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A Survey of Artificial-Intelligence Enabled Digital Transformation in Elderly Healthcare Field

Ching-Hung LEE[a], Chang WANG[a], Fan LI[b*], Qingqing DENG[c], Danni CHANG[d]
[a]*School of Public Policy and Administration, Xi'an Jiaotong University, China*
[b]*Department of Aeronautical and Aviation Engineering, The Hong Kong Polytechnic University, China*
[c]*School of Design, Harvard University, USA*
[d]*School of Design, Shanghai Jiao Tong University , China*

Abstract. With the rapid growth of the elderly population, traditional elderly healthcare services can hardly meet the dynamic and uncertain demand and higher customer expectations. With the digital transformation with digital technological enablers of the elderly-related industry rising globally, Artificial Intelligence (AI) has begun to play a disruptive and critical role in the elderly healthcare industry. But there is still a lack of a holistic review about AI-enabled digital transformation (DT) in the elderly healthcare field. Therefore, 59 works of literature published from 2000 through 2021 were extracted and analysed from Web of Science. This study focuses on the application scenarios, the AI approach used, and the benefits of AI-enabled DT. And this literature review lays the foundation for future research in the elderly healthcare field.

Keywords. Artificial Intelligence, elderly healthcare, digital transformation

Introduction

Population aging is a significant problem of social development in the 21st century. The World Health Organization (WHO) reported that one in six people will be over age 60 by 2030. Almost every country in the world is experiencing the growth of the elderly population. Take China, for example, 18.7% of 1.41 billion people were over 60 years and 13.5% were over 65, according to China's Seventh National Census in 2021. With the rapid growth of the elderly population, traditional elderly healthcare services can hardly meet the dynamic and uncertain demand and higher customer expectations. What should be the possible and required aging healthcare services in this new era of the digital economy? Some new scenarios related to "aging-home-care service" or "smart healthcare for the elderly" are developed into the market as pilot solutions attempting at bringing new changes for the elderly's life[1]. Digital transformation (DT) is a process that aims to enable an entity's value creation by triggering significant changes and effectiveness to its external market strategy and internal organization tactics by using digital technologies through combinations of information, computing, communication, and connectivity capabilities, and DT with digital technological enablers of the elderly-related industry has risen globally in decades[2-4], mainly including big data, Internet of Things, Artificial Intellignence (AI) and so on. Among all the technological enablers, Artificial Intelligence plays a disruptive and critical role in the elderly healthcare field[1]. With the in-depth integration of AI, smart elderly healthcare services are considered as a future direction for achieving high-quality supply accessibility in the elderly healthcare industry[5]. AI can be applied in creating intelligent systems or platforms and intelligent elderly care products, services, or product-service systems (PSS) with smart learning abilities. But there is even a lack of a holistic review about the applications based on AI with the advantages of DT in the elderly healthcare field. The consumption needs of the elderly for healthcare services are different from others, and the elderly are less receptive to new things such as digital technology. So it is necessary to explore the role of AI in the aging society. So this study intends to report a survey on the literature related to AI-enabled DT in the elderly healthcare field and addresses four research questions: 1. What are the application scenarios of AI in the field of elderly healthcare? 2. What are the future directions of AI applications in this field? 3. What are the AI approaches commonly used for DT in the elderly healthcare field? 4. What are the benefits of AI-enabled DT for this field?

The organization of this study is as follows. The methods of collecting related literature are presented in Section 1. Studies about applications of AI in elderly healthcare services are summarized in Section 2. Section 3 presents and discusses AI approaches used. Section 4 summarizes the impacts and advantages of AI-enabled DT in the elderly healthcare field, and Section 5 concludes the overall work.

1. Literature review methodology

The existing publications are extracted from an acknowledged scientific dataset, i.e. Web of Science. To obtain a comprehensive set of pieces of literature, we defined six sets of topics keywords: a. "Artificial Intelligence" and "elderly"; b. "deep learning" and "elderly"; c. "machine learning" and "elderly"; d. "semantic network" and "elderly"; e. "neutral network" and "elderly"; f. "knowledge base" and "elderly." The literature range from 2000 to 2021, with a query in November 2021. Among all initiated papers, all conference papers, patents, and non-journal papers were removed. Secondly, to identify the most related and valuable literature, papers from Scientific Citation Index (SCI) Q1 high-impact journals in engineering, computer science, neurosciences, and instruments were selected. In total, 446 pieces of paper were collected. Thirdly, screening criteria were defined as the following principles: the studies are 1) related to DT 2) with practical application scenarios. Finally, 59 pieces of literature were screened from all collected publications.

