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Machine Learning Application for Augmented Reality and Virtual Reality in Wearable Goods

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Abstract: Wearable technologies can significantly impact people's daily lives by providing innovative ways to experience the world through augmented reality (AR) applications. From accessories to integrated clothing and even body-integrated electronics, these devices offer many benefits. However, their widespread use raises significant data protection issues and complex data security issues. This paper provides an in-depth survey of recent applications in the analysis of large data sets collected by wearable sensors for privacy preservation. It has a strong focus on security and privacy when it comes to wearables. The study also explores the possibility of combining deep learning algorithms for wearable sensors with encryption. It includes a case study that evaluates the performance of a privacy-preserving deep learning framework both theoretically and empirically. The paper investigates the implementation of a secure prediction service using a convolutional neural network (CNN) model and the Cheon-Kim-Kim-Song (CHKS) homomorphic encryption algorithm. Recent advances in computing, communication and artificial intelligence technologies, along with the widespread availability of smartphones and the proliferation of multimedia data and edge computing devices, have led to new designs and frameworks for mobile devices. This article explores and classifies smart clothing and experimental designs that use machine learning and artificial intelligence techniques. The main goal is to explore these emerging paradigms for the application of machine learning and artificial intelligence in wearable technology, covering several technological aspects, including (1) smart wearables enhanced by machine learning and artificial intelligence; (2) data collection architectures and models for smart wearables powered by artificial intelligence; and (3) versatile applications of smart wearables controlled by AI. Augmented reality (AR) offers the opportunity to fundamentally change the way people interact in a dynamic urban environment. However, the design and evaluation of these new urban AR experiences present several challenges, including technical limitations and safety issues associated with using AR outdoors. In this regard, our contribution is to explore the use of virtual reality (VR) to simulate portable urban AR experiences, providing people with a realistic, safe and controlled environment to interact with potential AR interfaces. This paper presents two urban AR applications for mobile devices (pedestrian navigation and autonomous mobility) simulated using VR technology. In recent years, there have been significant advances in the field of mobile devices, and the integration of Augmented Reality (AR) and Virtual Reality (VR) technologies has played a key role in transforming the industry. Machine learning (ML) has emerged as a powerful tool to improve the features and functionality of AR and VR wearables, leading to new applications that improve user experience, personalization and overall product efficiency. This brief provides an overview of the intersection of ML, AR and VR in the field of wearables. Wearable AR and VR have gained popularity in various industries, including gaming, healthcare, education and retail, providing an immersive digital experience by superimposing virtual elements over the real world (AR) or completely immersing users in a virtual environment (VR).

Keywords: Prototyping, Augmented Reality, Virtual Reality, Urban Applications, Artificial Intelligence (AI), Smart Wearables, Deep Learning, Wearable Technology, Privacy-Preserving, Big Data.

1. INTRODUCTION

Augmented reality (AR) refers to a technology that combines computer-generated graphics with the real world in a three-dimensional (3D) space, allowing for real-time interaction with virtual elements [1]. Over the last two decades, there has been significant growth in AR research and development. The accessibility of AR experiences has expanded to a wide audience, thanks to the prevalence of smartphones that meet the necessary hardware requirements for AR and the availability of various development frameworks that simplify the creation of AR applications. Additionally, AR has captured the interest of the public, exemplified by the global phenomenon of the location-based AR game, Pokémon Go, in 2016 [2]. This phenomenon underscores the broader potential of AR, particularly in urban contexts.

In recent years, there has been a rapid advancement in computational, communication, and artificial intelligence (AI) technologies, as well as a notable increase in the prevalence of smartphones, multimedia computing, and edge computing devices. Concurrently, new data collection architectures and information processing technologies like cloud computing have become widely available. These converging trends have ushered in fresh models and paradigms for smart wearables and related technologies. This section will provide a brief overview of the progression of AI in wearable devices, starting from the initial need for wearables, elucidating how AI can enhance their functionality, and addressing the primary challenges they present. Subsequent sections in this paper will delve into more comprehensive discussions of various facets of this topic.

Japan's "Society 5.0" initiative envisions a society centered around human well-being, harnessing the economic potential of artificial intelligence and big data applications[1]. Within the framework of Society 5.0, the Japanese government and IT sectors are collaborating to remotely implement technological advancements through cloud platforms, with a particular focus on the integration of AI and big data[1,2]. Figure 1 illustrates the stages of societal evolution, leading to the emergence of Society 5.0, which aims to strike a balance between economic growth and addressing societal challenges. In the era of 5G and AI, Society 5.0 presents a promising technological paradigm, permeating all facets of human life and generating vast datasets involving individuals and institutions. These datasets are aggregated into big data repositories, facilitating diverse analytical applications, including medical research, financial decision-making, and online advertising. Consequently, the capability to assimilate extensive information, analyze it effectively, and derive meaningful insights and conclusions is commonly referred to as "big data analytics."

Figure 1 Technology Evolution Towards “Society 5.0”.

Smartphones popularized augmented reality (AR), yet head-mounted displays (HMDs) seek to seamlessly integrate virtual imagery into a user's view, enhancing reality awareness [3]. However, HMDs face limitations in urban AR, such as navigation and tourism, due to technical challenges like outdoor use, ergonomics, and tracking stability [5,6]. This paper explores virtual reality (VR) as a solution to prototype AR experiences, particularly in urban contexts. VR is effective in simulating interfaces, simplifying precise AR visualizations without extensive infrastructure [6], and manipulating contextual factors for realistic user responses [7,15][8,16]. Studies use VR to simulate wearable urban AR interactions, like AR-assisted police operations [17] and AV-pedestrian interactions [18]. This paper analyzes two case studies: pedestrian navigation and AV-pedestrian interfaces, addressing research questions about the effectiveness and limitations of VR simulations in prototyping urban AR experiences and providing recommendations for optimization.

The demand for continuous monitoring technologies in clinical health and well-being is rising, with wearables increasingly used for health monitoring and activity recognition. Advances in sensing technologies have enabled compact devices integrating various sensors, from temperature to heart rate monitoring. These wearables find applications in sleep monitoring, fatigue detection, fall detection for the elderly, and emotion and stress recognition. They're also utilized for monitoring animal behavior. Machine learning and artificial intelligence are integral to smart wearables, used in healthcare, sports, entertainment, and surveillance. They enable the monitoring of conditions like heart failure, diabetes, and emotional states. Various AI and machine learning techniques, including classical methods like support vector machines and recent ones like convolutional neural networks, are employed. This paper will discuss both classical and recent machine learning approaches for smart wearables and applications.

