-based DT and edge-based DT and comparing their performances. Although Khan et al. (2022) compared cloud-based against edge-based DT, they did not provide any empirical evidence. According to our knowledge, there is no study implementing and comparing both edge-based DT and cloud-based DT frameworks.

In this study, we aim to offer both an edge-based DT and a cloud-based to compare their performance. Hence, we present a cloud-based DT framework and an edge-based DT framework and contrast them in terms of latency, scalability, mobility, and centralizing. To represent the frameworks on this basis, we implemented a case study to predict cardiac patients and monitor the risks of heart diseases, reporting those to users and healthcare providers in real time. To this end, we trained common ML classifiers with extracted features over electrocardiogram signals. To improve the prediction results, we applied data preprocessing and used various feature binning and feature selection techniques. We presented an empirical study on a dataset based on an open-source database, namely, PTB Diagnostic ECG Database (Bousseljot et al., 1995; Goldberger et al., 2000). The dataset consists of 549 samples collected from 290 persons (209 men and 81 women). While 69 of the samples are labelled as healthy, 378 of them are labelled as patients. We applied various sampling methods with different parameters due to the imbalanced structure of the dataset. We compared the ML model results in terms of accuracy, precision, recall and F-score. According to our results, we outperformed a benchmark study (Cardiac Twin) (Martinez-Velazquez et al., 2019) on the same dataset.

Structure of the Paper. Section 2 summarizes previous related works on cloud-based DTs, edge-based DTs and DT applications in healthcare. In Section 3, we describe DT frameworks for cloud and edge, separately. Section 4 provides a case study in which we explain the dataset and also present data preprocessing, classification methods and evaluation metrics. In Section 5, the detail of obtained results is reported and discussed. Finally, we conclude the paper and present the future work in Section 6.

2 RELATED WORK

Researchers have widely studied DT, which uses other popular technologies including cloud computing, edge computing, AI and IoT, in various fields such as manufacturing, energy, aerospace, construction and healthcare. In this section, we discuss the studies in the literature which utilize DTs on cloud, DTs on edge and DTs in healthcare, respectively.

2.1 Digital Twins on Cloud

The utilization of DT with cloud computing technology which has many capabilities like unlimited storage capacity, dynamic scaling, and high availability allows considerable advancements to be experienced in several fields (Liu et al., 2019; Wang et al., 2022, 2020). Liu et al. (2019) presented a cloud-based DT Health (CloudDTH) reference framework including key technologies, i.e., cloud computing, health IoT and DT, to create effective solutions for elderly health services. CloudDTH, which consists of eight layer architecture, is based on DT Healthcare (DTH) conceptual model. Moreover, they conducted a case study that made drug recommendations to patients or healthcare professionals using online ECG data (Liu et al., 2019).

In (Wang et al., 2022), a Battery Management System, which has a 4-layer architecture and utilizes the power of cloud and DT technologies, was provided. The architecture processes big data using the capabilities of cloud technology such as high storage and processing power capacity, while also using the capabilities of DT technology to digitize the behavior and real processes of the battery. Authors argue that real time optimization studies can be implemented throughout the whole life cycle of batteries for more complicated and intelligent battery management with BMS, or various analyzes and predictions can be made by obtaining insights from the data using historical data and AI models. Besides, they stated that sensitive management processes of systems with more complex structures, such as large-capacity lithium-ion battery packs, can be done effectively with DT and cloud technologies.

Wang et al. (2020) proposed a DT framework for connected vehicles. The proposed DT framework uses the V2C (vehicle-to-cloud) communication based Advanced Driver Assistance System to twin the connected vehicles in the cloud. According to their results, the proposed system can benefit transportation with acceptable communication delays.

2.2 Digital Twins on Edge

In literature, to utilize the advantages of edge computing such as latency and mobility, there are also studies that present DT on edge in various fields (Martinez-Velazquez et al., 2019; Bellavista et al., 2021).