The content analysis consisted of two stages. In the first stage, the selected papers were preliminarily coded based on the research objectives. In the second stage, all papers were coded and summarized for practical applications and AI approaches of elderly healthcare in Sections 3 and 4 respectively. Meanwhile, the AI-based elderly healthcare service scenarios and challenges and DT-triggered changes are addressed in-depth.

2. Applications of AI in Elderly Healthcare Services

According to the purposes of selected literature and authors' previous research on DT[1, 6], this research will analyze the scenarios and functions based on AI technology from three directions: health prevention, health screening and health management.

2.1 Health prevention

The "**fall detection prevention**" category (11 articles) mainly discusses the systems or methods for fall prevention combined with AI technology. We can see there mainly exists two kinds of fall detection systems: the first kind is wearable systems based on portable or external sensing devices. Wearable systems consist of sensors that can be attached to the human body for data collection. Some researchers presented new fall detection systems by using data from accelerometers and gyroscopes sensors attached to the body of the elderly[7-9]. Nowadays, smartphones have also become an important sensor device medium[10, 11]. The other kind is non-wearable systems based on external sensing devices. Non-wearable systems are composed of sensors placed around the human proximity for data collecting, the most common sensor used is video cameras[12, 13], while some researches applied infrared array[14], radar[15], WIFI[16].

Different limitations should be considered to ensure the reliability of the system in different living environments[16]. For instance, in areas such as restrooms and bathrooms, privacy issues should be faced firstly, compared to video-based sensors, wearable sensor- and wifi, infrared array, radar-based systems would be better at protecting personal privacy, nevertheless, it is difficult for wifi, infrared array, or radar-based systems to identify a person's activity in a multi-person environment. Wearable sensors may cause inconvenience to old adults carrying them. So how to balance the above problems and design a suitable PSS system is what researchers need to think about further.

2.2 Health screening

One of the main topics of health screening is "**chronic disease screening**"(18 articles). Chronic disease is considered as the top 10 causes of death worldwide reported by WHO. Alzheimer disease (AD) is a kind of chronic disease that affects an individual's life seriously. As AD is preceded by a transitional stage of Mild Cognitive Impairment (MCI), it is important to diagnose this stage as early as possible to avoid its conversion into AD with suitable measures. Some researchers designed methods mainly by the results of neuroimaging[17-19], while Zhang et al. [20] presented an approach combining the results of AI applied multi-modal neuroimaging diagnosis with the results of clinical neuropsychological diagnosis to improve the accuracy of MCI identification. Also, many researchers used AI to help identify and classify the stages of AD[21-23]. Besides, researchers began to utilize different types of data collected from the elderly to identify

AD, such as speech data[24, 25] and gait characteristics data[26]. Moreover, AI techniques were developed to identify common elderly chronic diseases including Age-related Macular Degeneration[27], stroke[28], diabetes[29], hypertension[29], Parkinson's disease[30], the prediction of depression has also attracted attention [31, 32].

Another main topic of health screening is "**elderly health evaluation**" (6 articles). Regular health evaluation is valuable in an older population to prevent health status decline at the earliest possible stage[33]. Frailty condition is considered an intermediate state in the aging trajectory, but the measurement often requires the assistance of health professionals. Combined with sensor technology, AI helps provide more convenient and more accessible ways to measure frailty[33-35], for example, Garcia-Moreno et al. [34] proposed a platform for assessing the frailty of older adults, which used data acquired from older adults while they performed Instrumental Activities of Daily Living (ADL) such as shopping. As for other health indicators, including basic physical function[36], standing balance[37], and quality of life[38], the use of AI in measuring the above indicators has also attracted attention.

In the context of "big data", the most common challenge faced by most of the above studies is the lack of data to train the models[24]. Besides, the models need to be validated on multiple sites and in a clinical setting[19], which helps to improve the generality of the models[22]. Moreover, the various methods or systems of health evaluation should be further used for remote monitoring and managing the rehabilitation exercises[33], so more new products, new services, and new PSS can be designed.

2.3 Health management

One of the main topics of health management is "**in-place remote healthcare assistance**" (10 articles), mainly including health monitoring and health guidance. Some researchers utilized AI technology to design and improve the health monitoring system of the elderly, including Cardiovascular disease[39], Dementia[40], physical abilities[41-44], and depressive symptoms monitoring systems[45], while other researchers developed AI-based systems for elderly health guidance, such as drugs management[46], rehabilitation assistance [47], and depression management[48].