In recent decades, the Internet has globally connected devices, including computers and wearable sensors, revolutionizing communication and information access. However, ensuring data security and privacy during the handling of vast datasets remains a significant challenge. While cryptographic security measures like encryption and blockchain technologies offer solutions for data protection during transmission and storage, the challenge lies in preserving data privacy during processing.

This paper explores the role of security technology in safeguarding data collected from wearable sensors, enhancing privacy-preserving machine learning analytics in the 5G era and beyond. It also delves into cross-big data analytics in emerging AI-5G applications, where user information assets are encrypted and stored in cloud servers for statistical analysis without exposing user secrets. Collaboration between cryptography and machine learning efficiently and securely utilizes private information assets for big data applications.

The study provides an overview of privacy-preserving machine learning techniques in 5G environments and examines security encryption applications for big data analytics using statistical analysis in AI-5G applications. It aims to offer researchers and practitioners insights into secure big data analytics. The paper concludes with discussions and challenges related to emerging AI-5G applications.

2. LITERATURE REVIEW

In recent years, cities have become increasingly connected, utilizing technology and data to address everyday challenges and enhance residents' lives and long-term resilience. Urban interfaces, like urban AR applications, can bridge the gap between individuals and a city's technological infrastructure. These applications span various urban domains, including navigation, tourism, civic participation, and autonomous mobility. While many urban AR applications have been designed for smartphones, they can be problematic in certain contexts, such as pedestrian navigation, where they may distract users and pose safety risks. Wearable AR devices, although still in early development stages, hold promise for urban applications by seamlessly integrating information into the user's view.

Designing effective wearable urban AR experiences presents challenges related to functional benefits and the impact of the urban environment. Users must perceive tangible benefits from these experiences, and the urban setting's complexity can potentially interfere with their usability. Moreover, safety concerns and social acceptance issues add further complexity to their adoption. To address these challenges, this research explores the use of simulated environments to evaluate wearable urban AR applications.

Simulating Wearable AR Experiences in VR is a method of focus in this paper. Various AR prototyping methods, including immersive VR simulations, offer the advantage of allowing users to experience AR in a controlled environment. High-fidelity VR systems provide powerful processors and graphics capabilities, enabling the simulation of different AR systems and the study of their effects. Additionally, VR simulation allows for the evaluation of AR systems in diverse dynamic situations that may be unsafe or impractical in real-world settings. It also provides control over environmental factors, such as weather and lighting conditions, and can replicate contextual changes in context-aware AR interfaces.

These benefits of VR simulation are particularly relevant to the development of wearable urban AR applications, as they can replicate urban settings and contextual factors. However, there is a lack of knowledge regarding the effectiveness of VR simulation for evaluating wearable urban AR applications and the factors to consider when simulating these experiences. This research aims to address these gaps and facilitate the prototyping and evaluation of wearable urban AR applications in context.

Category/Domain Area	Year	Main Contributions
Research works for smart wearable wristbands and bracelet technologies	2018	Wrist wearable device for elderly fall detection—three sensor types (accelerometer, gyroscope and magnetometer), three signal types (acceleration, velocity and displacement), and two direction components (vertical and non-vertical).
	2017	Wrist-worn wearable device for classification of atrial fibrillation (AF)—deep neural network classification from pulsatile photoplethysmography (PPG) signals, wavelet, and convolution neural network.
	2020	Wearable smart device with the convolution neural network for real-time quality inspections in the smart manufacturing industry; classifies a worker’s actions based on acoustic and accelerometer data.
	2019	Smart wristband with iGenda to recognize the emotional states of human beings, especially elderly people; neural networks and the PAD method to interpret bio-signals into emotion.
Research works for smart wearable waist device and belt technologies	2020	Wearable belt device for fall detection using machine learning and signal processing; IMU sensor unit with an inbuilt combination of an accelerometer and gyroscope.
	2020	Waist wearable device—combined an accelerometer with a waist-mounted gyroscope; the machine learning algorithms utilized were ensemble learning, random forest, and gradient boosting.
Research works for smart wearable bowel recorder technologies	2020	The edge bowel sound (BS) wearable system aimed at selecting idle BS events while effectively eliminating audio segments that contain only background information noise such as voice and white Gaussian noise.
	2022	Lightweight BS recognizer for use with a convolutional neural network (CNN) portable system.
Research works for smart wearable neural interface technologies	2020	HTSMNN (heuristic tubu optimized sequence modular neural network) smart wearable neural interfaces to identify Parkinson’s disease.

Table 1. Some representative works on wearable and smart device technologies.

3. MACHINE LEARNING APPROACHES FOR AI AND SMART WEARABLES

Machine learning holds a pivotal role in the realm of artificial intelligence and smart wearables due to its integration into wearable device architectures. These AI and smart wearables find applications across various sectors like healthcare, sports, rehabilitation, entertainment, and smart home surveillance. This section explores diverse AI and machine learning approaches, with an emphasis on recent deep learning techniques.

- Machine Learning Approaches for Smart Wearable Technologies

Various machine learning approaches, including deep learning, are deployed in AI and smart wearables, focusing on tasks like human behavior analysis, activity recognition, and pattern recognition. Recent machine learning methods require feature engineering and classification to achieve precision. For instance, (Lu et al., 2020) introduced a deep learning method to address challenges in movement detection, utilizing a confidence index and adjusting confidence index thresholds for stability in intent recognition.

Machine learning approaches can also mitigate limitations in existing systems. For instance, fall detection sensors face issues like false alarms and maintenance costs. Integrating machine learning with the Internet of Things (IoT) significantly improves fall detection wearable sensors, as demonstrated by (Chaudhuri et al., 2020). They proposed a machine learning-based wearable device for predicting pulse rates and skin temperature, introducing the enhanced predicted thermal state (ePTS) to forecast the thermal state index. Another example is (Rubio-Solis et al., 2020), which employed extreme learning machines and multilayer interval type-2 fuzzy logic to identify walking actions and patterns using wearable devices.