Martinez-Velazquez et al. (2019) presented an edge-based DT architecture, namely Cardio Twin, working at the edge for monitoring the heart conditions of patients. Cardio Twin consists of three layers, i.e. Data Source, AI-Inference Engine, and Multimodal Interaction. Besides, as a PoC study, they implemented the AI-Inference Engine based on those layers and built a CNN model using PhysioNet's "PTB Diagnostic ECG Database" dataset. They obtained data on the mobile phones used as edge devices during the real time test phases. The performance results of the model obtained at the end of the PoC study are accuracy 85.7%, precision 95.5% and recall 86.3%. The authors emphasized that edge-based DT architecture takes the advantages of edge computing and prevents the latency caused by cloud (Martinez-Velazquez et al., 2019).

Bellavista et al. (2021) argue that manual configurations of networks in industrial environments are time-consuming and error-prone. To this end, authors presented the Application-Driven DT Networking (ADTN) middleware. ADTN middleware consists of semantically enriching simple DTs, namely SDT, deployed to edge nodes and composed DTs, namely, CDT, that perform flexible arrangements. According to their results, ADTN middleware is the feasibility and efficient, however, there are issues to be investigated in the future to promote its use in real industrial environments

In (Glatt et al., 2021), the edge-based DT concept was introduced to ensure sustainability through the assessment of ecological conditions in cross-company production networks. The presented concept consists of two levels, namely the Network level and the Company level. While the Network level includes the processes and activities of several companies, the Company level focuses on individual processes in detail. The authors mentioned that the difficulties that may be encountered with the application of this concept in an industrial environment can be determined and the effect of the presented approach on performance can be examined (Glatt et al., 2021).

2.3 Digital Twins in Healtcare

Problems relating to an inability to accession patients' historic data, corrupt/miss health data and undiagnosed or delayed diagnoses cause thousands of deaths each year (Tyagi et al., 2016). On the other hand, technologies facilitating the digitization of medicine, in general, allow ML methods to be trained on sufficiently large dataset and achieve clinical accuracy that is vital in medicine (Halepmollası et al., 2021). Thus, those technologies lead a new paradigm reducing costs while improving the quality of health services. According to a recent research report (Kalis et al., 2022), almost 80% of healthcare executives stated that their organizations' usage of IoT/Edge devices had increased enormously during the previous three years. Also, nearly half of them believe that DT technology will make a breakthrough in the future by building a bridge between the digital and physical worlds and have a positive impact on healthcare (Kalis et al., 2022). Moreover, there exist many studies presenting DT applications in healthcare based on Human/Patient (Kamel Boulos and Zhang, 2021; Shengli, 2021), Hospital/Health Institutions (Hassani et al., 2022; Singh et al., 2022) and Medical (Björnsson et al., 2020).

Personalized and holistic healthcare can be provided for the whole life cycle of humans through Human/Patient-oriented DT research. Those health services include monitoring persons' health state, early detecting and diagnosing diseases, applying personalized treatment methods according to genetic, physiological, and other characteristics of persons, and examining the effect of the therapies used (Kamel Boulos and Zhang, 2021; Singh et al., 2022). DT after life can be benefit for organ transplant procedures such as recipient-donor matching and organ transplant (Hassani et al., 2022). Shengli (2021) presented Human DT (HDT) that is based on the Augmented DT conceptual model to provide the lifecycle management of a human. To represent human in cyberspace, the proposed model overcome challenges like the complexity of human, social ethic issues, safety etc. Thus, author states that DT is an important technology that provides the interaction between physical and cyberspace (Shengli, 2021).

Although human DTs have the aforementioned benefits, they also have several challenges that must be overcome to create them holistically and comprehensively. For instance, collecting health data such as blood analysis and X-ray required to create human DTs can be time consuming and costly (Shengli, 2021). Also, the collected data can be person-based and diverse and has security and privacy concerns (Shengli, 2021; Jimenez et al., 2020).