Another topic of health management is "**in-place living management**" (14 articles), mainly including activity recognition and ambient assisted living services. For the activity recognition of the elderly, some researchers focused on easily recognized events[49-51], such as sleeping, going out, bathing, etc. Moreover, some researchers studied the recognition of complex daily activities of the elderly[52-57], especially their abnormal behavior. Also, researchers developed and designed systems and robots for the ambient assisted living services for the elderly, including pressure ulcers prevention system[58], robots for medicines identifying and daily physical activities planning[59, 60], smart kitchen[61], and smart homes[62],

All the proposed elderly health management systems should be tested and evaluated in practical application scenarios and more extensive user groups to get into details of challenges under real-life settings [62], thus making sure they can help enhance the quality of life of the elderly[61], moreover, health management systems need a stable operation, so the analysis should focus on overall system responsiveness, including the performance of core system components, real-time behavior for data exchange and even battery life of sensors[58]. Besides, given that older adults are less receptive to digital life, follow-up research and analysis on the user experience should be focused on [45].

3. Applications and AI approaches applied in elderly healthcare services

As a rapidly developing field of AI technique, Machine Learning (ML) is viewed as an important means to realize the successful DT of elderly healthcare.

Among the literature, Support Vector Machines (SVM) is the most popular method in classic ML models. Owing to its stable performance, it has been selected as the standard baseline classifier repeatedly and widely applied in various scenarios in health prevention, screening, and management of the elderly. But in general, SVMs were originally designed for binary classification, so their capacity to solve multiclass classification problems requires further discussion. Other simple classic ML models have also been applied when the features are well designed and extracted. Besides, since supervised ensemble learning can combine multiple weakly supervised models to gain a model with improved robustness, stability, and accuracy, it has been mostly utilized in the fields of chronic disease diagnosis and physical health evaluation that require high accuracy. All the above classic ML models do well in handling small datasets, but their performance can not be improved apparently with the amount of data growing. With the upgrade of computational power, Deep Learning (DL) has been widely used by researchers. The application of Convolutional Neural Networks (CNN) and Recurrent Neural Networks has prevailed in this field. As for the specific applications of the AI approaches, this research will illustrate them in terms of health prevention, screening, and management, as shown in Figure 1.

3.1 AI approach applied in health prevention

In terms of health prevention, the main application scenario is fall detection. In recent years, DL has been widely applied in the design of systems for fall detection of the elderly. In addition to single DL models, the hybrid DL models which combine superior features of CNN and Long Short-Term Memory (LSTM) models have also shown improved performance. Hassan et al. [10] applied a deep CNN-LSTM model and used a public dataset called MobiAct to train, and they reported more than 96% accuracy. Liu et al. [7] proposed a deep neural network that combines CNN with LSTM algorithms for fall detection and found out that the network achieves higher accuracy than traditional classification algorithms.

3.2 AI approach applied in health screening

In terms of health screening, supervised learning has been mainly used in the diagnosis of dementia-related diseases and the evaluation of elderly health indicators. In contrast, DL has often been applied in the diagnosis of chronic diseases. As mentioned above, supervised ensemble learning algorithms can combine multiple machine learners to complete learning tasks, thus having unique advantages in the field of diseases diagnosis, Xu & Pan [30] proposed a novel ensemble learning model fusing Random Forest (RF) classifiers to diagnose Parkinson's disease with better results than single Logistic Regression or SVM. As for the application of DL, Xu et al. [31] used an LSTM model to predict the risk of depression in the elderly. Choi et al. [28] compared different DL models to predict stroke disease and found out that the CNN-bidirectional LSTM model had high accuracy. There are also studies comparing different models for disease risk prediction, especially in predicting geriatric depression. Su et al. [32] found out that the

Multivariate LSTM model was the most successful model for early diagnosis and intervention of depressive disorder of elderly compared to other six classical ML models. As for the health evaluation of the elderly, most researchers compared the results of different learning algorithms and determined the most suitable algorithms by calculating indicators such as accuracy. Garcia-Moreno et al. [34] chose the K-Nearest Neighbor (KNN) model in the platform for frailty prediction with the highest accuracy, F1-score, sensitivity and specificity. Jung et al. [35] combined the RF model and LSTM classifier to identify frailty after experimenting with other models, including Naïve Bayes, KNN and SVM.

