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No Soldiers Left Behind: An IoT-Based Low-Power Military Mobile Health System Design

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ABSTRACT There has been an increasing prevalence of ad-hoc networks for various purposes and applications. These include Low Power Wide Area Networks (LPWAN) and Wireless Body Area Networks (WBAN) which have emerging applications in health monitoring as well as user location tracking in emergency settings. Further applications can include real-time actuation of IoT equipment, and activation of emergency alarms through the inference of a user's situation using sensors and personal devices through a LPWAN. This has potential benefits for military networks and applications regarding the health of soldiers and field personnel during a mission. Due to the wireless nature of ad-hoc network devices, it is crucial to conserve battery power for sensors and equipment which transmit data to a central server. An inference system can be applied to devices to reduce data size for transfer and subsequently reduce battery consumption, however this could result in compromising accuracy. This paper presents a framework for secure automated messaging and data fusion as a solution to address the challenges of requiring data size reduction whilst maintaining a satisfactory accuracy rate. A Multilayer Inference System (MIS) was used to conserve the battery power of devices such as wearables and sensor devices. The results for this system showed a data reduction of 97.9% whilst maintaining satisfactory accuracy against existing single layer inference methods. Authentication accuracy can be further enhanced with additional biometrics and health data information.

INDEX TERMS Multilayer inference algorithm (MIA), multilayer inference system (MIS), mobile health (mHealth), wireless body area network (WBAN), low power wide area network (LPWAN), emergency alarm notification, military mobile (health) network.

I. INTRODUCTION

Significant research in the area of mobile health (mHealth) has been conducted including its applications and informatics. Internet of Things (IoT) and Low Power Wide Area Networks (LPWAN) networks are now emerging to replace previous sensor networks and technologies. These two networks together provide a suitable solution for military applications as they can satisfy the unique requirements for military mobile networks which needs to be adaptable to changing and often unpredictable environmental conditions and needs. Computational and battery constraints remain a challenge for military mobile network sensors and devices as many use portable batteries which have power constraints. To mitigate these problems, this paper proposes a Multilayer Inference System (MIS) to build a framework for military mobile networks. The following sections describe an overview of the motivation, problem statement and the chosen approach with methodologies used to develop the solution.

A. MOTIVATION

The Australian Department of Defence established the Human Performance Research network (HPRnet) focusing on the enhancement of military personnel, including

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outcomes of research in soldier performance management: Modelling of load, adaptation and performance. This is inclusive of the "*assessment and description of the physical demands and physiological responses of soldiers during military training and prediction of soldier outcomes and responses using wearable sensor data and psychometric inventories*" [1]. Additionally, a separate research program titled The *Fight Recorder* studies "*the use of a small, light and robust emergency beacon unobtrusively worn by the combat soldiers to capture the data required for incident investigation, insight into the demands of military service in a deployed environment*." In this application, there is an emergency beacon that is activated by the wearer or a medical professional. When this occurs, the device connects to satellites and the geographic location is transmitted which allows for location of personnel in an emergency e.g. an evacuation [2].

The ability to monitor the health and well-being of soldiers during training operations and in real life missions can provide crucial enhancement to mission performance and success. Recent developments have occurred in the field of Internet of Things (IoT) networks, where there has been an explosion of wireless sensors and devices that can connect to ad-hoc networks including Wireless Body Area Networks (WBAN) and Low Power Wide Area Networks (LPWAN). A more specific term of Mobile Health (mHealth) can be used when these networks and sensors/devices are used in healthcare applications, such as monitoring soldiers' health status, though the aforementioned network types are not necessarily limited to such applications.

WBAN and LPWAN networks feature several components including: availability of network without reliance on infrastructure-based networks e.g. Internet cables, cellular towers; both short and long data transmission distances; sensor devices; long-lasting batteries; and, smaller data size.