- Deep Learning Approaches for Smart Wearable Technologies

Deep learning is a crucial methodology for analyzing data in smart wearables. (Saeedi et al., 2017) introduced a deep learning architecture that combines convolutional neural networks (CNNs) and long-short term memory (LSTM) to recognize human activities robustly. This architecture consists of eight layers, including recurrent LSTM and convolutional layers, allowing it to capture both features and temporal dependencies in activity data.

(Young et al., 2020) utilized deep learning-based wearable Internet of Things (IoT) systems to aid people with hearing disabilities in communication. Their approach converts speech to text using Google's Online speech recognition and displays the content on a micro-display for deaf individuals. They also implemented a deep learning-based urban emergency system using Inception-v4 for sound recognition and classification, alerting users about traffic congestion, fires, and road accidents.

(Jacobson et al., 2021) proposed a deep learning-paired technique with a wearable sensor-based device to forecast changes in anxiety and panic disorder symptoms. Similarly, (Bauer et al., 2020) employed deep learning with a wearable sensor device to promote movement in individuals with vision impairments. The system provides a 3D presentation of the surroundings, aiding users in detecting obstacles through a smartwatch.

(Janarthanan et al., 2020) introduced an unsupervised deep learning approach for improving human activity recognition by integrating a coder architecture with the Z-layer approach. This approach enhances precision by eliminating reconstruction errors and utilizes data collected from wearable sensors, including various actions like standing, walking, sitting, jogging, ascending stairs, and descending stairs.

- Deep Learning Approaches Using Convolutional Neural Networks (CNNs)

Convolutional neural networks (CNNs) are commonly used for feature extraction. For example, (Alarifi & Alwadain, 2021) employed a heuristic-optimized CNN technique to detect falls in elderly individuals using a wearable sensor system. This approach achieved accurate fall detection by utilizing a magnetometer, gyroscope, and accelerometer tri-axial device.

(Hernandez et al., 2021) utilized deep learning, specifically deep convolutional recurrent neural networks (DeepConvLSTM), to estimate lower limb kinematics during gait analysis. This approach combined convolutional and long-short term memory (LSTM) recurrent layers, effectively extracting features and modeling temporal dependencies.

(Rad et al., 2018) introduced a wearable device for detecting motion in patients with autism spectrum disorder using a CNN. (Mai et al., 2021) employed a 1D-Convolutonal Neural Network approach with an EEG-based brain-computer interface (BCI) to recognize emotional states.

- Deep Learning Approaches Using Recurrent Neural Networks (RNNs)

Recurrent neural networks (RNNs) are also used in wearable devices. (Zhang et al., 2018) presented an approach for classifying and monitoring sleep using wearables, combining bidirectional long short-term memory (BLSTM) with tiered feature learning. (Torti et al., 2019) integrated RNNs into wearable devices for real-time fall detection, emphasizing the importance of constant wireless connectivity and portability.

(Martindale et al., 2021) used RNN-based wearable devices for gait and activity segmentation, while (Coutts et al., 2020) employed deep recurrent neural networks (LSTM) to predict patient health using heart rate variability data.

- Deep Learning Approaches Using Long Short-Term Networks (LSTM)

Some authors have proposed using long short-term networks (LSTM) for AI and smart wearables. (Chung et al., 2019) introduced an LSTM model for human activity recognition using on-body positioning systems and IMU sensors. Their model combined convolutional neural networks (CNNs) and LSTM to process activity data effectively.

(Zhang et al., 2018) utilized bidirectional long short-term memory (BLSTM) for sleep monitoring using wearable medical devices, distinguishing between wakefulness, regular eye movement sleep, and irregular eye movement sleep.

- Hybrid Deep Learning Approaches Using a Combination of Deep Learning Techniques

Hybrid deep learning approaches combining various deep learning methods have been proposed for AI and smart wearables. (Xia et al., 2020) introduced an LSTM-CNN architecture with Global Pooling layers (GAP) to classify human activity, achieving faster convergence. (Rueda et al., 2019) combined deep neural networks with symbolic models to address subject and location dependency in activity recognition.

(Mukherjee et al., 2020) proposed EnsemConvNet, a hybrid approach utilizing a combination of deep learning, traditional machine learning, and statistical techniques for human activity recognition. (Ascioglu and Senol 2020) developed a hybrid deep learning approach called ConvLSTM for monitoring human activities in outdoor environments.

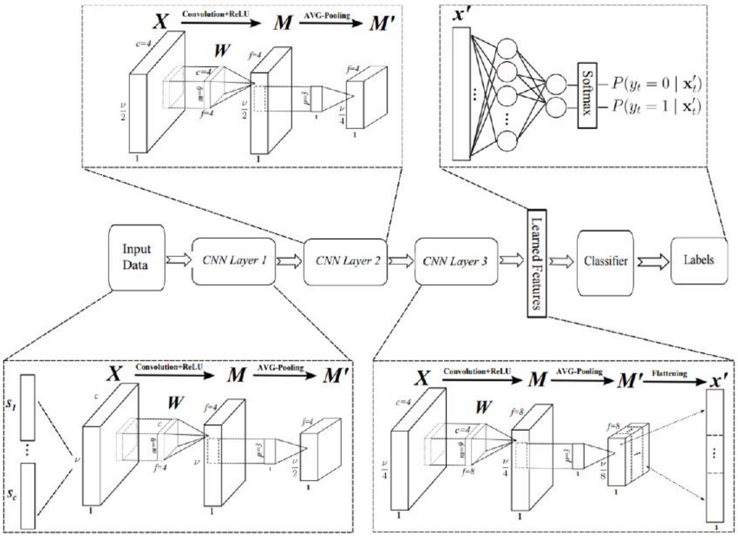

Figure 2 The Architectural View of the stereotypical motor movement (SMM) detection.

4. SECURITY AND PRIVACY IN WEARABLE SENSORS IN THE ERA OF 5G AND AI

The rapid growth and commercial availability of AR technologies have raised significant security and privacy concerns, primarily related to the scope and application of AR systems. These difficulties cover a range of factors:

1. AR devices and sensors collect abundant data, including GPS and microphone information.
2. Innovative wearable sensors offer multiple interactive features like touchscreens and voice commands.
3. Many device platforms support multiple simultaneous applications and wireless connections among AR devices, fostering collaboration and enhancing virtual reality performance, particularly with on-device AI technology.