AI Applied	Scenario	reference
Health Prevention		
Supervised learning (KNN, SVM)	(a)Fall risk evaluation (1 literature) (b)Fall detection (4 literatures)	[9], [10], [13], [16], [63]
Supervised ensemble learning (RF)	(a)Activities classifying and fall detection (1 literature)	[16]
Deep learning (DCNN, LSTM)	(a)Activities identifying and fall detection (6 literatures)	[7], [8], [10], [12], [14], [15]
Health Screening		
Supervised learning (KNN, SVM, DT, NB, CNN, LR)	(a)AD and MCI diagnosis (5 literatures) (b)Frailty, standing balance and quality of life evaluation (5 literatures)	[17], [64], [22], [24], [25], [33], [34], [36], [37], [38]
Supervised ensemble learning (AdaBoost, GB, GBDT, RF)	(a)Parkinson's disease, diabetes and hypertension diagnosis (2 literatures) (b)Frailty evaluation (2 literatures) (c)The risk of depressive disorder prediction (1 literature)	[29], [30], [32], [34], [35]
Deep learning (DCNN, LSTM)	(a)Age-related Macular Degeneration, stroke disease and AD diagnosis (7 literatures) (b)The risk of depressive disorder prediction (2 literatures) (c) Physical function evaluation (2 literatures)	[18], [19], [20], [26], [21], [23], [65], [27], [28], [31], [32]
Health Management		
Supervised learning (KNN, SVM, CNN, NB, DT)	(a)Health guidance: medicines identifying (1 literature) (b)Health monitoring: real-time health monitoring, health risk assessment (5 literatures) (c)Activity recognition: daily life behavior recognition (3 literatures)	[39], [41], [42], [44], [48], [54], [56], [59], [55]
Deep learning (DCNN, LSTM)	(a)Health guidance: telerehabilitation and telecare (1 literature) (b)Health monitoring: pressure ulcers prevention; real-time health monitoring (2 literatures) (c)Activity recognition: daily life behavior recognition; abnormal behaviors prediction (8 literatures) (d)Assisted living services: physical exercises planning(1 literature)	[40], [43], [47], [50], [49], [54], [56], [57], [53], [52], [58], [60]
Unsupervised learning (Fuzzy C-Means, K-SVD)	(a)Health guidance: depressive symptoms progression (1 literature) (b)Activity recognition: daily life behavior recognition (1 literature)	[45], [51]
Supervised ensemble learning (AdaBoost)	(a)Activity recognition: daily life behavior recognition (1 literature)	[54]

Figure 1. AI approach applied in elderly healthcare services

3.3 AI approach applied in health management

In terms of health management, three pieces of literature mainly introduced the workflow of a health management system designed for the elderly, namely smart kitchen system, smart home and precision medicine platform. But the specific AI algorithm utilized was not mentioned. Supervised learning has been mainly used in the design of health monitoring systems for the elderly, with the function of real-time health monitoring, health risk assessment and so on. Calatrava-Nicolas et al. [48] introduced a robotics-based system applying SVM to help monitor and predict the mood of the elderly. Akbulut

& Akan [39] designed a cardiovascular disease monitoring system by using multiple supervised learning algorithms. DL has been mainly applied in the activity recognition of the elderly to collect ADL data and support the independent living of old adults. Minvielle & Audiffren [43] designed a system recognizing the activity of the elderly in nursing homes by using Deep Convolutional Neural Networks (DCNN). Ramos [52] et al. used bidirectional LSTM networks and proposed a system capable of recognizing the usual activities of older adults in real-time. Zerkouk & Chikhaoui [57] developed a model to identify and predict the abnormal behaviors of older adults by investigating many DL models such as DCNN and LSTM. Some researchers have also compared various types of learning models and selected the optimal solution according to the algorithm results. Xu et al. [54] employed different ML and DL classifiers, including Decision Trees, SVM, KNN, AdaBoost and DCNN, and designed a model to recognize activities of solitary elderly. Only a few researchers have applied unsupervised learning and supervised ensemble learning, and the application scenarios are relatively single.

4. AI-enabled DT of Elderly Healthcare Services

AI-enabled DT has begun to trigger changes of various new wearable products, sensor-based PSS, and new service models in elderly healthcare.

For health prevention, with the innovative integration of various high-fidelity sensors and high-precision AI algorithms, more prototypes of new products have emerged in the field of fall detection for the elderly, including fall risk detection and fall recognition systems. Through the real-time, autonomous, effective and rapid identification of the fall, the elderly can receive timely help from others after a fall, so the serious health consequences caused by "long-lie" can be prevented effectively.

For health screening, many researchers have begun to apply ML in the process of diseases diagnosis by using many kinds of data collected from older adults innovatively, for example, the traditional diagnosis of AD is mainly based on the evidence shown by neuroimaging, Liu et al. [25] proposed a new method that applies ML and speech data of older adults to help identify AD. Also, due to the application of AI, new PSS have been created. For example, Garcia-Moreno et al. [34] introduced a platform that can automatically measure the frailty of older adults without disturbing their shopping, thereby reducing hygiene costs and time of relevant health professionals.

For health management, in China, the traditional health management services that the elderly regularly have access to are physical examinations and health consultation services provided by the government. With the rapid development of digital technologies such as AI, various remote health monitoring systems and living assistance systems have been designed, which can support independent living and provide more diversified and personalized services for the elderly. At present, there are PSS that aim to monitor and give guidance to the elderly's physical health, including real-time monitoring systems for cardiovascular disease[39], telerehabilitation and telenursing guidance systems for the elderly [47], etc. Also, there are PSS designed for the elderly's mental health, including the elderly emotion prediction systems [48] , and depression detection and care systems [45], etc.