In an mHealth system, sensors (implanted or attached to the body) collect data about the user and transfers this to an intermediary device, such as a smart phone or other smart device. This is then forwarded to a cloud server where this data can be processed or further analyzed or viewed e.g. by a healthcare provider [3]. Two challenges exist when applying an mHealth system to military applications and for use in emergency situations. The first is that sensor data that is collected may not be sufficient to accurately provide information about the true health status of a soldier, and secondly, the environment may not offer access to public networks such as the internet or cellular networks for data transfer. Previously, activity recognition has been proposed as an additional variable to help determine the validity of an emergency alarm activation [4], [5]. The issue of reliance on public networks can be overcome by existing network technologies, such as Long Range (LoRa), NB-IoT and Sigfox [6]. An inference system proposed in [7] which includes algorithms to assist in situation determination can also be used in an mHealth system for a military mobile network to improve the alarm notification system accuracy.

In summary, it is crucial to observe the activity status and health conditions of soldiers in the field. mHealth can support the monitoring of soldiers' health conditions and their activity status in military networks using sensor (IoT) devices that are available and affordable with low-cost networks e.g. LPWAN. Smaller data packets can be used to transfer health data information such as vital signs. An enhanced Multilayer Inference Algorithm (MIA) can improve battery life by further reducing data volume while maintaining high accuracy through smarter energy consumption allocations. This is achieved by reducing the frequency of transmission data from sensors to a smart device which collects sensed data and transmit to a server in the cloud. When data is transferred by sensors, the most significant battery consumption is in relation to radio communications, significant savings can be made by reducing the frequency of transmissions.

This paper proposes a framework of military mHealth networks using a Multilayer Inference System (MIS) along with various military applications using mHealth in conjunction with LPWAN.

B. APPROACH AND NETWORK SETUP

Automatic alarm notification abilities can be vital when military personnel are in an emergency, such as being injured or experiencing loss of consciousness. Despite the advancement in technology and equipment being carried during modern field operations (illustrated in Figure 1), there are no automated functions dedicated to raising alarms or sending distress signals during an emergency. Furthermore, the load carried by soldiers are weight-limited and devices requiring battery packs can result in significant additional weight.

FIGURE 1. **Devices and batteries used by a US soldier during an operation – carrying a total of 70 batteries weighing at 7kg [9].**

IoT networks and military mobile health networks using inference systems that control data transmissions to the command office can be used to conserve battery power. Improving the accuracy of data processing and pinpointing data selection can extend battery life. In addition, this approach can reduce logistical cost and reduce the overall weight of equipment carried by soldiers.

A centralized power supply for equipment can be one option for improvement [8] such as consolidating compatibility of battery types. However, another approach is to reduce battery consumption of devices such as reducing the frequency of radio transmissions using a smart algorithm that can infer data. The following approach is considered:

- Structured infrastructure networks such as cellular and wireless networks are not reliably available in the combat setting
- In an emergency situation e.g. a soldier being rendered unconscious, identifying the health status and location of personnel is crucial
- Monitoring personnel devices is important to check availability, battery level, remaining equipment supplies, and require conserving battery power using an algorithm
- Remote control (actuation) of the equipment is not currently viable

An mHealth network converged with IoT networks collects health data from users, and obtains device management data such as sensor battery levels. This information is transferred to a smart device within a WBAN, which will connect to a gateway in an LPWAN as an ad-hoc node. The LPWAN gateway transfers data to a regional headquarter server, which further connects to central servers via internal (proprietary) networks. Battery consumption is reduced by performing data inference at the sensor nodes prior to transmission within the WBAN.

The standard for efficiency and accuracy expectations are predetermined according to application requirements. The presented work is based on a framework that was proposed in a previous publication [10], which proposed emerging mHealth and LPWAN networks for military mobile networks. This paper further extends this research with additional insights and experiments by applying a novel multiplayer inferencing algorithm. Five areas require integration in developing a solution to this problem:

mHealth network captures health data for monitoring of personnel and equipment. It connects with IoT networks through a smart device as an aggregation node, which will communicate with a server in the command centre.

Alarm notification is used during an emergency using Activity Recognition (AR). This function requires learning the posture and activity of personnel to avoid false alarms.