The services provided by the various organizational structure components of the health institutes can be utilized effectively through Hospital-oriented DT research. For example, to improve patient care and treatment, health services can be improved by scheduling further studies in all processes (Singh et al., 2022). Besides, monitoring electronic devices in terms of maintenance and repairs can save money and time while also ensuring that patients receive non-stop service and preventing the breakdown of devices. Hospitals that increase staff productivity, treatment success rate, patient satisfaction, and effective execution of operations can be designed and constructed via DT technology (Hassani et al., 2022; Karakra et al., 2019). For instance, Siemens Healthineers use DT techniques to streamline hospital operations in the radiology department of a hospital in Dublin, Ireland (Scharff, 2018). Moreover, in (Hassani et al., 2022; Tao et al., 2022), authors stated that medical-oriented DT benefits to observe the effects and determine the best intervention method can be obtained by performing applications on DT before any surgical intervention or performing experiments on DTs in the development of new medical equipment and drugs or healthcare education can be done practically on DTs.

3 DIGITAL TWIN

In this study, we aim to compare the performance of two different DT frameworks in predicting cardiac patients. While the first framework is based on cloud computing, the second framework is based on edge computing (Figure 1).

We offered a DT framework on cloud that provides scalability, resource sharing, and service-on-demand. As illustrated in Figure 1a, the framework consists of three layers:

Edge Layer. In this layer, there exist devices (e.g. cell phone or smart watch) used to create digital copies of the physical assets. The ECG signals of the patients are sent from this layer to the cloud layer.

Cloud Layer. The digital copy of the physical entity is created on this layer that contains the storage and AI modules. The storage module contains two databases, one holding the historical ECG signals of the patients in the system and the other holding prediction results. As shown in Figure 2, AI module has two main tasks (i) the first task is to preprocess the historic data and build ML models; (ii) the second task is to predict cardiac or not through deployed ML model in real time and send prediction results to the database on storage module.

Application Layer. The status of the physical asset can be continuously monitored in this layer. Thus, the layer includes screens on which prediction results can be visualized and also rules that send notifications to the expert based on prediction results.

3.1 Digital Twin Framework on Edge

We also provided a DT framework on edge that deals with latency issues and allow mobility. As shown in Figure 1b, the edge-based DT framework also includes three layers:

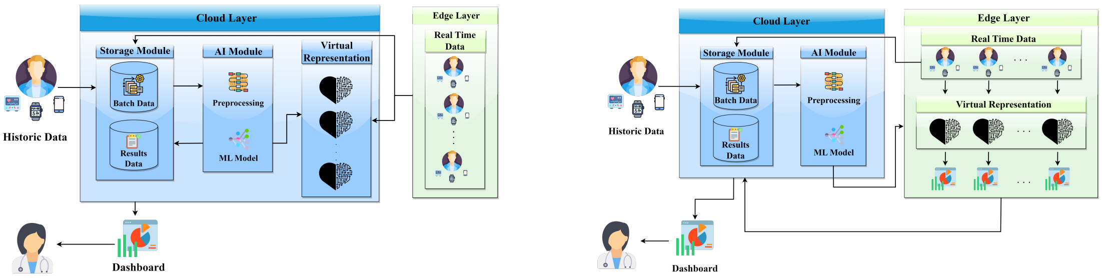
Edge Layer. In this layer, there are devices used to create digital copies of assets. Also, in the edge-based DT framework, ML models that were trained on the cloud are deployed to those devices on edge.

Cloud Layer. It is similar to the cloud-based DT framework, cloud layer includes Storage and AI modules. On the other hand, ML models are trained on cloud layer and utilized on edge layer in predicting cardiac patients.

Application Layer. In edge-based DT framework, this layer is not only available on the cloud, but also on the edge. Thus, users can monitor their own status in real time and notifications can be sent to experts according to the prediction results.

4 CASE STUDY

In this section, we define the problem statement, present the details of the dataset obtained from PTB Diagnostic ECG Database (PTBD) (Bousseljot et al., 1995; Goldberger et al., 2000) and explain the details of AI module in which ML models were constructed. Also, we describe the evaluation metrics used to compare the prediction results of ML models.



