A Digital Healthcare Service Architecture for Seniors Safety Monitoring in Metaverse

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***Abstract*—We have been witnessing an unprecedented increase in the aging population in human history. It is nontrivial to ensure the health and safety of seniors living alone. The prohibitive human labor cost necessitates more sustainable, technology-oriented approaches instead of labor-intensive solutions. The raising digital healthcare services (DHS) leveraging the Internet of Medical Things (IoMT), Digital Twins (DT), and advanced fifth-generation and beyond (B5G) wireless communication technology, are widely recognized as promising solutions. By enabling a seamless interwoven of the physical world and cyberspace, Metaverse makes an ideal home for the next generation of DHS. Thanks to characteristics of decentralization, traceability, and unalterability, Blockchain is envisioned to enhance security properties in Metaverse. This paper proposes MetaSafe, a DHS architecture for seniors' safety monitoring in Metaverse. Based on monitoring data collected by sensors, the activities and status of seniors, who are considered as the physical objects (PO), are mirrored to corresponding logical objects (LO) in a virtual community in the Metaverse, where activity recognition, potential risk prediction, and alert generation are realized. By leveraging Non-Fungible Token (NFT) technology to tokenize identities (POs and LOs) and data streams of the DHS on the blockchain, an NFT-based authentication fabric allows for verifiable ownership and traceable transferability during the data-sharing process. Specifically, an instant alerting system is introduced in this work that leverages a hybrid algorithm combining the singular spectrum analysis (SSA) approach with the long-short-term memory (LSTM) networks. Through an extensive experimental study, MetaSafe is validated as a feasible and promising approach to protect seniors living alone.**

***Index Terms*—Digital Healthcare Services (DHS), Digital Twins (DT), Senior Safety Monitoring, Internet of Medical Things (IoMT), NFT, Blockchain.**

I. Introduction

We have been witnessing an unprecedented increase in the aging population in human history [19]. Figure 1 presents the statistics from U.S. Census Bureau by 2020. The number of seniors aged 65 and above in the U.S. has reached 54 million by 2019 and would approximately reach 80 million by 2040. Along with the fast-growing aging population body, a trend is observed that more elders are living alone. Consequently, seniors' safety becomes a compelling need in health service systems, which necessitates 24/7 real-time monitoring and timely dangerous action recognition. Owing to factors like geographical location or low visiting rate to medical institutions, there are increasing risks and a need for medical support.

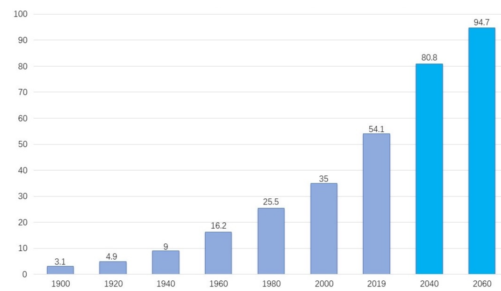

Fig. 1. Number of persons age 65 and older in the U.S.

Specifically, seniors require both regular medical consultation and timely emergency assistance.

It is nontrivial to ensure the health and safety of seniors living alone [36]. The prohibitive human labor cost necessitates more sustainable, technology-oriented approaches instead of labor-intensive solutions. The raising digital healthcare services (DHS) [26] leveraging the Internet of Medical Things (IoMT) [40], Digital Twins (DT) [12], and advanced fifth-generation and beyond (B5G) wireless communication technology [10], are widely recognized as promising solutions. Utilizing digitized information, such as real-time IoMT data and electronic medical records (EMR), continuous monitoring and simulation are able to promote seniors' safety, especially for abnormal behavior recognition, unusual activity prediction, and medical resource allocation. As an emerging concept of the interconnects between physical and virtual entities, DT virtually represents both the structural elements and dynamics of any physical entity (e.g., a patent) throughout its lifetime [34]. Therefore, integrating DT with IoMT and data-driven methods (e.g., machine learning) will provide efficient and accurate personalized healthcare services for seniors' safety. At present, research in DT-based elderly healthcare mainly focuses on monitoring long-term diseases and medicine precision [25], [34]. However, there are rarely platforms or systems for senior safety that focus on the detection and prediction of potential threats to senior citizens, like stroke, fall down, and other emergency events. Moreover, existing solutions don't consider data authentication in the healthcare data-sharing process.