AR applications often need access to sensor data such as video, audio, and GPS to function properly. Balancing the need for functionality with the risk of data misuse poses a major challenge for AR systems. Malicious apps could compromise user privacy by accessing location or video data. Moreover, VR/AR systems can potentially collect more personal data than conventional systems, raising the need for security measures.

Chen et al. proposed a mobile edge computing framework using federated learning for AR applications, addressing low-latency object detection while minimizing privacy concerns. However, federated learning introduces its own security issues, suggesting the potential use of cryptography alongside machine learning to ensure user privacy in VR/AR applications.

AR applications utilize computer-generated graphics to enhance reality using big data and machine learning, particularly in industrial VR applications. These apps are growing rapidly, supported by the proliferation of wearable devices. While smart glasses are prominent in AR, many applications use data from various wearables, like smart clothing, to improve realism. However, these developments raise concerns about privacy and security, especially in healthcare wearables.

The small size and accessibility requirements of wearables limit their ability to enhance human performance, potentially necessitating separate screens or controllers. AR often relies on smartphones for data entry, with 5G-based cloud computing supporting machine learning tasks but introducing privacy and security challenges.

Addressing these AR challenges, especially in post-5G applications, requires comprehensive information security measures. Familiar threats like malware and ransomware can affect VR/AR systems. Some VR/AR platforms lack encryption for network connections, unlike conventional messaging apps. Many platforms rely on untrustworthy third-party services, potentially requiring cryptographic protection. To mitigate privacy and security risks in wearable projects, privacy-preserving deep learning techniques involving cryptography offer a promising approach.

Our main aim is to assess the latest solutions for statistically analyzing sensitive data while preserving user privacy. These techniques should support advanced analytics on large and diverse datasets with encrypted private information, allowing computations to be delegated to third parties like cloud providers. Additionally, the expertise of data analysts has led to advancements in privacy-preserving deep learning for big data analysis, resulting in various techniques developed to evaluate the usability, security, and performance of homomorphic encryption in big data scenarios [19-21]. Several deep learning algorithms have been examined for their suitability in secure data handling.

In this section, we delve into contemporary studies on privacy-preserving deep learning for extensive data analytics, focusing on techniques employing homomorphic encryption algorithms to protect privacy. Aono et al. explored various homomorphic encryption methods for constructing logistic regressions and found them to scale effectively with homomorphically encrypted data [22]. Esperanca et al. emphasized the need for specially tailored computational approaches to achieve efficient and scalable statistical analysis of encrypted datasets, which can significantly differ from state-of-the-art techniques for plaintext settings [23]. Yonetani et al. used a homomorphic encryption algorithm for visual learning, including face recognition, to determine how private information could be accessed [24].

This section shifts its focus to implementing security measures for database servers and clients using homomorphic encryption, as described in the literature [25-28]. Fully homomorphic cryptosystems can be deployed on cloud servers within virtual reality platforms to achieve analytical performance. Extensive exploration of privacy-preserving big data challenges has led to the proposal of various privacy-preserving protocols [29-31]. These protocols generally fall into two categories: randomization-based and secure multiparty computation (SMC)-based approaches. Given our study's focus, we will concentrate on privacy-preserving deep learning techniques [12,13]. Secure multiparty computation-based approaches are commonly used to develop methods that allow participants to collectively compute a function using their data while maintaining privacy.

We present a practical scenario involving the use of homomorphic encryption for privacy-preserving deep learning in extensive data analytics. Initially, private prediction is introduced as a service where the data owner outsources analytics or the prediction of privately encrypted data to a third party. For example, envision an untrustworthy data analyst with a trained model and the computational capability to perform analytical tasks. Two possibilities were explored between the data owner and the data analyst. Thus, private prediction as a service constitutes the first phase, enabling the data owner to outsource the analysis of their encrypted data (referred to as ciphertext) to a cloud or third party. In another scenario, consider an untrustworthy data analyst equipped with a trained model and the computational capacity to handle prediction challenges. The second phase involves a training service where the data owner provides ciphertext to the cloud to train an encrypted-ready model, w_encr. Subsequently, w_encr is used to analyze new ciphertexts (psi), and the model is ready for analytic requests. In both scenarios, the encrypted results are returned to the data owner for decryption. In the first case, the data owner is aware of the data and results but remains unaware of the model w, which is kept secret from the untrustworthy data analyst.

It's important to note that implementing homomorphic encryption for statistical analysis can maintain metric reliability even when randomization is introduced. However, similar challenges to those encountered in privacy-preserving machine learning arise. Data analysts employ various deep learning algorithms to achieve desired predictions, including convolutional neural networks [14], recurrent neural networks [15], and linear means classifiers [16]. For instance, Li et al. introduced a machine-learning scheme using two homomorphic encryption algorithms to protect user dataset privacy [17]. Although this approach conducts model training with distinct public keys, it increases the computational load due to additional encryption and decryption operations in each iteration. Bost et al. deployed and trained three different classifiers—naive Bayes, hyperplane decision, and decision trees—over encrypted data. Recent advancements have enabled GPU usage for prediction in deep learning algorithms [18]. Takabi et al. utilized a GPU to expedite the arithmetic operations of convolutional neural networks (CNNs) on encrypted data [19]. The authors of PrivFT [20] conducted a study on the CKKS method based on GPU implementation. Jung et al. subsequently demonstrated the first GPU implementation for bootstrapping CKKS using approximate arithmetic [21], achieving a significant 40.0 speedup compared to the previous eight-thread CPU deployment under the same experimental conditions, highlighting the improved efficiency.