(a) Cloud-based Digital Twin Framework (b) Edge-based Digital Twin Framework

Figure 1: Cloud-based and Edge-based Digital Twin Framework Structures and Components.

4.1 Problem Statement

It's crucial to continuously monitor cardiac patients to reduce the rate of sudden death that heart diseases often might result in it (WHO, 2020).Therefore, personal health monitoring tools, such as mobile apps or built-in sensors, can continuously monitor key health indicators of a user (e.g. ECG, blood pressure, heart rate, etc.) and reduces the risk of incorrect data entry. Meanwhile, anonymous data can be captured and transferred to the cloud by those devices and compared with historical data to detect any disease or notify the appropriate health personnel. In this context, monitoring heart health indicators enables quick intervention in emergency situations and provides early diagnosis of diseases by predicting possible risks. Thus, healthcare services and patients' quality of life can improve.

Creating a virtual representation of each patient could be one of the best ways for healthcare systems in monitoring key health indicators, increasing control over health, and enhancing healthcare services. To this end, in this study, we offer two different DT frameworks that allow continuously monitoring of patients' heart health indicators and compare them in terms of latency, scalability, etc.-. Also, we build an ML model to predict in real time whether people whose heart health data are monitored are healthy or have heart disease. For this purpose, we combine DT with data analytics, ML, cloud computing, edge computing and IoT technologies in both cloud-based DT and edge-based DT frameworks.

4.2 Dataset

We used a publicly available dataset obtained from PhysioNet's "PTB Diagnostic ECG Database" (Bousseljot et al., 1995; Goldberger et al., 2000). In this dataset, the ECGs were recorded using an experimental, non-commercial PTB recorder that satisfied the various requirements including 16 input channels, input voltage, input resistance, resolution, bandwidth, noise voltage, online recording of skin resistance, and noise level recording during signal collection. The details of requirements are explained in (Goldberger et al., 2000).

The dataset contains 549 records from 290 people, 209 men and 81 women. The registered individuals range in age from 17 to 87 and mean age of men is 55.5 while mean age of women is 61.6. Also, some people may have 5 records, while others only have one record. Each record contains 15 signals measured simultaneously (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6, vx, vy, vz). In the dataset, there are 69 samples with healthy labels, 378 have patient labels and the rest have no labels.

4.3 Preprocessing Steps in AI Module

There are 15 different ECG signals that are generally sensitive to noise. We used v4 signals as it is received from the closest location to the heart and best represent the status of the heart. Moreover, five fiducial points P, Q, R, S, and T were extracted from the signal data and also obtained the distance, amplitude, angle, slope and height between the points using the fiducial points. The stages performed on the signal data are as follows (Figure 2):

4.3.1 Cleaning the Signal Data, Denoising and Smoothing

ECG signals define how the heart beats electrically. The ECG signals are produced when the heart's atrial and ventricular muscles contract and relax. However, ECG signals have four primary types of artifacts, i.e., baseline wander, powerline interference, EMG noise, and electrode motion (Kher et al., 2019). Artifacts are unwanted signals and sometimes prevent doctors from making a correct diagnosis. Therefore, to remove artifacts from ECGs, we used appropriate signal-processing filters that are generally utilized to remove or reduce noise and cure data quality.