By enabling a seamless interwoven of the physical world and cyberspace, the Metaverse makes an ideal home for the next generation of DHS. Thanks to attractive features such as

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decentralization, immutability, transparency, and availability, Blockchain has demonstrated great potential to revolutionize centralized framework and guarantee security in the Metaverse. This paper proposes MetaSafe, a DHS architecture for senior safety monitoring in Metaverse. Based on monitoring data collected by sensors, the activities and status of seniors, which are considered as the physical objects (PO), are mirrored to corresponding logical objects (LO) in a virtual community in the Metaverse, where activity recognition, potential risk prediction, and alert generation are realized. By leveraging Non-Fungible Token (NFT) technology to tokenize identities (POs and LOs) and data streams of the DHS on the blockchain, an NFT-based authentication fabric allows for verifiable ownership and traceable transferability during the data-sharing process. Specifically, an instant alerting system is introduced that leverages a hybrid algorithm combining the singular spectrum analysis (SSA) approach with the long-short-term memory (LSTM) networks.

The key contributions of this paper are as follows:

(1) From the architecture aspect, we present a comprehensive MetaSafe system consisting of a hierarchical DT-based DHS and an NFT-based authentication scheme along with details of workflows in a senior safety scenario.
(2) We implemented an instant alerting system that adopts a hybrid change point detection and SSA-LSTM prediction scheme to predicate behaviors of objects and notifies medically anomalous events in DHS; and
(3) A proof-of-concept prototype is implemented and tested under a physical network that simulates the case of seniors' safety. The experimental results validated that the proposed MetaSafe achieved the design goal.

The rest of this paper is structured as follows. In Section II, the background knowledge of IoMT, Metaverse, Digital Twins, and NFT is described and related work is introduced. Section III presents our MetaSafe system architecture along with workflows. Section IV discusses the hybrid SSA-LSTM senior safety detection, prediction, and alarming scheme. The experimental results are presented in Section V. Finally, Section VI provides conclusions.

II. Background and Related Work

A. Metaverse, Digital Twin, and Digital Healthcare System

As the successor to the mobile Internet, Metaverse comprises a seamless integration of interoperable, immersive, and shared virtual ecosystems through the convergence between the Extended Reality (XR), communication technologies and Digital Twin (DT) to enhance the immersive experience of users [43]. Through modeling and data fusion, DT provides the digital representation of a physical entity within Metaverse such that the virtual world and physical world are able to interact with each other in real-time. The concept of DT was introduced in 2002 for the formation of a Product Lifecycle Management (PLM) [16]. Essentially, a DT is a digital representation of components or dynamics of a physical system [13]. A typical DT system consists of physical objects (PO), logical objects (LO), and the data connecting them. DT systems can be roughly categorized into monitoring DTs, simulational DTs, and operational DTs according to their functionalities [38]. The monitoring twins enable system operators to learn the status of a physical system, while simulation twins are used to predict the future status of the physical system with help of different simulation tools and Machine Learning (ML) algorithms. Similar to human-machine teaming [9], the operational twins aim to construct a *complex sensing and control system* that allows human operators to interact with cyber-physical systems and perform different actions in addition to monitoring, analysis, and prediction [21].

Earlier studies of DT mainly focused on the area of industrial processes that covers different key factors to achieve intelligent manufacturing and control systems. Recently, redefined DT is adopted by healthcare scenarios that contain living objects and physical medical devices to enable reliable and smart healthcare systems [12]. DT technique allows create a digital representation of the patients and contributes to establishing and updating medical records reporting historical and current statements about them. With the development of IoMT-based wearable devices and sensor technology, researchers and industry have shown more interest in the integration of DT and AI to develop Metaverse applications for digital healthcare, such as telemedicine, medical education, healthcare supply chain, and fitness and wellness [29].

B. Blockchain and NFT

As a public distributed ledger technology underlying prevalent digital crypto-currencies [6], [30], blockchain has emerged as a critical facilitator for the advancement of decentralized security infrastructures [32], [44]. Using a peer-to-peer (P2P) network architecture for message propagation and data transmission, all miners cooperatively execute a cryptographic consensus protocol to store blocks on a completely-ordered distributed ledger. Blockchain provides a decentralized and trust platform such that all participants maintain a transparent, immutable, and auditable distributed ledger, as opposed to establishing trust through a centralized third-party authority. A smart contract (SC) combines protocols with user interfaces to formalize and secure the relationships over computer networks [37]. Smart contracts can tokenize digital information or assets in the form of cryptographic tokens saved on the blockchain to facilitate transactions [41]. Fungibility defines whether digital assets are identical and interchangeable during a transacting process, and tokens are roughly categorized into fungible tokens (FT) or non-fungible tokens (NFT) [20]. While FT are interchangeable and identical in all respects and they are divisible, such as crypto-currencies and stakes, NFT cannot be substituted for other tokens of the same kind and they are indivisible [20]. By using NFTs on blockchains, a creator can easily prove the existence and ownership of digital assets in the form of images, videos, and games [42]. Recently, NFTs are widely used for protecting digital assets, like patents and intellectual property [8], event ticketing applications [33], and scarcity of art [22]. Thanks to key characteristics in terms of verifiable originality (authenticity), auditable ownership, and traceable transferability, NFT and blockchain are promising to tokenize digital objects and enhance decentralization and security properties in a DHS.