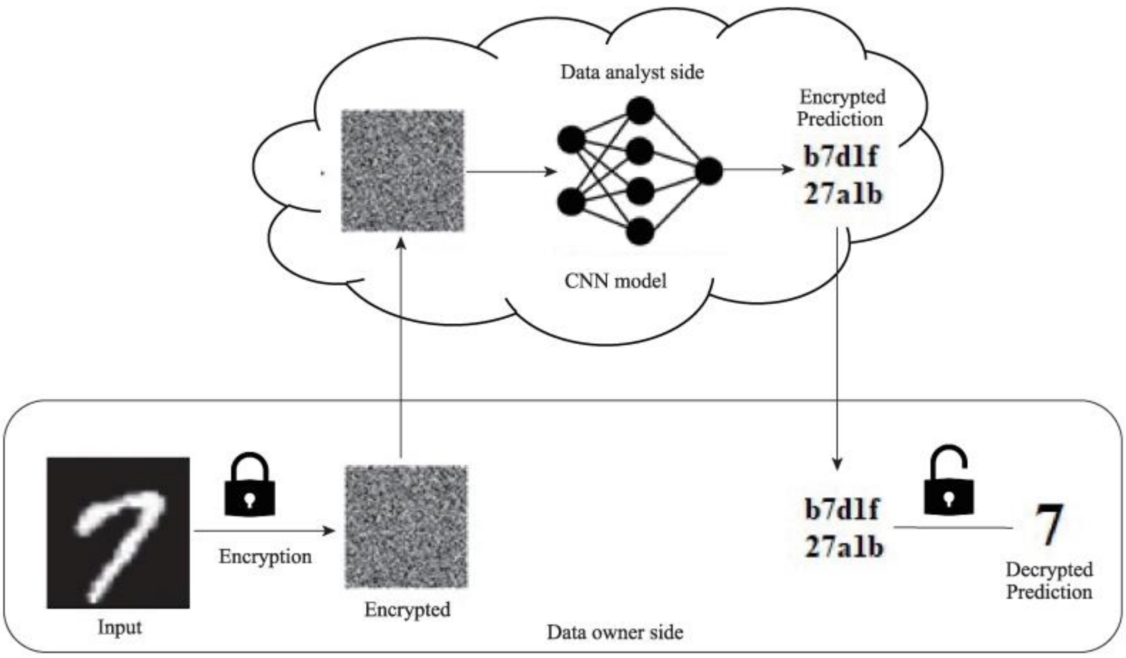

Figure 3 Privacy-Preserving Deep Learning as a secure Prediction Prototype.

5. DATA COLLECTION ARCHITECTURES AND PROCESSING MODELS FOR AI AND SMART WEARABLES

This section explores various data collection architectures and processing models for AI and smart wearables, organized into the following categories: (1) standalone architectures for AI smart wearables; (2) smartphone and smartwatch architectures; and (3) IoT and cloud-based architectures.

- Standalone Architectures for AI Smart Wearables

In this subsection, we discuss self-contained architectures for AI smart wearables. Orfanidis et al. (2021) [22] introduced a cost-effective wearable device that integrates three components to detect foot movements and send emergency messages over long distances. The device, based on standard shoes and off-the-shelf electronics, accurately identifies specific foot movements during activities like walking to trigger urgent messages with a 98% accuracy rate.

Ravi et al. (2017) [23] proposed a self-contained wearable architecture employing deep learning for real-time activity classification. It enhances classification accuracy by combining inertial sensor data with additional flat features and addressing the limitations of standard deep learning frameworks. Spectral domain pre-processing is applied for on-node real-time computation. Experiments on laboratory and real-world datasets demonstrated the superiority of this approach over other methods.

Mai et al. (2021) [24] developed a self-contained smart wearable architecture for emotion detection using EEG signals. A one-dimensional CNN model in a Brain-Computer Interface (BCI) system accurately detects emotions, capturing EEG signals non-invasively with eight drywall electrodes and a cordless custom EEG device.

- Smartphone and Smartwatch Architectures

Numerous architectures have been proposed for smart AI and wearable technologies. Rakhman et al. (2014) [24] introduced a smartphone-based fall detection system using an accelerometer and gyroscope. It detects falls and daily activities by analyzing tilt angles and acceleration thresholds.

Zhang et al. (2018) [33] presented a two-stage method involving multi-level feature learning and classification using neural networks with recurrent connections (RNNs). Low- and mid-level features are extracted, and raw signals are processed to capture temporal and frequency domain characteristics.

Yin et al. (2017) [25] introduced a hierarchical health decision support system that integrates health data from Wearable Medical Sensors (WMSs) into Clinical Decision Support Systems (CDSSs). The system supports disease diagnosis modules for individual diseases.

Kalantarian et al. (2015) [26] used gyroscope and accelerometer data from a smartwatch to distinguish between actions like "Opening a pill bottle" and "pouring pills into hand" with a six-second success criterion.

Fozoonmayeh et al. (2020) [27] developed a smartwatch-based medication intake detection system using gyroscope and accelerometer sensors.

- IoT and Cloud-Based Architectures

Positive computing integrates mobile communications, wearables, and IoT technologies. Lee et al. (2019) [28] proposed a conceptual framework and discussed key components for studying intelligent positive computing systems, highlighting opportunities, challenges, and ethical concerns.

Gao et al. (2020) [29] introduced a cellular network-based control system for intelligent wearable rehabilitation robots. Biofeedback and fuzzy control rules encourage patient participation in rehabilitation training.

Hong et al. (2022) [30] proposed a collaborative AI IoT-based solution with the Multiposture Recognition (MPR) algorithm to improve pose detection accuracy.

Tao et al. (2011) [31] presented a smart shoe system using sensors to detect falls and predict changes in brain function, utilizing MLP for continuous analysis of data from wearable IoT mental health sensor devices for early prediction of brain function changes.

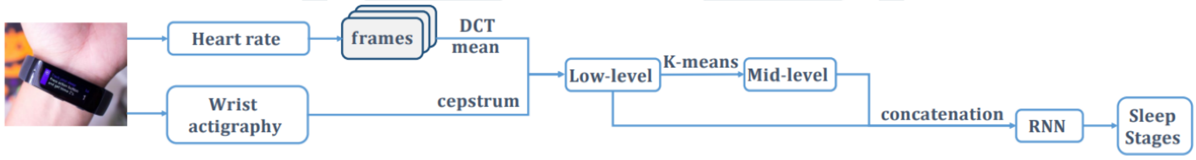

Figure 4 Proposed sleep stage wearable method.