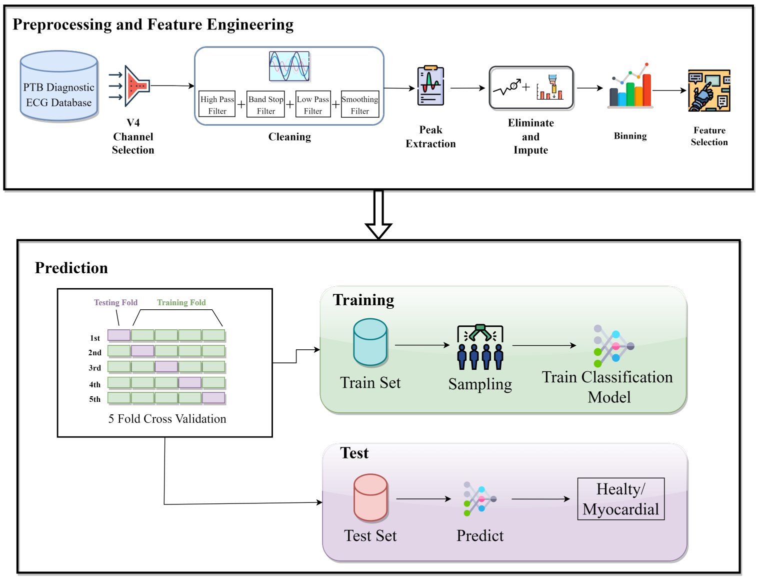


Figure 2: AI Module Flow Diagram.

High-pass Filter. Baseline wander is an effect that causes a signal to zigzag rather than to straight. Those zigzags may cause the signal to move from regular base and can be eliminated by using a high-pass filter. The maximum ripple of the filter is set to 12 db and the Kaiser window technique (Wang et al., 2022) is used to determine the filter window parameters.

Band Stop Filter. Powerline interference represents a common noise source caused by electromagnetic fields and muscle contractions. The noise is identified by 50 or 60 Hz sinusoidal interference and affects low-frequency ECG waves. We determined the cut-off frequencies, used for the band-stop filter, as 59.5 and 60.5 Hz to remove noise.

Low-pass Filter. We used to Low-pass filter to eliminate high order harmonics.

Smoothing Filter. We applied smoothing filter, namely Savitzky-Golay filter (Luo et al., 2005), on the signal after removing the noise. As a result of this filter, we can capture important patterns on the signal and detect peaks with high accuracy.

4.3.2 Peak Extraction

We extracted the peak points over the ECG signal. To this end, we firstly identified the R peaks over the signal then we identified the T, Q, P and S peaks using the R peaks.

4.3.3 Eliminate and Impute the NaN Values

We performed K Nearest Neighbour method on each list of peaks to deal with the NaN values. For this purpose, we calculated a mean of its k nearest neighbours for each missing data in the training set and used those to impute the NaN values with the means.

4.4 Methodology in AI Module

Besides to aforementioned preprocessing steps, we also applied the feature engineering techniques - i.e., feature binning, feature selection methods and sampling, respectively- to improve the ML model results (Figure 2).

4.4.1 Feature Binning

The process of converting continuous or numerical values into categorical features is called binning or discretization. In this study, the features extracted from the signal data are continuous. Hence, to investigate the effects of discrete features on the prediction process, we binned the features. For this purpose, we employed a quantile-based discretization function.

Quantile-Based Discretization. It is the process of creating equal-sized bins by discretizing the variable based on order or sample quantiles. We applied Quantile-based discretization for each continuous feature column (quantile number is 4).

4.4.2 Feature Selection

The success of the prediction models is directly related to the use of relevant feature selection methods. In order to select the features that best represent the model, we applied two feature selection methods, i.e., Chi-square and mRMR, which are the most preferred in the literature (Rachburee and Punlumjeak, 2015) and we also compared their performance. We extracted 58 different features over the ECG signals by implementing the above methods.

Minimum Redundancy and Maximum Relevance (mRMR). It is the filtering process that selects the features with the highest correlation with the target classes using the relationship between the feature and the target class (Rachburee and Punlumjeak, 2015). In the study, in order to observe the effect of the selected feature number on the model performance, the dataset obtained by changing the selected feature number with mRMR were used in model training (The number of different selected features is 4, 10, 15, 18 and 20).

Chi-Square. Chi-square makes feature selection by guessing whether the class label is independent of a feature(Rachburee and Punlumjeak, 2015). In the study, different results were interpreted by choosing 10 and 15 features with this method.