C. Related Work

As a healthcare-related Mataverse domain, several digital personal healthcare has been proposed to provide more accurate and fast service for personal healthcare. To provide small healthcare services for senior citizens, a framework of the cloud DT based healthcare system (CloudDTH) is proposed [25]. CloudDTH relies on the cloud environment to manage wearable medical devices, and monitor and diagnose the health of individuals. in addition, CloudDTH implemented a digital twin healthcare (DTH) model to achieve interaction and convergence between medical physical and virtual spaces. The experimental results verify the feasibility of real-time supervision, scheduling, and optimization service for the elderly on the CloudDTH. By using DT for continuous monitoring and forecasting, a DT-Driven reference model is proposed for the design, development, and operation of treatment management systems in precision healthcare [34]. The novel DT-Driven reference model designs three feedback loops to ensure adaptive management, contextual monitoring, and adaptive behavior models. By monitoring personalized risk factors such as behavior and vital signs, a layer model of DT is proposed for the assessment and maintenance of personal health [35]. However, neither [34] nor [35] provides numerical results to evaluate system performance.

In the past decade, blockchain and NFT have been adopted in healthcare systems to enhance security and decentralization. MedRec [7], a blockchain-enabled EMR authentication and management framework, was proposed to provide patients with user-friendly access to their own information. MedRec ensures the sharing process of the EMR is maintained in a decentralized form and off-chain storage brings great convenience and the participating entities involved help to avoid a single point of failure. Similar to MedRec, off-chain data storage is adopted in multiple blockchain-based medical information management systems and used along with other technologies. For instance, BlocHIE [18] combines on-chain and off-chain storage techniques to secure privacy and authentication of medical data sharing and storing. Inter Planetary File System (IPFS) is introduced to store sensitive data of the patients [23]. Thanks to the properties of NFT such as unique ownership, verifiability, and traceability, an NFT-based reference architecture is designed to represent and transfer the consent of patients regarding the use of their medical data [11]. A health record marketplace based on NFT was proposed to provide dual ownership along with finer access control and efficiency in data sharing [24]. Similarly, a user-friendly mobile application was created to store patient health records in a single platform [39]. The corresponding patient would be able to track the usage of their personal medical information with the help of NFT.

In sum, unlike aforementioned DHS solutions [25], [34], [35] that adopt a centralized architecture, our MetaSafe leverages Blockchain and NFT to ensure decentralization and data authentication under a trust-less distributed network environment, which is promising to mitigate risks of single point failures and performance bottleneck by centralized cloud servers. Moreover, MetaSafe implements an instant alerting

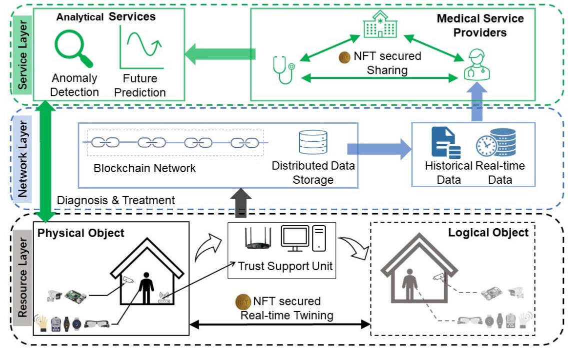

Fig. 2. Illustration of MetaSafe system architecture consisting of DT-based DHS and NFT-enabled authentication fabric.

system based on a novel SSA-LSTM method to enable real-time threat detection and prediction for elderly healthcare rather than analysis of chronic diseases.

III. MetaSafe System Architecture

To meet the compelling demands for seniors' safety monitoring, we propose MetaSafe, which leverages IoMT, DT, and NFT technologies to provide reliable and trustful safety monitoring and healthcare consulting services. As a potential technology to integrate Metaverse with digital healthcare systems, the rationale of DT is utilized to design a conceptual function framework of MetaSafe for senior safety. Because this paper focuses on NFT-based authentication, and SSA-LSTM detection and prediction mechanism given a senior monitoring scenario, we briefly describe key components and workflow of MetaSafe while leaving detailed DT designs in future work. Figure 2 demonstrates an overview of MetaSafe system architecture that consists of two function units: (1) a hierarchical DT-based virtual healthcare application for seniors, and (2) an NFT-enabled authentication fabric based on Blockchain and distributed data storage (DDS).