6. CASE STUDY

The following sections detail two case studies involving the development and assessment of two urban AR applications for wearables. Both applications were created using immersive VR as a prototyping tool. In the first case, we evaluated an AR pedestrian navigation app with different map displays. In the second case, we assessed a wearable AR app designed to assist pedestrians in autonomous traffic. Despite sharing an urban context, these apps were conceptualized, prototyped, and evaluated independently and at different times. These studies were led by the primary author, and Table 1 provides prototype characteristics and participant demographics for each case study. It's important to note that the primary focus of these studies was to evaluate their respective AR concept prototypes, as reported in previous publications [30,31]. In this paper, we analyze the qualitative data collected from both studies together to illustrate the effectiveness of VR in simulating wearable AR experiences in a generalized manner.

	Pedestrian Navigation
Number of Conditions	3
VR Exposure per Condition	3–5 min
Movement	Joystick-based
Interaction	Controller
AR Content	Maps, turn arrow
Number of Participants (m/f)	18 (9/9)
Previous VR Experience	
Never	2
Less than 5 times	15
More than 5 times	1
Study Location	Australia

Table 2 Prototype Characteristics and participant's demographics.

1. Pedestrian Navigation

1.1 Design Context

Urban wayfinding in complex cityscapes is challenging. AR has the potential to enhance guidance by overlaying directional cues onto the real world. However, limited research has explored AR Head-Mounted Displays (HMDs) for navigation despite their potential advantages. This study investigated three map positions: (1) in front of users at a distance, (2) on the street's surface, and

(3) on the user's hand. The VR simulation provided an idealized interface free from real-world AR constraints. This approach was chosen for safety and control over the experimental environment.

Figure 5 The AR application to support pedestrian navigation featured a directional arrow to display turn directions when the map was not in use (as shown in the far left image). For the AR map view, we investigated three different map positions: up-front map (A), on-street map (B) and on-hand map (C).

1.2 Prototype Development

The prototype was created using Unity and experienced with an Oculus Quest 1 VR headset. A virtual city was designed with 3D models from the Unity Asset Store to create an urban atmosphere. The map interface was designed and integrated into the virtual city, allowing users to switch between map and arrow views. Participants navigated using the VR controllers, remaining seated for safety. The focus was on visual immersion rather than bodily immersion.

Figure 6 The simulated environment of the navigation study (left) and a participant using controllers for movement and interactions (right).

1.3 Evaluation Study

The study used a within-subjects design with three map placement conditions. Participants were tasked with navigating to predetermined destinations. Eighteen participants were recruited, and the study was conducted in a lab setting. Data collection included questionnaires, HMD-logged data, qualitative feedback forms, and semi-structured interviews.

We present a case study on privacy-preserving machine learning using encryption as a secure prediction service. We employed the widely-used Modified National Institute of Standards and Technology (MNIST) dataset, comprising [28×28] grayscale images representing decimal numbers from zero to nine, with 50,000 training images and 10,000 test images.

Our model architecture is a basic Convolutional Neural Network (CNN) with two linear layers. We implemented homomorphic encryption using the CKKS algorithm from the Seal toolkit, utilizing a square activation function to accommodate encryption constraints, including a poly modulus degree of 8192 and 128-bit security. We fine-tuned precision settings and coefficient modulus to balance accuracy and degradation.

The model consists of convolutional layers with a 2D convolution applied to input data. Our privacy-preserving deep learning approach, including a convolutional layer with 7×7 kernels and a 3×3 stride, employing a square activation function. We used linear layers with input/output sizes of 256/64 and 64/10, respectively. After training a PyTorch model on the MNIST dataset, we performed encrypted evaluations using the pre-trained prototype, involving complex and time-consuming operations.

Additionally, we explored the use of polynomials to approximate activation functions, with higher-degree polynomials offering better performance but slowing down computations on encrypted data. Practical Homomorphic Encryption (HE) schemes favor low-degree polynomial calculations, balancing accuracy and efficiency.

Our CNN model was trained on both plaintext and encrypted datasets, demonstrating its ability to learn from encrypted data. showing slightly higher accuracy in the plaintext dataset (99.78% training, 99.75% testing) compared to the encrypted dataset (99.57% training, 99.45% testing).

These results indicate the network's capability to learn effectively from encrypted data, making it suitable for integration into security-enhanced AI-5G applications. The proposed cryptosystem has potential applications in various VR and AR contexts, including speech emotion recognition, neural network image reconstruction, and other relevant neural network applications.

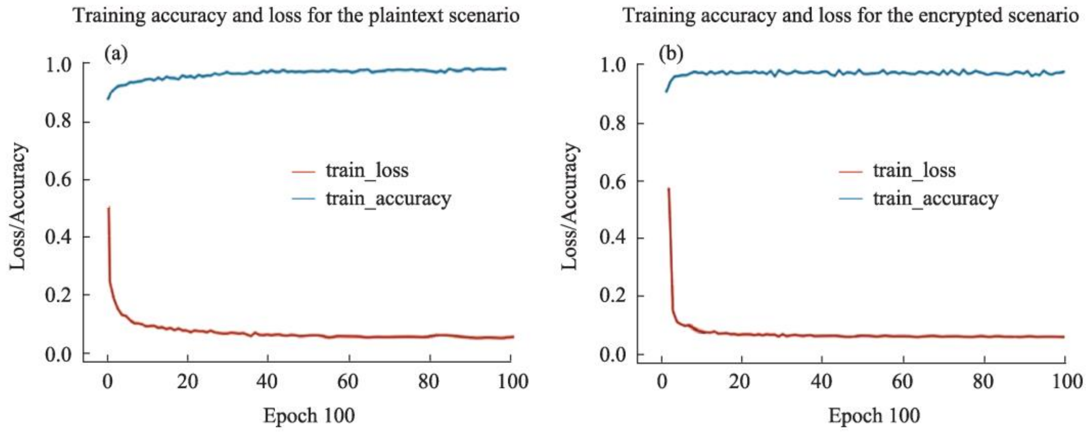

Figure 7 Performance of the suggested CNN model on both the plaintext and encrypted sets: (a) plaintext and (b) encrypted set.