4.4.3 Sampling

In our dataset, each instance has a corresponding label of “0” or “1”, where “1” means cardiac and “0” means healthy persons. The samples labelled as healthy persons only account for a small portion of the whole dataset (15,4%). Meanwhile, the imbalanced distribution of classes in the dataset directly affects the prediction performance as ML algorithms usually suppose a balanced class distribution (Murphy, 2018) Furthermore, training classification models directly with imbalanced data may cause bias in the prediction performance and result in a low prediction score in terms of some evaluation metrics. Thus, we implemented sampling methods to address the problem of a serious imbalance between cardiac and healthy classes. We performed several sampling techniques including random under-sampling, random over-sampling and SMOTE with several rates.

Random Under Sampling (RUS). To deal with issues caused by imbalanced dataset and obtain a balanced dataset, we applied the random under-sampling technique. Under-sampling creates a balanced dataset consisting of classes with the same number of samples by making as much selection as the minor class from the major class in the imbalanced dataset.

Random over Sampling (ROS). There are a number of methods available to obtain balanced dataset. One of them is oversampling that creates multiple copies of the minority class in the training data, up to the number of members of the major class.

SMOTE: Synthetic Minority Oversampling Technique (SMOTE) is one of the most frequently used method in the literature to balance the number of samples in classes (Turlapati and Prusty, 2020). Minority instances are increased by using linear interpolation for training to balance the number of samples between the two classes (Turlapati and Prusty, 2020).

4.4.4 Stratified K-fold Cross-validation

K-fold cross-validation involves splitting the dataset into k folds. With this method, iteratively the k-1 fold is used in training and the k. fold is used in the test, thus allowing each k to be used as test data. In our study, we used the stratified k-fold cross-validation method, which is suitable for unbalanced dataset, which is more suitable for our problem as it preserves the class distribution in each k (used as k 5 in the study).

4.4.5 Machine Learning Model

Our objective in the study is to develop a DT that predicts whether the person is sick using ECG signal data and sends a notification to the specialist in case of illness. In this way, stream ECG signal data will be processed and emergency intervention will be provided in case the person is sick. For this purpose, we first performed preprocessing, feature binning, selection and sampling operations on the data, and then we used the model that gave the best results in DT framework by obtaining the performance results in different ML methods. In this study, we built the cardiac patient prediction model using ML algorithms, namely, Gradient Boosted Tree and Linear Regression as they are commonly used techniques for binary classification problems.

Logistic Regression (LR): In this study, we used LR is often used in binary classification problems in modelling the probability of a discrete outcome corresponding to an input variable. We also performed hyperparameter tuning on this model and the best results were obtained with default parameters (penalty:

l2, solver: lbfgs and maximum iteration: 100) (McCullagh and Nelder, 2019).

Gradient Boosting Classifier (GB). Boosting is an ensemble transforming method for weak learners into strong learners by adding new models to fix the errors made by existing models. Models are added incrementally with iterations until no improvement is detected. Gradient Boosting creates new trees after creating the first leaf, taking into account the prediction errors and utilizes the gradient descent algorithm to minimise the loss. We also performed hyperparameter tuning on GB using the grid search and the best results were obtained when the learning rate was 1, max depth 9 and the number of estimators 50 (Friedman, 2001).

4.5 Evalutation Metrics

In this study, we chose to analyze accuracy, recall, precision, F-score over confusion matrices to assess the predictive performance of classifiers. Accuracy is the most common evaluation metric to identify the correct prediction rate of classifiers. However, precision, recall, and F-measure metrics should be used together with accuracy which can be misleading in dataset where the imbalance and predictions belonging to the less class are important.

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

Precision is important when FPs are costly for us, as it gives information about percentage of actual cardiac patients among the predicted cardiac patients (Eq. 1).

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

On the other hand, Recall is also important when the FNs are critical, and calculated as shown in Eq. 2. This metric shows to what proportion of accurately a classifier predicts cardiac patients.

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

We also would like to measure he trade-off between recall and precision. Therefore, the F-score is used as the harmonic mean of these metrics (Eq. 3).

$$F-score = \frac{2*recall*precision}{recall+precision} \quad (3)$$

5 RESULTS AND DISCUSSION

In this section, we explain the details of the experimental results obtained by several ML models. Also, we compare cloud-based DT against edge-based DT.