Remote actuation of devices enables the ability to locate personnel in an emergency. Search and rescue teams can access and actuate devices to pin-point locations.

Security of the network includes identification of personnel using health data combined with biometrics for enhanced multi-factor authentication.

Prediction of health conditions is critical to optimize placement of personnel during mission planning.

Due to the nature of military operations, reliable infrastructure networks are not available for establishing an LPWAN. Hence, ad-hoc networks are used consisting of devices from other personnel in the local area with a dedicated gateway device, which is then connected to a server in a regional headquarter. Appropriate security measures are applied at the gateway to protect the network. A WBAN gateway connects to a gateway of a neighbouring WBAN through LPWAN, which provides security functions with more computational power and higher battery consumption. Devices operating in a WBAN can include personal health devices that collect data and transfer them to a smart device, which functions as a node within an LPWAN. Military-grade wearables would also connect to the same smart device for management and actuation purposes. The following aspects need to be considered for a military network setup:

- Ad-hoc networks can be established with devices from other personnel
- A gateway in LPWAN collects data and connects to other autonomous systems
- WBAN has multiple routes to connect gateway devices for redundancy
- IoT/LPWAN network can be established to connect mHealth sensors, IoT devices and gateways
- A smart device plays a key role as a gateway for both networks, i.e. WBAN and IoT

This paper contributes the design of an IoT-based low power military mHealth system by emerging mHealth and IoT/LPWAN with resolving the security issues for identification of personnel and weaponry equipment via applying a novel algorithm of a multiplayer inference system.

II. RELATED WORKS

This section describes the related works, including the areas of tracking location using health data and IoT devices and network, wireless and mobile networks for military, inference system, alarm notification for health status (using AR activity recognition) and identification of personnel using health data (biological, physiological and biometrics).

A. TRACKING LOCATION AND MONITORING SYSTEM

While the emphasis has been on tracking assets and directing potential changes during missions including changes in route, or a change in destination, the rapid advancement of technologies in this space has given rise to the concept of the ''connected soldier,'' where IoT is used to integrate biometrics, biomedical devices, environmental sensors and other equipment (e.g. weapons) to monitor and enhance soldier performance. In the field, the convergence of IoT and the military battlefield is also known as the Internet of Military Things (IoMT) or Internet of Battlefield Things (IoBT). The primary goals of IoMT and IoBT are to: 1) improve the performance of soldiers in the battlefield; 2) allow for rapid identification of the enemy using Edge computing, and 3) identify and detect real-time changes to health conditions. As Figure 1 shows, soldiers have weapons systems and combat gear which are embedded with a variety of sensors and computing devices. These sensors/devices can capture real-time biometric data including information from the user's face (e.g. iris, periocular space, facial expressions), fingerprints, gestures, gait and positioning as well as physiological data such as vital signs [11], [12].

Technological advances in IoT and big-data analytics have the potential for early detection, diagnosis, and treatment [13] of a soldier's health status while they are in the field. In emergency situations, early detection of casualties and the ability to predict potential outcomes from a combat-related injury can assist triage and prioritisation for medical support. Aggregate location tracking of soldiers could provide valuable information about the live casualty status during a particular mission in a geographical region. Unit commanders could use this data to rapidly revise mission strategies and to deploy more troops or medical staff to required areas [14]. Wearables are frequently used in healthcare applications, and are becoming used more frequently to remotely monitor a variety of health-related physiological signs [15] including vitals (blood pressure, heart rate, respiratory rate, temperature), blood glucose monitoring, cardiac function monitoring, physical activity and exertion, sleep, and calories burned. IoT has the potential for high-speed processing of big data, however several issues exist including integration and communication of IoT devices, real-time transmission, network challenges, and issues facing remote geographical locations [16].