7. COMPARISON OF EXISTING COMPUTATIONAL APPROACHES

In the quest for privacy protection, computational methods leverage CNNs for encrypted data processing, employing established encryption techniques. Privacy-preserving advancements, such as CryptoNets and CryptoDL, adapt NNs to handle encrypted data while adhering to encryption protocols. However, these adaptations impact network performance due to heightened computational complexity, potentially causing delays in results for data owners. This complexity results from nested additions and multiplications in all functions and potential data size expansion. Encrypted data can be one to three times larger than unencrypted data[8], highlighting the significance of these alterations.

It offers an overview of computational approaches using encrypted data, detailing the dataset used, classification model accuracy, NN type, convolutional layer count (NN depth), and references to homomorphic encryption techniques.

CryptoDL strives to enhance the speed and latency of CryptoNets by employing deeper neural networks for encrypted data. Nonetheless, it has limitations. Notably, CryptoNets and CryptoDL employ distinct activation algorithms and approximation techniques. CryptoNets use the sigmoid approximation for activation, whereas CryptoDL explores multiple activation functions before settling on ReLu approximation. Additionally, CryptoNN adopts a different encryption approach, based on Fully Homomorphic Encryption (FE), ensuring data privacy without modifying NN functions or structure. While CryptoNets and CryptoDL categorize encrypted data using NNs built on unencrypted data, CryptoNN allows both training and testing on encrypted data[23]. Although CryptoDL outperforms CryptoNets in terms of lower computing cost on the MNIST dataset, it shares similar limitations, particularly regarding the number of hidden layers and dataset complexity.

It's vital to note that all approaches is primarily tested on basic datasets like MNIST and CIFAR-10, raising questions about their scalability to extensive industrial applications with larger data. To address this, utilizing and evaluating larger and more representative big data samples is recommended. These methods, tested on small datasets and compact networks, revealed complexity and latency issues, highlighting the challenges in applying them to advanced CNNs and real-world scenarios.

	Dataset	Accuracy	Artificial Neural Network	Homomorphic Encryption
CryptoNN	MNIST	95.49%	CNN 3 NN depth	Functional Encryption
CryptoNets	MNIST	99%	CNN 2 NN depth	YASHE scheme
CryptoDL	MNIST	99.52%	CNN 5 NN depth	HELib

Table 3 Computational Methods Comparison

8. RESULTS

- Feedback on AR Prototypes & Participant Behavior in Immersive Virtual Environments

This section summarizes feedback from participants on AR prototypes and their behavior in immersive virtual environments.

Participants from the navigation study are represented as N (e.g., N18), while those from the AV study are denoted as A (e.g., A18). The number of participants in each study is indicated as navi and av (e.g., navi = 6, av = 3).

- Feedback on AR Glasses

Participants' opinions on AR glasses were largely based on their interactions with prototypes. Factors influencing adoption included wearable nature (navi = 3, av = 4), unfamiliarity (av = 4), potential costs (av = 4), and concerns about forgetting or taking care of glasses (av = 2). Some saw AR glasses as non-essential for street crossing (av = 3) and suggested smartphones as alternatives (navi = 1, av = 3).

A potential broader ecosystem for AR glasses was noted, but concerns about ads and disconnection from reality arose. Safety and focus were discussed as benefits.

- Functionality

Participants valued spatial directions integrated into the environment (navi = 4). In the AV study, convenience in sending crossing requests was highlighted (av = 6). The usefulness of graphical augmentations varied.

Complex real-world scenarios were considered in the AV study, including mixed traffic feasibility, local compliance, and data privacy concerns.

- User Experience

Participants found AR applications "useful," "easy to use," "convenient," and "intuitive" (navi = 12, av = 4). Safety was a key concern, with effects on activities and feelings of safety with AVs (av = 11). Hedonic aspects like "cool" and "exciting" were less frequent but mentioned.

- Information

Participants offered feedback on the usefulness of information cues. Differences existed between designer intent and user interpretation. Zebra crossings played a role in crossing decisions. Additional desired information included cardinal directions, estimated time, nearby locations, and warnings (navi = 7, av = 23).

- Visualisation

Visualisation feedback addressed recognisability, clarity, and aesthetics. Recognisability issues with car overlays were noted (av = 10). Clarity and comprehensibility were valued. Some participants preferred text prompts over graphics (av = 7, av = 5).

- Sound

Sound feedback was limited but suggested potential for voice-guided navigation (navi = 4). In the AV study, sounds accompanying interactions were less commented on, but some felt pressured to cross quickly (av = 5).

- Spatial Positioning

Placing AR content in the 3D environment posed challenges. Preferences varied, with some wanting content in their field of vision (navi = 10). Placing content in the lower region raised concerns about divided attention (navi = 5). Anchoring the map to the user's hand was seen as a natural interaction method, though some found it awkward (navi = 6, navi = 4).

- Interactivity

Participants expressed desire for interaction hints and system feedback (navi = 4, av = 2). Interaction simplicity was appreciated, but concerns about accidental interactions were noted. Some expected environmental sensing by AR glasses (navi = 2, av = 1).

- Participant Behavior in Immersive Virtual Environments

Joystick-based navigation resulted in more motion sickness feedback than real walking (navi = 12, av = 3), with mild discomfort decreasing over time. The AV study's VR simulation received less positive feedback on perceived realism than the navigation study (navi = 8, av = 5). Realism was influenced by ambient sounds and social activities, but differences in sensory inputs affected participant behavior and reactions (navi = 3, av = 6).

9. CHALLENGES FOR AI SMART WEARABLES AND FUTURE RESEARCH DIRECTIONS

- Technical Challenges for AI Smart Wearables

Schnell et al.'s (2022) study [4] highlights technical challenges relevant to both medical IoT and general smart AI devices. These challenges encompass battery consumption, energy efficiency, and data privacy/security. They can be categorized into three main areas: (1) networking and communication, including routing and communication overheads; (2) information processing and computational aspects, involving computational complexity and storage; and (3) algorithmic and application-specific aspects, such as training and inference.

The first two areas share common challenges with application-specific IoT (ASIoTs) outlined by Ang et al. (2019) [15], including interoperability, energy efficiency, computational complexities with edge and fog machine learning models, and security/privacy concerns. Further details on networking, communication, algorithmic, and application-specific challenges can be found in these references.