A. Hierarchical DT-based DHS

The hierarchy of a three-layered DT-based DHS system is shown in Figure 2. The functions of each layer will be briefly introduced below.

1) Resource Layer: As an infrastructure framework across multiple personal healthcare networks, the resource Layer consists of various IoMT devices and sensors for measuring human body data and collecting environmental information. We assume a permissioned smart home environment for each domain network, and it relies on a trust support unit (TSU) deployed on a personal computer (PC) or an edge server to manage registered devices within a domain. From a data transmission aspect, a support unit works as a gateway that aggregates data streams from IoMT devices and enforces access control strategies for data and service access requests from users outside a domain. The physical objects (POs) in a smart home network are wearable devices, smart cameras, and sensors. By continuously monitoring the elderly, physical objects transmit real-time data and important messages to a TSU. A TSU leverages a set of DT modeling procedures to synchronously process various data streams and then construct a corresponding virtual space consisting of virtual objects (LOs) that keep a real-time mapping of POs. A TSU can send DT healthcare data of a smart home to the upper service layer for evaluating, analyzing, and predicting seniors' healthcare conditions and risks. Moreover, A TSU also receives decision-making results and orders from the service layer to perform on-site emergency alarms for senior safety or early warning for potential healthcare risks of the seniors.

2) Network Layer: As a fundamental network infrastructure atop the Blockchain and DDS, the network layer provide decentralized security services to handle huge amount of DT data in MetaSafe under a distributed network environment. We assume that the majority (51%) of the miners are honest, the Blockchain network uses a PoW consensus protocol to ensure the immutability and integrity of NFT tokens stored on the distributed ledger. The Blockchain network provides a decentralized and trust-free platform to enable an NFT-based authentication fabric. Also, the network layer uses DDS rather than a centralized cloud server to improve availability and efficiency for data storage and access. The real-time DT data and historical data are encrypted and then stored in DDS, and raw data stored on the DDS can be addressed by their unique references, which can be encapsulated into NFT tokens as proofs for data authentication during the data storing and sharing process.

3) Service Layer: The service layer is the "system brain", which provides intelligent healthcare applications. The DT-based elderly health service data sent by a TSU contains information including personal body status, environment data, and location coordinates. By combining real-time DT data with historical records, analytical services deployed on a cloud server uses statistical algorithms and ML methods to achieve anomaly detection and future prediction. If decision-making rules satisfy certain emergency conditions, abnormal alerts and warning messages will be sent to patients and healthcare professionals. At the same time, medical resources like ambulances and hospital beds can be assigned automatically if no response from patients. Moreover, the service layer is considered as a trust data marketplace such that DT data owned by patients and history EMR managed by medical service providers can be shared with third-party professionals. With proper privacy preservation, big data analytics based on large samples of shared data can help healthcare institutions and governments to optimize medical resources.

B. NFT enabled Authentication Fabric

To guarantee the security of continuous data synchronization between POs and LOs and the verifiability of data-sharing among healthcare professionals, MetaSafe implements a decentralized authentication fabric that uses two NFT tokens deployed on Blockchain: NFT-DT and NFT-EMR. The integrity and authenticity of data streams in the real-time data exchange between POs and LOs are important to ensure high QoS and reliability for DT models. Therefore, an NFT-DT token is introduced to ensure tamper-proofing data synchronization in the twinning process, as shown at the bottom of Fig. 2 in the resource layer. In a real-time twinning process, TSUs periodically store encrypted DT data steams into DDS which returns references (hash value) as audit proofs. Following that, TSU mints NFT-DT tokens that contain the basic information of DT data steams along with their references on the Blockchain. As a result, each data stream can be uniquely addressed from DDS, and any user with granted permissions can easily verify retrieved data streams by using NFT-DT tokens.

Regarding personal healthcare data sharing operations, an NFT-EMR token is proposed here to ensure integrity, traceability, and impenetrability of the data sharing process, as shown at the top of Fig. 2 in the service layer. First of all, data owners like patients or healthcare institutions that store EMR mint NFT-EMR tokens. Following that, data owners update NFT-EMR tokens with properties of shared data like data address, tamper-proofing proofs, access control policies, recipient information, etc. Therefore, data owners can fully control their data in sharing process by updating access policies given the status of data usage and even stop sharing data if any violations are detected. Moreover, an NFT-EMR records all parties participating in the whole lifetime of the data-sharing process such that anyone can track and verify ownership of shared data.