Above all, we can see that Smart PSS with applications of AI can meet the diversified and personalized needs in a sustainable manner of the users by integrating smart, connected products and their generated digitalized and e-services. The development of Smart PSS should be focused on in future research.

5. Conclusion

In this research, we conducted a broad and in-depth discussion of AI-enabled DT in the elderly healthcare field to answer research questions 1 to 4. The application scenarios and AI approaches were presented in health prevention, screening and management. Meanwhile, this research also summarized the benefits brought by AI-enabled DT to the elderly healthcare field. By designing, upgrading and integrating AI-based smart new products, services, PSS with functions such as perception and interaction, smart product groups will be created, and the diversified needs of users can be met. Besides, as a review study, this research also summarizes various approaches on new product development with multidisciplinary design optimization and especially human-centered design under Industry 4.0. It is hoped that this work will provide more valuable insights into the engineering practice and transdisciplinary theories in the elderely healthcare field. In the future, we believe that AI in DT will be a highly integrated interdisciplinary research topic in the academic and practical areas. Researchers should pay more attention to the theories and methodologies of the development about smart PSS, smart products and smart services driven by the DT enablers in the future elderly healthcare field.

Reference

[1] C. H. Lee, C. L. Liu, A. J. C. Trappey, J. P. T. Mo and K. C. Desouza, Understanding digital transformation in advanced manufacturing and engineering: A bibliometric analysis, topic modeling and research trend discovery, *Adv. Eng. Inform.,* Vol.50, 2021, pp. 1-17.

[2] C. H. Lee, D. N. Wang, K. C. Desouza and R. Evans, Digital Transformation and the New Normal in China: How Can Enterprises Use Digital Technologies to Respond to COVID-19?, *Sustainability,* Vol.13, 2021, pp. 1-11.

[3] F. Li, C. H. Lee, C. H. Chen and L. Khoo, Hybrid data-driven vigilance model in traffic control center using eye-tracking data and context data, *Adv. Eng. Inform.,* Vol.42, 2019, pp. 1-10.

[4] C.-H. Lee, A. J. C. Trappey, C.-L. Liu, J. P. T. Mo and K. C. Desouza, Design and management of digital transformations for value creation, *Adv. Eng. Inform.,* 2022, Vol. 52, April 2022, 101547.

[5] Y. C. Lee, C. H. Chen and C. H. Lee, Body anthropometric measurements of Singaporean adult and elderly population, *Measurement,* Vol.148, 2019, pp. 1-9.

[6] A. J. Shie, C. H. Lee, S. Y. Yu and C. Wang, A Fuzzy Design Decision Model for New Healthcare Service Conceptualization, *Int. J. Fuzzy Syst.,* Vol.23, 2021, pp. 58-80.

[7] L. Liu, Y. Hou, J. He, J. Lungu and R. Dong, An Energy-Efficient Fall Detection Method Based on FD-DNN for Elderly People, *Sensors,* Vol.20, 2020, pp. 1-16.

[8] A. Alarifi and A. Alwadain, Killer heuristic optimized convolution neural network-based fall detection with wearable IoT sensor devices, *Measurement,* Vol.167, 2021, pp. 1-10.

[9] M. Fanez, J. R. Villar, E. de la Cal, V. M. Gonzalez, J. Sedano and S. B. Khojasteh, Mixing user-centered and generalized models for Fall Detection, *Neurocomputing,* Vol.452, 2021, pp. 473-486.

[10] M. M. Hassan, A. Gumaei, G. Aloi, G. Fortino and M. Zhou, A Smartphone-Enabled Fall Detection Framework for Elderly People in Connected Home Healthcare, *IEEE Netw.,* Vol.33, 2019, pp. 58-63.

[11] A. Shahzad and K. Kim, FallDroid: An Automated Smart-Phone-Based Fall Detection System Using Multiple Kernel Learning, *IEEE Trans. Ind. Inform.,* Vol.15, 2019, pp. 35-44.

[12] L. Alhimale, H. Zedan and A. Al-Bayatti, The implementation of an intelligent and video-based fall detection system using a neural network, *Appl. Soft. Comput.,* Vol.18, 2014, pp. 59-69.

[13] K. de Miguel, A. Brunete, M. Hernando and E. Gambao, Home Camera-Based Fall Detection System for the Elderly, *Sensors,* Vol.17, 2017, pp. 1-21.