In this article, we presented DT solution for real time monitoring of heart disease, which is one of the diseases that affect human life most with fast intervention.

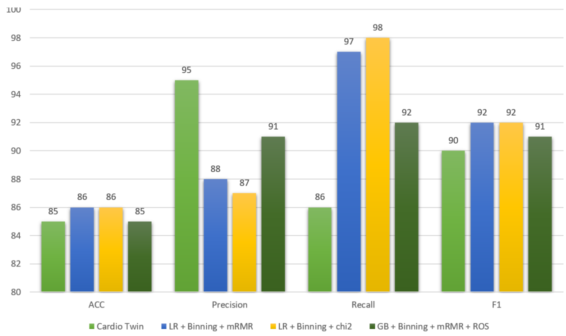


Figure 3: Comparison of AI Module Best Results and CardioTwin.

5.1 Machine Learning Results

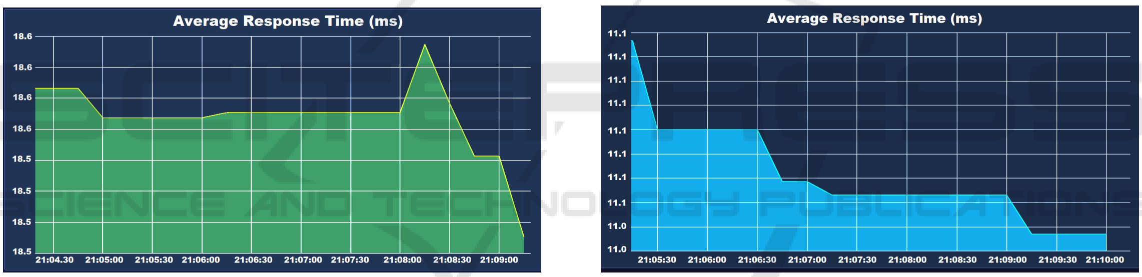
The proposed DT frameworks allow the users in the system to be monitored in real time whether they are cardiac or not. Also, they send notifications to the experts in case of cardiac. In this study, we used two different ML classifiers, namely GB and LR, with different preprocessing, feature selection, and sampling methods. Then, we selected the model that has the best prediction result to deploy DT. To validate models, we performed 5-fold cross validation method and the analyzed results through different experiments. Table 2 summarizes the results obtained from the experiments of all cardiac patients prediction models.

When the results were examined, we obtained the best results with the LR when the feature binning (the number of bins is 4) and chi2 feature selection (the number of features is 15) methods were applied to the data. This combination achieves 86% accuracy rate, 98% recall rate and 92% F-score rate. Also, we achieved the highest precision rate (92%) with the combination of GB+Binning+mRMR+ROS model in predicting cardiac. On the other hand, the results in our reference study called CarrdioTwin; accuracy is 85% and F-score is 90%.

When we analyzed the results in Table 1, we observed that the best results were obtained LR + Binning + chi2 combination. The reason why the results obtained with feature binning are better may be because the features in the dataset we use are continuous and they need to be expressed categorically. The better results we get when feature selection is applied may be due to the fact that both the features (it is applied after feature binning) and the label are composed of discrete values. In addition, during the ex-

Table 1: AI Module Benchmark Results.