IV. Hybrid SSA-LSTM Detection and Prediction

Thanks to continuous healthcare data monitoring in DT-based DHS, MetaSafe designs an instant alerting system that utilizes an SSA-based algorithm for anomaly detection like fall and faint or prevent risks in advance and a SSA-LSTM prediction scheme to predict certain future risk in certain vital signs like SaO2 level or body temperature. Compared to supervised machine learning methods like Support Vector Machine (SVM) and Recurrent Neural Networks (RNN), the SSA algorithm is widely adopted in sequential time series processing and demonstrates efficiency in change-point detection and prediction [31]. In addition, SSA is a non-parametric method that does not require any prior knowledge of the parametric model for the series such that it demands a relatively small size of time series for training. Furthermore, by calculating the main contributing components of time series, SSA can extract features like seasonal patterns and historical trends without containing noises. Therefore, using SSA for processing data is promising to improve the quality of detection and prediction

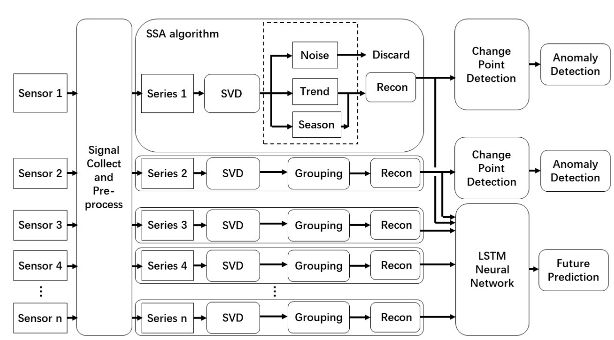

Fig. 3. Hybrid SSA-LSTM prediction scheme for an instant alerting system.

methods. As a particular version of Recurrent Neural Networks (RNN), LSTM [17] uses four neural network layers rather than a simple repeating module structure to construct memory cells. Thus, the combination of SSA and LSTM is a promising way to provide detection and predication for seniors living alone. Figure 3 illustrates a hybrid detection and prediction scheme that consists of three stages: data collection, SSA-enabled processing, and anomaly detection along with LSTM-based prediction. The details of workflows are explained as follows.

A. Sensing Data Collection

In MetaSafe, we use DT data sources generated from different types of sensors for detection and prediction, such as ECG sensors, PPG sensors, acceleration sensors, etc. These sensors are operated in various hardware and software environments and sometimes under different sample rates. Following that, the simultaneously collected data will be unified into time series with the same sample rate. Then, each pre-processed DT data source is fed to a SSA processor.

B. SSA enabled Data Processing

In data processing stage, time series of a DT data source is handled by an SSA processor that aims to extract features and remove noise from raw data. We use the body temperature parameter as an example to explain the workflow of an SSA processor below as four steps:

1. **Embedding:** The input of an SSA is a one-dimensional time series, for example, the body temperature collected from a certain sensor. We denote a time series of body temperature as $X = [x_1, ..., x_N]$, where N is the series length. By choosing the proper window length L, we can transfer the times series into multi-dimensional series of vectors $\vec{X_i}$. Combine these vectors results in the trajectory matrix $X = [\vec{X_1}, \vec{X_2}, ..., \vec{X_K}]$, where $K = N - L + 1$.
2. **Singular Value Decomposition (SVD):** To get the eigenvalues and eigenvectors, we process SVD to the mentioned trajectory matrix X. The eigenvalues are denoted as $\lambda_1, ..., \lambda_L$ in decreasing order of magnitude and the eigenvectors $U_1, ..., U_L$ where the matrix $U = [U_1, U_2 ..., U_L]$ and $\|\mathbf{U_i}\| = 1$ is orthogonal. Then, the eigentriples are $(\sqrt{\lambda_i}, U_i, V_i)$, by denoting $V_i = X'U_i/\sqrt{\lambda_i}$.
3. **Grouping:** Then we group the matrices according to a subset index $I = i_1, i_2, ..., i_l$ where $l < L$. And the sum of the groups is $X_I = X_{i_1} + ... + X_{i_l}$. By observing their essential characteristic, these different components can be categorized into noise, trend, and season.
4. **Reconstruction:** Using diagonal averaging, we can transfer X_I into time series X_I. By selecting certain subset indices $I = i_1, i_2, ..., i_l$, we can reconstruct(denote as Recon in Figure 3) the time series by only keeping certain features, like trends and season, while discarding noise. In this work, we choose $I = i_1$ to reconstruct the target sequence, which is used as an extracted feature of a parameter.