[14] S. Tateno, F. Meng, R. Qian and Y. Hachiya, Privacy-Preserved Fall Detection Method with Three-

Dimensional Convolutional Neural Network Using Low-Resolution Infrared Array Sensor, *Sensors,* Vol.20, 2020, pp. 1-23.

[15] H. Sadreazami, M. Bolic and S. Rajan, Contactless Fall Detection Using Time-Frequency Analysis and Convolutional Neural Networks, *IEEE Trans. Ind. Inform.,* Vol.17, 2021, pp. 6842-6851.

[16] Y. Wang, K. Wu and L. M. Ni, WiFall: Device-Free Fall Detection by Wireless Networks, *IEEE. Trans. Mob. Comput.,* Vol.16, 2017, pp. 581-594.

[17] D. Yang, R. Huang, S.-H. Yoo, M.-J. Shin, J. A. Yoon, Y.-I. Shin and K.-S. Hong, Detection of Mild Cognitive Impairment Using Convolutional Neural Network: Temporal-Feature Maps of Functional Near-Infrared Spectroscopy, *Front. Aging Neurosci.,* Vol.12, 2020, pp. 1-17.

[18] X. Pan, T.-L. Phan, M. Adel, C. Fossati, T. Gaidon, J. Wojak and E. Guedj, Multi-View Separable Pyramid Network for AD Prediction at MCI Stage by F-18-FDG Brain PET Imaging, *IEEE Trans. Med. Imaging,* Vol.40, 2021, pp. 81-92.

[19] B. Solano-Rojas and R. Villalon-Fonseca, A Low-Cost Three-Dimensional DenseNet Neural Network for Alzheimer's Disease Early Discovery, *Sensors,* Vol.21, 2021, pp. 1-17.

[20] F. Zhang, Z. Li, B. Zhang, H. Dua, B. Wang and X. Zhang, Multi-modal deep learning model for auxiliary diagnosis of Alzheimer's disease, *Neurocomputing,* Vol.361, 2019, pp. 185-195.

[21] S. Liang and Y. Gu, Computer-Aided Diagnosis of Alzheimer's Disease through Weak Supervision Deep Learning Framework with Attention Mechanism, *Sensors,* Vol.21, 2021, pp. 1-15.

[22] C. M. Carvalho, F. L. Seixas, A. Conci, D. C. Muchaluat-Saade, J. Laks and Y. Boechat, A dynamic decision model for diagnosis of dementia, Alzheimer's disease and Mild Cognitive Impairment, *Comput. Biol. Med,* Vol.126, 2020, pp. 1-12.

[23] S. Zolfaghari, E. Khodabandehloo and D. Riboni, TraMiner: Vision-Based Analysis of Locomotion Traces for Cognitive Assessment in Smart-Homes, *Cogn. Comput.,* 2021, pp. 1-22.

[24] Z. Fan, F. Xu, X. Qi, C. Li and L. Yao, Classification of Alzheimer's disease based on brain MRI and machine learning, *Neural Comput. Appl.,* Vol.32, 2020, pp. 1927-1936.

[25] L. Liu, S. Zhao, H. Chen and A. Wang, A new machine learning method for identifying Alzheimer's disease, *Simul. Model. Pract. Theory,* Vol.99, 2020, pp. 1-12.

[26] D. Jung, J. Kim, M. Kim, C. W. Won and K.-R. Mun, Classifying the Risk of Cognitive Impairment Using Sequential Gait Characteristics and Long Short-Term Memory Networks, *IEEE J. Biomed. Health Inform.,* Vol.25, 2021, pp. 4029-4040.

[27] J. H. Tan, S. V. Bhandary, S. Sivaprasad, Y. Hagiwara, A. Bagchi, U. Raghavendra, A. K. Rao, B. Raju, N. S. Shetty, A. Gertych, K. C. Chua and U. R. Acharya, Age-related Macular Degeneration detection using deep convolutional neural network, *Futur. Gener. Comp. Syst.,* Vol.87, 2018, pp. 127-135.

[28] Y.-A. Choi, S.-J. Park, J.-A. Jun, C.-S. Pyo, K.-H. Cho, H.-S. Lee and J.-H. Yu, Deep Learning-Based Stroke Disease Prediction System Using Real-Time Bio Signals, *Sensors,* Vol.21, 2021, pp. 1-17.

[29] M. Recenti, C. Ricciardi, K. J. Edmunds, M. K. Gislason, S. Sigurdsson, U. Carraro and P. Gargiulo, Healthy Aging Within an Image: Using Muscle Radiodensitometry and Lifestyle Factors to Predict Diabetes and Hypertension, *IEEE J. Biomed. Health Inform.,* Vol.25, 2021, pp. 2103-2112.