The third challenge, specific to algorithmic and application aspects, applies directly to AI smart wearables. Training AI algorithms in these wearables demands a significant amount of data, especially for deep learning algorithms. This necessitates recruiting individuals for real-world usage scenarios to gather authentic training data. Optimizing the use of multimodal data is another challenge, enhancing performance and accuracy. For instance, a smart wearable for activity recognition may integrate data from multiple sources like smartwatches, smart clothing, and smart helmets.

- Social Challenges for AI Smart Wearables

AI smart wearables face social challenges, particularly in the context of elderly adoption of AI-enabled medical devices in China, as explored by Xing et al. (2021) [6]. Six categories of barriers include: (1) technological challenges, (2) managerial challenges, (3) clinical challenges, (4) financial challenges, (5) legal challenges, and (6) personal challenges.

Technological challenges involve balancing device size, accuracy, battery life, and cost-effectiveness in design. Solutions require tailored devices to meet specific needs. Managerial challenges include securing top management support and establishing collaborations with public health organizations. Clinical challenges entail demonstrating efficacy and addressing concerns about changes in doctors' workload.

Financial challenges encompass production costs and sustainable business models, often hindered by limited public funding. Legal challenges include legislative deficiencies and data privacy issues, especially for elderly users concerned about legal risks and data tracking. Personal challenges involve building user trust, providing personalized analytical services, and addressing psychological resistance to AI smart wearables.

- Future Directions for AI Smart Wearables

The field of AI and smart wearables continues to evolve with recent innovations and potential future directions. Emerging sensing technologies, such as electronic skin (e-skin) [27] [28], offer new possibilities for transmitting health data without additional hardware or batteries. E-skin's flexibility allows for extended wear on the body.

Novel applications are emerging, including soft robotics and smart wearables for pediatric assistive devices, catering to infants below two years. These devices must adapt to smaller body proportions and increased activity levels [20] [21].

Another critical research direction is the development of interpretable or explainable AI (XAI) for health-based applications within smart wearables. This ensures transparency and trust by explaining AI-generated results to human practitioners, particularly important in healthcare settings.

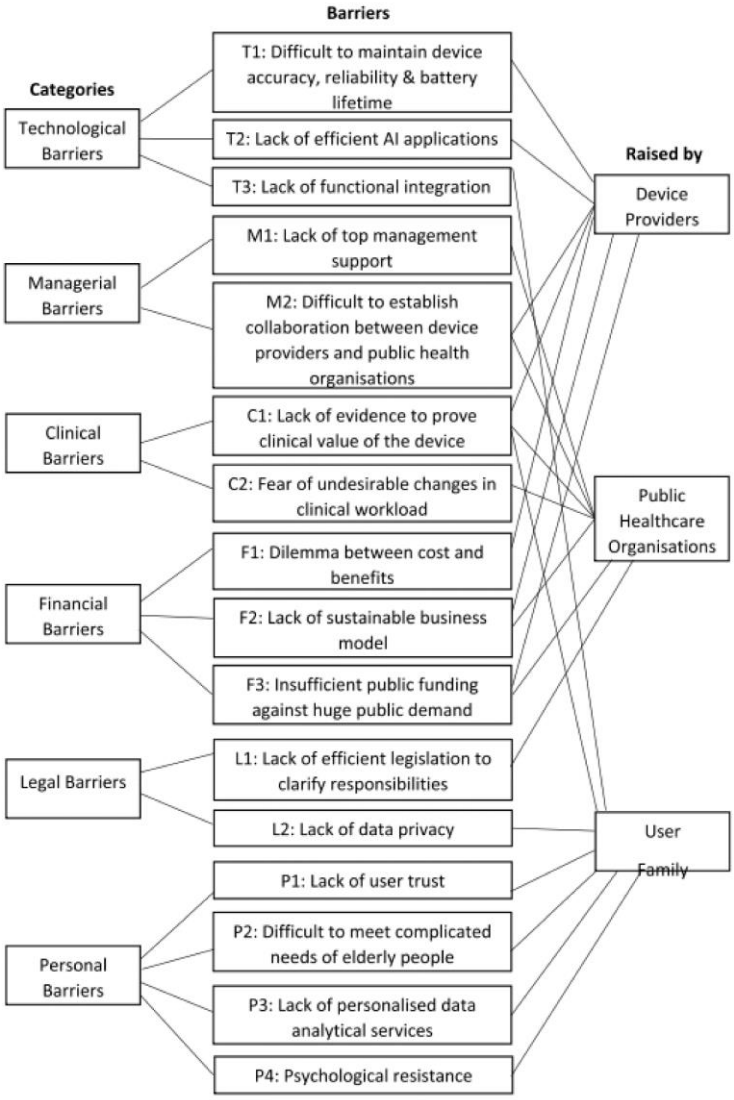

Figure 8 Barriers or challenges for AI smart wearables.

10. CONCLUSION

Wearable AR apps offer substantial potential for reshaping urban interactions, especially concerning emerging technologies like autonomous vehicles (AVs) and connected systems. The success of these immersive experiences hinges on users' perceptions of practical benefits in specific contexts, necessitating thorough investigation during design. This paper employs qualitative data analysis from two urban AR wearables to demonstrate VR simulations' feasibility for assessing comprehensive, context-aware user experiences. It significantly contributes to wearable urban AR design by providing empirically supported insights into VR simulations' effectiveness for evaluating practical benefits and urban influences. It also offers VR simulation guidelines to tackle prototyping and evaluation complexities. The paper extensively explores AI and smart wearable technology paradigms, serving as a valuable reference for applying these paradigms to sensor-driven environments. It covers deployment methods, interfaces, and insights into traditional machine learning and deep learning techniques. Additionally, it highlights unresolved challenges and outlines future research directions, recognizing limitations and potential research sources outside prominent databases. The paper offers a concise overview of privacy-preserving big data analytics, particularly focusing on homomorphic encryption algorithms. It discusses scenarios for analytical techniques between data owners and analysts, addressing real-world implementation challenges. It posits that homomorphic encryption holds promise for secure data collaboration, anticipating further advancements, especially in large-scale data analytics. A key challenge is formulating practical use cases for multimedia data due to slow security techniques, arising from limited wearable computational capacities and complex encryption. While online applications require minimal delays, offline operations like medical research statistics tolerate longer processing times. As cryptographic and security algorithms improve, industrial use cases are poised to expand, making this solution increasingly relevant for safeguarding wearable data privacy and security.

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