Finally, all features of parameters are extracted from different sensors by SSA processors and sent to the decision-making stage for detection and prediction.

C. SSA-LSTM Hybrid Detection and Prediction

1) Anomaly Detection: Monitoring DT data like acceleration and heart rate is extremely important for seniors living alone, and any anomaly signals that appear in the time series of these parameters or vital signs may indicate abnormal events like fall down or injury. Therefore, an SSA-based change point detection scheme is introduced to detect anomalies in time series data. Focusing on the timely detection of falls, accelerometer data is selected as an example to explain our detection scheme. After the four steps of the SSA algorithm, the time series $\mathbb{A} = [a_{n+1}, ..., a_{n+N}]$ is embedded into the trajectory matrix (base matrix) $A = [\vec{A_1}, \vec{A_2}, ..., \vec{A_K}]$, where N is the series length, L is the window length and $K = N - L + 1$. Then the columns of the trajectory matrix would be the vectors:

$$\vec{A_i} = (a_{n+i}, ..., a_{n+L+i-1})', i = 1, ..., K. \tag{1}$$

After SVD we can get L eigenvectors which can be grouped into certain subsets $I = i_1, i_2, ..., i_l, l < L$. Similarly, we select integers p,q and Q where $Q = q - p > 0$. Then we construct the test matrix of size $L \times Q$:

$$A_{test} = [\vec{A_{p+1}}, \vec{A_{p+2}}, ..., A_p \vec{+} Q], \tag{2}$$

and the columns of the matrix are the vectors:

$$\vec{A_j} = (a_{n+j}, ..., a_{n+L+j-1})', j = p + 1, ..., p + Q, \tag{3}$$

Generally, there are three detection statistics: the sum of the squared Euclidean distances between the l-dimensional subspace from the base matrix and the vectors $\vec{A_j}$ from the test matrix, the normalized sum, and the Cumulative Sum (CUSUM) of the normalized sum. We denote them as $D_{n,I,p,q}$, S_n, and W_n. For anomaly detection, we can monitor the value of these three detection statistics($D_{n,I,p,q}$, S_n and W_n). Compared to the two other statistics, the CUSUM W_n shows better sensitivity and we adopt it to test anomaly detection in our scheme. Any large value of W_n exceeding a certain threshold h can be identified as an anomaly. The detailed calculation of mentioned parameters can be found in [28].

2) Near-Future Prediction: In general, vital signs such as body temperature and SaO2 level are stable and do not change instantaneously, thus, they can help evaluate the long-term healthcare conditions of senior patients. Given multiple types of DT data sources, a hybrid SSA-LSTM-based prediction framework is developed to provide future predictions on elderly healthcare status. As shown in Figure 3, the outputs of multiple SSA processors contain several time series as different features including one feature(e.g. Body temperature or SaO2) which is the target of near-future prediction. And they are used as a simulating dataset which is further divided into a training set and a testing set. Then the training data are fed to a LSTM network including two 50-node LSTM layers, a dropout layer, and a dense layer. And to have a intuitive observation of the results, we use the testing set which is essentially the final part of the recent data to generate predicted value to compare with the real value.

TABLE I
CONFIGURATION OF EXPERIMENTAL NODES.

Device	HPC	Dell Optiplex 760	Raspberry Pi 4 Model B
CPU	Intel Core TM i5-3470 (4 cores), 3.2GHz	Intel Core TM E8400 (2 cores), 3GHz	Broadcom ARM Cortex A72 (ARMv8) , 1.5GHz
Memory	16GB DDR4	4GB DDR3	4GB SDRAM
Storage	500GB HHD	250GB HHD	64GB (microSD)
OS	Ubuntu 20.04	Ubuntu 16.04	Raspbian (Jessie)

V. EXPERIMENTAL RESULTS

A. Experimental Setup

A proof-of-concept prototype for MetaSafe is implemented in Python language. We use a micro-framework called Flask [1] to develop RESTful web services. All security primitives like symmetric cryptography and hash functions are developed by using standard python library cryptography [3]. We use Solidity [4] and openzeppelin-contracts [2] to develop NFTs, which are deployed on a private Ethereum test network. The experimental infrastructure worked under a physical local area network (LAN) environment and included multiple desktops and IoT devices. Table I describes the devices used for the experimental setup. Dell Optiplex 760 (desktop) simulates edge servers that run local support units, while Raspberry Pi 4 (RPi) simulates IoT gateways that collect data from IoMT. The HPC works as a cloud server that supports data sharing among healthcare professionals. A private Ethereum network consists of six miners that are deployed on the HPC as six containers separately. While RPis only work in a light-node mode without mining blocks. To simulate a DDS, we built a private Swarm network [5] consisting of five desktops as service sites. The Analytical Service of MetaSafe including anomaly detection and future detection is realized using Python. All SSA algorithm and ML methods are implemented and tested on a Desktop with an i7-7700K CPU, 16GB DRR4 memory, 1TB SSD, and Windows 10 OS.