[30] S. Xu and Z. Pan, A novel ensemble of random forest for assisting diagnosis of Parkinson 's disease on small handwritten dynamics dataset, *Int. J. Med. Inform.,* Vol.144, 2020, pp. 1-13.

[31] Z. Xu, Q. Zhang, W. Li, M. Li and P. S. F. Yip, Individualized prediction of depressive disorder in the elderly: A multitask deep learning approach, *Int. J. Med. Inform.,* Vol.132, 2019, pp. 1-7.

[32] D. Su, X. Zhang, K. He and Y. Chen, Use of machine learning approach to predict depression in the elderly in China: A longitudinal study, *J. Affect. Disord.,* Vol.282, 2021, pp. 289-298.

[33] G. Akbari, M. Nikkhoo, L. Wang, C. P. C. Chen, D.-S. Han, Y.-H. Lin, H.-B. Chen and C.-H. Cheng, Frailty Level Classification of the Community Elderly Using Microsoft Kinect-Based Skeleton Pose: A Machine Learning Approach, *Sensors,* Vol.21, 2021, pp. 1-20.

[34] F. M. Garcia-Moreno, M. Bermudez-Edo, J. Luis Garrido, E. Rodriguez-Garcia, J. Manuel Perez-Marmol and M. Jose Rodriguez-Fortiz, A Microservices e-Health System for Ecological Frailty Assessment Using Wearables, *Sensors,* Vol.20, 2020, pp. 1-23.

[35] D. Jung, J. Kim, M. Kim, C. W. Won and K.-R. Mun, Frailty Assessment Using Temporal Gait Characteristics and a Long Short-Term Memory Network, *IEEE J. Biomed. Health Inform.,* Vol.25, 2021, pp. 3649-3658.

[36] S. Fudickar, S. Hellmers, S. Lau, R. Diekmann, J. M. Bauer and A. Hein, Measurement System for Unsupervised Standardized Assessment of Timed "Up & Go" and Five Times Sit to Stand Test in the Community-A Validity Study, *Sensors,* Vol.20, 2020, pp. 1-19.

[37] E. Lattanzi and V. Freschi, Evaluation of human standing balance using wearable inertial sensors: A machine learning approach, *Eng. Appl. Artif. Intell.,* Vol.94, 2020, pp. 1-10.

[38] S. Nakagawa, D. Enomoto, S. Yonekura, H. Kanazawa and Y. Kuniyoshi, New telecare approach based on 3D convolutional neural network for estimating quality of life, *Neurocomputing,* Vol.397, 2020, pp. 464-476.