In addition to the logistical benefits of detecting casualties and remote triaging, physiological monitoring of soldiers provides numerous possibilities in general performance enhancement, and precision forecasting of soldier failure in response to physical, psychological and environmental stressors. Other benefits may include fitness and nutrition optimization and the prediction of long-term health risks, which allows for proactive medical management [14]. Presently available commercial systems such as smart watches and their proprietary algorithms limit their applicability for military grade purposes. Machine learning algorithms need to be developed based on the physiological measures which are significant predictors for soldiers. The use of clinically relevant information including soldier feedback of the context and events that may have resulted in acute changes in health can enhance activity recognition (e.g. injury). Dynamic Activity Recognition (AR) uses sensor data to predict the movement and positioning of a person, and has been primarily used to monitor movement in indoor or enclosed environments such as in smart homes. To integrate soldiers' measures of health data into military mobile networks, activity classification and decision support systems [17] are required in order to classify streams of health-related sensor data. These would include measures of physiological, psychological (e.g. abnormal behavioural responses) and environmental data (e.g. temperature and location). For complex event reasoning, these measures will need to be classified and contextualized based on desired classifications, including soldier performance, acute health events, forecasting soldier failure and long-term health outcomes as well as situational context [18]. A rules knowledge base can be used for complex event reasoning [17] where an X change in measure Y results in a health event Z. After complex event reasoning, the classified data can be integrated into the surveillance system along with other potential classifications such as weapons recognition and geospatial situation. Should the system detect an acute anomaly, the notification can be sent using a surveillance system interface and two-way decision-support system, allowing the soldier to respond to the notification where possible.

B. MILITARY NETWORK

A battlefield surveillance system is used to integrate multiple sensors and mobile devices. Several surveillance systems can then together form a surveillance network [19], which is critical for communication, teamwork and operations planning. Wireless and mobile networks for military use includes Integrated Tactical Networks (ITN) [20], [21]. Terahertz communication may have application to military use of wireless and mobile networks. Terahertz (THz) frequency band (0.1 - 10 THz) is a wireless radio communication with potential for wide bandwidth and high-speed sensor data transfer [22]. The host of sensors embedded in soldiers' gear and weapons will result in significant volume of sensor data requiring big data wireless cloud storage, making rapid retrieval of analytics imperative. It could potentially optimize telecommunications amongst soldiers, between soldiers and coalition members, and between soldiers and command centres. In summary, the ability to track soldiers on the modern battlefield is integral for soldier safety and mission success. While there may be feasible options for networks and big data storage that could already exist, the unique integration of biomedical, biometric, and environmental monitoring in an integrated surveillance system could optimize military mobile networks significantly. However, to apply this to the battlefield where soldiers' health status can be actively monitored and responded to for acute health situations, further activity classification and decision support systems need to be developed and complex event reasoning is required for accurate notifications. Ideally, the activity classification system should be a part of the integrated surveillance system.

Mobile ad-hoc networks have been used in many military and non-military applications, including healthcare settings, environmental monitoring, location tracking and activity recognition. The application of mobile ad-hoc systems in the healthcare industry is increasing with research focusing on improving and optimizing these systems. Mobile ad-hoc networks are useful for military applications due to their characteristics of autonomy, flexibility, adaptability and self-configurability [23]. Physical-layer performance of ad-hoc networks can be improved by increasing the number of relay nodes which increases spatial diversity [24]. Bands reserved for military applications, such as radar are relatively underutilized whereas spectrum bands for public cellular networks are used much more heavily [25]. Therefore spectrum-sharing opportunities and improvements are applied mainly in spectrum bands used for military applications [26].

A critical issue to address for military mobile networks is optimization of Wireless Sensor Network (WSN) energy usage. Mobile sinks are used to avoid the problem of WSNs with static sinks. Various mobility patterns in the field of sensor networks are used to increase energy efficiency and apply improved data gathering strategies [27]. Naghibi and Barati recently presented a solution to gather and deliver data to the sink node with minimal energy consumption using a wireless sensor network. To achieve this, mobile sinks were applied to divide the network into geographical cells [28].