B. Performance of NFT-based Data Authentication

This section discusses the performance of executing NFT-based authentication at the edge network. In a data authentication process, the user queries information from NFTs on the Blockchain and then performs verification on data streams. Thus, scaling up read requests has impacts on the performance of query operations. We evaluate processing time per query operation given different transaction sending rates Th_S as transaction per second (TPS). Data Encryption is not performed in NFT transactions. Finally, we analyze computation overheads incurred by accessing data to and from DDB and performing symmetric encryption on data. We conducted 50 Monte Carlo test runs for each test scenario and used the averages to measure the results.

1) Network Latency and Throughput by Query Operations: Figure 4a shows average delays that evaluate how long a data authentication request can be successfully handled by

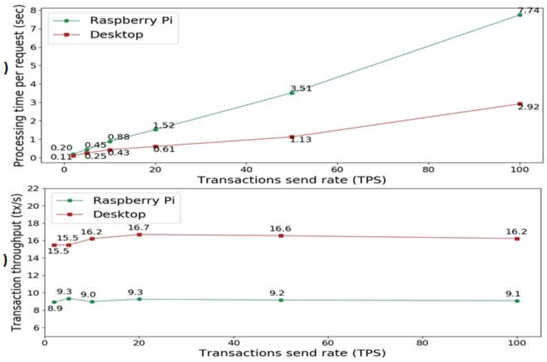

Fig. 4. a) processing time of query transactions, b) transaction throughput.

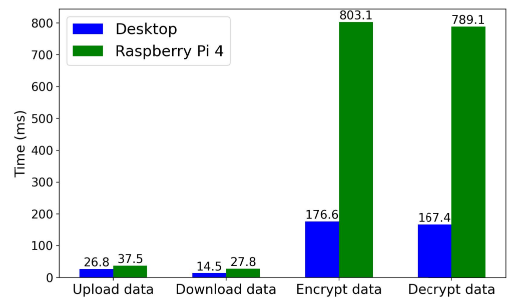

Fig. 5. Processing time of accessing Swarm and symmetric encryption.

the host machine as increasing Th_S from two tps to 100 tps. Regarding the fixed bandwidth of the test network, the capacity of host machines that provide NFT token services dominates the performance of query transactions. Because the desktop is more powerful than the RPi device, the delays of reading token data and then returning to the requester are higher than the desktop regarding the same Th_S. Thus, the higher Th_S also means a longer latency to handle a query token transaction given multiple service requests.

To evaluate the end-to-end network delay and transaction throughput of query token operations, we let a client send multiple query requests to a data service provider (can be hosted by a desktop or an RPi) and wait until all responses are received. Figure 4b presents the transaction throughput of data authentication when Th_S changes from two tps to 100 tps. As RPis have fewer computation resources than desktops, data service provides on the RPi device demonstrates a lower transaction throughput than those on desktops even if Th_S is the same. Moreover, transaction throughput is subject to system capacity. Therefore, it is almost saturated when $Th_S \geq 20$ on both platforms.

2) Processing Time of Accessing Data at DDB with Encryption: We assume that data streams of twinning a pair of PO and LO are encrypted and then recorded into DDS for each 30-sec duration by a support unit. As a result, each data file is about 128 KB, and we use these sample data to evaluate computation overheads incurred by DDS and encryption. Figure 5 shows the processing time of accessing data on swarm and data encryption given different host platforms. Regarding swarm operations, delays in uploading data to the swarm network and downloading from a service site are almost the same on both

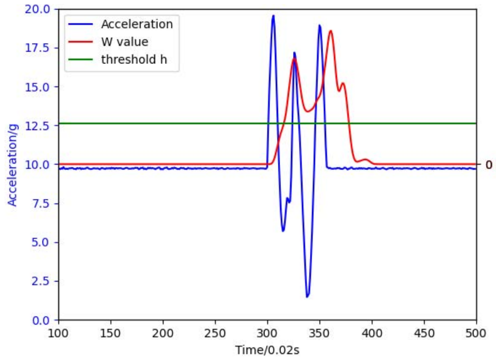

Fig. 6. SSA-based anomaly detection.