[39] F. P. Akbulut and A. Akan, A smart wearable system for short-term cardiovascular risk assessment with emotional dynamics, *Measurement,* Vol.128, 2018, pp. 237-246.
[40] H. Ghayvat and P. Gope, Smart aging monitoring and early dementia recognition (SAMEDR): uncovering the hidden wellness parameter for preventive well-being monitoring to categorize cognitive impairment and dementia in community-dwelling elderly subjects through AI, *Neural Comput. Appl.,* 2021, pp. 1-13.
[41] L. Syed, S. Jabeen, S. Manimala and A. Alsaeedi, Smart healthcare framework for ambient assisted living using IoMT and big data analytics techniques, *Futur. Gener. Comp. Syst.,* Vol.101, 2019, pp. 136-151.
[42] M. Hosseinzadeh, J. Koohpayehzadeh, M. Y. Ghafour, A. M. Ahmed, P. Asghari, A. Souri, H. Pourasghari and A. Rezapour, An elderly health monitoring system based on biological and behavioral indicators in internet of things, *J. Ambient Intell. Humaniz. Comput.,* 2020, pp. 1-11.
[43] L. Minvielle and J. Audiffren, NurseNet: Monitoring Elderly Levels of Activity with a Piezoelectric Floor, *Sensors,* Vol.19, 2019, pp. 1-19.
[44] T. Ba, S. Li and Y. Wei, A data-driven machine learning integrated wearable medical sensor framework for elderly care service, *Measurement,* Vol.167, 2021, pp. 1-7.
[45] A. S. Billis, E. I. Papageorgiou, C. A. Frantzidis, M. S. Tsatali, A. C. Tsolaki and P. D. Bamidis, A Decision-Support Framework for Promoting Independent Living and Ageing Well, *IEEE J. Biomed. Health Inform.,* Vol.19, 2015, pp. 199-209.
[46] D. Keine, M. Zelek, J. Q. Walker and M. N. Sabbagh, Polypharmacy in an Elderly Population: Enhancing Medication Management Through the Use of Clinical Decision Support Software Platforms, *Neurol. Ther.,* Vol.8, 2019, pp. 79-94.
[47] A. Barriga, J. M. Conejero, J. Hernandez, E. Jurado, E. Moguel and F. Sanchez-Figueroa, A Vision-Based Approach for Building Telecare and Telerehabilitation Services, *Sensors,* Vol.16, 2016, pp. 1-19.
[48] F. M. Calatrava-Nicolas, E. Gutierrez-Maestro, D. Bautista-Salinas, F. J. Ortiz, J. Roca Gonzalez, J. Alfonso Vera-Repullo, M. Jimenez-Buendia, I. Mendez, C. Ruiz-Esteban and O. Martinez Mozos, Robotic-Based Well-Being Monitoring and Coaching System for the Elderly in Their Daily Activities, *Sensors,* Vol.21, 2021, pp. 1-38.
[49] T. Matsui, K. Onishi, S. Misaki, M. Fujimoto, H. Suwa and K. Yasumoto, SALON: Simplified Sensing System for Activity of Daily Living in Ordinary Home, *Sensors,* Vol.20, 2020, pp. 1-24.
[50] H. Zhu, S. Samtani, H. Chen and J. F. Nunamaker, Jr., Human Identification for Activities of Daily Living: A Deep Transfer Learning Approach, *J. Manage. Inform. Syst.,* Vol.37, 2020, pp. 457-483.
[51] L. Yao, Q. Z. Sheng, X. Li, T. Gu, M. Tan, X. Wang, S. Wang and W. Ruan, Compressive Representation for Device-Free Activity Recognition with Passive RFID Signal Strength, *IEEE. Trans. Mob. Comput.,* Vol.17, 2018, pp. 293-306.
[52] R. G. Ramos, J. D. Domingo, E. Zalama and J. Gomez-Garcia-Bermejo, Daily Human Activity Recognition Using Non-Intrusive Sensors, *Sensors,* Vol.21, 2021, pp. 1-19.
[53] K. Qian, T. Koike, K. Yoshiuchi, B. W. Schuller and Y. Yamamoto, Can Appliances Understand the Behavior of Elderly Via Machine Learning? A Feasibility Study, *IEEE Internet Things J.,* Vol.8, 2021, pp. 8343-8355.
[54] Z. Xu, G. Wang and X. Guo, Sensor-based activity recognition of solitary elderly via stigmergy and two-layer framework, *Eng. Appl. Artif. Intell.,* Vol.95, 2020, pp. 1-14.
[55] M. Hamalainen, L. Mucchi, S. Caputo, L. Biotti, L. Ciani, D. Marabissi and G. Patrizi, Ultra-Wideband Radar-Based Indoor Activity Monitoring for Elderly Care, *Sensors,* Vol.21, 2021, pp. 1-20.
[56] J.-M. Liang, P.-L. Chung, Y.-J. Ye and S. Mishra, Applying Machine Learning Technologies Based on Historical Activity Features for Multi-Resident Activity Recognition, *Sensors,* Vol.21, 2021, pp. 1-19.
[57] M. Zerkouk and B. Chikhaoui, Spatio-Temporal Abnormal Behavior Prediction in Elderly Persons Using Deep Learning Models, *Sensors,* Vol.20, 2020, pp. 1-13.
[58] G. Cicceri, F. De Vita, D. Bruneo, G. Merlino and A. Puliafito, A deep learning approach for pressure ulcer prevention using wearable computing, *Human-centric Comput. Inf. Sci.,* Vol.10, 2020, pp. 1-21.
[59] M.-F. R. Lee, F.-H. S. Chiu, C. W. de Silva and C.-Y. A. Shih, Intelligent Navigation and Micro-Spectrometer Content Inspection System for a Homecare Mobile Robot, *Int. J. Fuzzy Syst.,* Vol.16, 2014, pp. 389-399.
[60] A. Costa, E. Martinez-Martin, M. Cazorla and V. Julian, PHAROS-PHysical Assistant RObot System, *Sensors,* Vol.18, 2018, pp. 1-19.
[61] R. Blasco, A. Marco, R. Casas, D. Cirujano and R. Picking, A Smart Kitchen for Ambient Assisted Living, *Sensors,* Vol.14, 2014, pp. 1629-1653.
[62] E. Borelli, G. Paolini, F. Antoniazzi, M. Barbiroli, F. Benassi, F. Chesani, L. Chiari, M. Fantini, F. Fuschini, A. Galassi, G. A. Giacobone, S. Imbesi, M. Licciardello, D. Loreti, M. Marchi, D. Masotti, P. Mello, S. Mellone, G. Mincolelli, C. Raffaelli, L. Roffia, T. S. Cinotti, C. Tacconi, P. Tamburini, M. Zoli and A. Costanzo, HABITAT: An IoT Solution for Independent Elderly, *Sensors,* Vol.19, 2019, pp. 1-23.