Model	**ACC**	**Precision**	**Recall**	**F-score**
CardioTwin	0.85	**0.95**	0.86	0.90
Logistic Regression (LR)	0.82	0.84	0.97	0.9
LR + Binning	0.83	0.89	0.91	0.9
LR + Binning + mRMR	0.86	0.88	0.97	0.92
LR + Binning + chi2	**0.86**	0.87	**0.98**	**0.92**
LR + Binning + chi2 + RUS	0.79	0.91	0.84	0.87
LR + Binning + chi2 + ROS	0.81	0.91	0.85	0.88
LR + Binning + chi2 + SMOTE	0.8	0.9	0.86	0.88
LR + Binning + mRMR + RUS	0.8	0.9	0.85	0.88
LR + Binning + mRMR + ROS	0.77	0.91	0.8	0.85
LR + Binning + mRMR + SMOTE	0.8	0.9	0.86	0.88
Gradient Boosted Tree (GB)	0.84	0.89	0.92	0.91
GB + Binning	0.82	0.88	0.91	0.9
GB + Binning + mRMR	0.85	0.91	0.91	0.91
GB + Binning + chi2	0.82	0.88	0.91	0.9
GB + Binning + chi2 + RUS	0.68	0.89	0.71	0.79
GB + Binning + chi2 + ROS	0.79	0.88	0.87	0.88
GB + Binning + chi2 + SMOTE	0.76	0.88	0.83	0.85
GB + Binning + mRMR + RUS	0.73	0.9	0.78	0.83
GB + Binning + mRMR + ROS	0.85	0.92	0.92	0.91
GB + Binning + mRMR + SMOTE	0.81	0.91	0.87	0.89



(a) Latency (ms) of Cloud-based Digital Twin Framework

(b) Latency (ms) of Edge-based Digital Twin Framework

Figure 4: Latency Comparison of Cloud-based and Edge-based Digital Twin Framework.

amining of the results, it is seen that the scores obtained by over sampling are generally better than under sampling.

When the results we obtained in the study are compared with the results of CardioTwin (Figure 3), our models are more successful in terms of accuracy, recall and F-score. On the other hand, CardioTwin reach higher rate in terms of precision. However, recall rate is vital in healthcare studies. Therefore, we tuned the models according to recall metric.

5.2 Digital Twin Frameworks

In this study, edge-based and cloud-based DT frameworks are presented and compared in terms of scalability, flexibility, latency and security. The incredible increase in IoT devices and generated data has made scalability an important criterion. Adding new nodes in edge-based DT is considerably better than cloud-based DT in terms of scalability as it has little effect on system latency performance (Khan et al., 2022). In order to keep up with the diversity of digitalization and IoT devices in every field, systems must meet very high requirements. DTs implemented in Edge meet this flexibility requirement quite well compared to cloud-based DTs (Khan et al., 2022). The latency is a major issue in scenarios where results are required in real time. To produce results on cloud-based DT, the data generated at the edge must be transferred to the cloud environment. The latency problem is minimized as the ML model on edge-based DT produces results where the data is generated. The results of our study support this, according to the results (Figure 4), it was observed that the latency of edge-based DT (average 10.6 ms, Figure 4b) is lower than cloud-based DT (average 18.8 ms, Figure 4a). Security is important to provide secure and reliable services to users, so it is a metric we should consider in the systems we develop (Asim et al., 2020). Edge-based systems are more secure than cloud-based systems because of their decentralized architecture, whereas cloud-based systems are more vulnerable to attacks because they transmit long distances between users and the cloud (Asim et al., 2020).

6 CONCLUSION

The concept of Industry 4.0, which combines the domains of Informatics and Industry, has spread from the industrial sector to all other sectors. IoT, 5G and 6G networks, cloud and edge computing, big data, AI and DT technologies are at the center of these developments.

In this paper, we discussed the comparison of cloud-based DT and edge-based DT via a case study. In this study, we built ML models on PTBD healthcare dataset to predict human heart diseases in real time and thus to apply quick treatments. In this context, we performed preprocessing stages such as cleaning the signal data, denoising, smoothing, peak extraction, eliminate the NaN values, imputer for missing values and feature engineering stages such as feature binning, feature selection, sampling. Even though in Cardio Twin (Martinez-Velazquez et al., 2019) paper was obtained the highest precision rate, we tuning it based on the recall metric because TP value is more vital in detecting diseases in the health field. Thus, we outperformed better in terms of recall, F-score and accuracy.

A major future step of this study is to apply a solution to the data security and privacy concern, which is frequently encountered in health studies, by combining cloud computing, edge computing, federated learning and DT technologies. In addition, our future work also will include on trying different ML models with the new feature dataset containing the clinical findings of the patients and validating models with different health dataset. Additionally, a case study includes data which is collected from sensors can be added for the real world usage experiment.

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