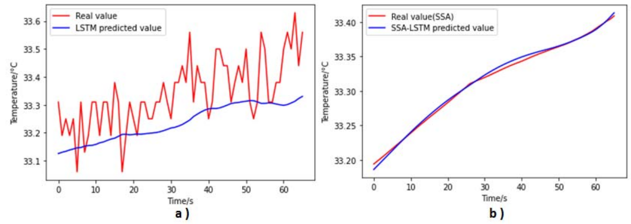

Fig. 7. a) LSTM prediction, b) hybrid SSA-LSTM prediction.

platforms. However, RPi takes longer process time to encrypt and decrypt data than a desktop does.

C. Anomaly Detection and Prediction Analysis

The target data of the detection are extracted from an open dataset [14], [27]. The acceleration is obtained by calculating the norm of the vector of the three-dimensional accelerations (g, 500Hz) in (x, y, z) directions. We re-sample the signal to 50Hz and turn it into a time series. Regarding SSA-based change point detection, we follow the recommendations from earlier researchers [15] and set $N = 40$ considering the size of the time series, $L = 20$ to the half size of N, $p = 20$, and $q = 30$. We choose $I = i_1$ as the first component of the decomposition that can represent a trend of the time series.

1) SSA-based Anomaly Detection Results: Figure 6 presents the results of the proposed detection scheme. The blue line is the acceleration value of the patient, while red line is the w_n value calculated using the SSA algorithm as the score. The green line is a threshold $h = 0.524$ which is computed with $t_\alpha = 1.2815$. The fluctuation of the blue line starting around $t = 6s(300\times0.02)$ implies a significant change in acceleration compared to the sitting state where the acceleration is almost static around 9.8g. The preliminary results show that our method is promising to detect anomaly events of the elderly by using acceleration monitoring. However, the actual model of a person falling down is more complicated and it may consider numerous scenarios and various behavior modes given different individuals. We leave a comprehensive evaluation based on behavior models in future efforts.

2) Hybrid SSA-LSTM Future Prediction Results: As the target parameter of temperature would not change so fast, we unify the sample rate as 1 Hz for all parameters including 3-lead ECG, acceleration in the x-direction, and temperatures from three different locations of the body. In the training process, we adopt mean square error (MSE) as the loss function and use the Adam optimizer to improve convergence speed and learning effect given an epoch size is eight. The first 383 data points are used for the training model and a prediction value is generated to compare with the actual value of 66s from body sensors.

Figure 7(a) shows results of predicting body temperature by using a conventional LSTM model. The large variants of raw data have greatly influenced prediction value although they demonstrate the similar trend. In contrast, applying SSA processor on raw data can extract features and remove noise. Therefore, the body temperature point predicted by SSA+LSTM method closely match SSA processed data points, as Fig. 7(b) shows. Our hybrid SSA-LSTM-based prediction is promising to accurately predict elderly healthcare status in the future such that early warnings and suggestions are provided to mitigate potential risks and even prevent abnormal events.

TABLE II
PREDICTION RESULTS

Model	RMSE	MAE	MAPE
SVM	0.4954	0.4690	1.4278
RNN	0.1042	0.0869	0.2600
LSTM	0.0978	0.0814	0.2438
SSA-LSTM	0.0087	0.0082	0.0247

Table II presents the comparison of prediction results between our solution with existing approaches like VM, RNN, and LSTM. Three major metrics are considered to evaluate the accuracy of the models: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The smaller values indicate more accuracy in future prediction given different benchmarks. Our hybrid SSA-LSTM model outperforms the listed conventional models with the highest accuracy.

VI. Conclusions and Future Work

To meet the compelling need for seniors' safety, leveraging Blockchain, NFT, and DT technology, we propose MetaSafe, a digital health service framework in Metaverse to ensure verifiable ownership and traceable transferability during the data storage and sharing. In addition, a hybrid SSA-LSTM prediction scheme is introduced to eliminate noise from the collected data in form of a time sequence. Compared to a traditional single LSTM neural network, the prepossessing of data highly improves the results of future prediction. We implemented proof-of-concept prototype NFTs and performed the case study of MetaSafe system for seniors' safety. The experimental results are encouraging, and they demonstrate the efficiency and effectiveness of the proposal.

Our preliminary experiment system tested the feasibility of the framework. To evaluate the availability of NFT-based algorithms, we need further study in a large-scale network including the investigation of accuracy and efficiency. The emergency alarm highly relies on emerging artificial intelligence techniques including ML and information fusion. Apart from the skeleton recognition algorithm [36], we will investigate more onsite diagnosis mechanisms and integrate them into MetaSafe to improve the accuracy of identifying emergent events. The application of blockchain and NFT in health care should not violate local governmental policies. Further investigation and studies are required and certain standards need to be established.

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