C. INFERENCE SYSTEM AND IOT/LPWAN NETWORKS

A user-feedback system has been used for activity recognition to minimize the occurrence of false alarm notifications. The use of such a system aims to decrease the frequency at which data transmission occurs at sensors in WBANs [4], [29]. A novel method of activity recognition integration was developed to combine mHealth data of a soldier with vehicular data to modify a vehicle safety system using a cloud information system. This system is implemented by integrating the new mHealth technologies with military vehicular applications through WBAN sensors and devices [30]. Kang *et al.* also developed an inference system based on short and long-term health status prediction, inferred from health information. This system, which is built using big data in the cloud, is useful for preventing life-threatening situations [31]. This novel solution utilized an inference system that reduced data transfer to other networks from sensors, without the additional burden from IoT on sensor devices. The goal in this method is to infer data at the sensors to reduce unnecessary or redundant data transmission at the first instance, as well as reducing overall battery consumption that occurs with additional data transfer [32]. The inference system was modified and further improved with the use of beacon data points that are transferred at set intervals, regardless of the initial inference. This is to maintain a regular transmission of data at set time intervals to improve data accuracy where the inference system may not transfer data for a period, and the frequency can be adjusted using variance rates [3].

An advantage of military mobile network converged with IoT and LPWAN is to allow for tracking of users in the field. For the purpose of location tracking using health data and IoT devices and network, it is feasible to implement a functional, low cost, low data rate tracking and locating system of personnel and objects with low power consumption based on the Zigbee/XBee technology [33]. They decreased battery consumption and extended the battery life to be able to work for 126 days with a battery capacity of 1000mAh. Santos *et al.* [34] presented an IoT-based mobile gateway to extract information about location, heart rate, and possible fall detection of users or patients for mHealth scenarios when a network of body sensor tracks a person and their environment. Furthermore, this IoT-based mobile gateway can instantaneously transmit the gathered information to a caretaker Intelligent Personal Assistant (IPA) which allows them to manage alarms and a group of actions in a timely and effective manner. Further, Santos *et al.* proposed algorithms for mobile gateway services as a communication channel. They found three indices for accessing the algorithm, which includes power consumption of devices, the accuracy of each monitoring service available at the mobile gateway, and the interoperability with other objects available on the environment. Patii and Iyer [35] proposed a reliable, low priced wireless IoT based system or mechanism to monitor and track soldiers on the battlefield as a solution to high noise, installation cost and signal loss. This system features instantaneous data transmission, location tracking of soldiers, and monitoring of physiological data such as heart rate, body temperature and environmental oxygen levels. Lagkas *et al.* [36] developed a new algorithm named Hot-Cold to locate mobile monitored targets or individuals concerning the IoT system in dynamic environments with ill-defined or ill-designed infrastructure. This technique can guarantee the proximity maintenance formed from the power of the output RF signal sent by the individuals or targets to transmit its extracted data from sensors indicating their location.

Due to the development of new mobile networks, smartphones have the capacity of running complex algorithms for tactical support for low-ranking commanders and individual soldier support. Tactical data (unit location, composition, tasks) in dynamic mobile military networks can be utilized to access information anywhere during the mission and for providing practical support for decision superiority. Combat decision support has been one of the required fields in the military application using mobile ad-hoc networks [37]. They focussed on designing quantitative methods and algorithms for combat decision support using the mobile application. Their analytical tools evaluate the usefulness of implementing mobile applications for combat support, situation awareness development, and in delivering augmented reality.

Another important field of using the mobile network is health status alarm notification and activity recognition which can be implemented using sensor nodes. This feature can raise an alarm notification using sensed physiological data and activity recognition sensors [4]. AR has become a critical research subject, along with personal real-time sensors and mobile monitoring devices based on health information and predicting health status [30]. These systems and sensors require significant work to increase the accuracy of activity determination based on the situation. Some studies have focused on increasing accuracy by increasing the number of sensors in different locations of the body [38]–[40]. Some studies in health informatics have developed alarm systems using smartphones for simpler and smaller applications in pill dispensers [41], intelligent pillboxes [42] and wound assessment systems [43].

Leier *et al.* developed a human activity recognition and fall detection algorithm, which can be used to increase the safety of people in challenging working conditions. This system uses real-time information of workers which can produce alarms in the case of abnormal conditions [44]. Santamaria *et al.* developed a wearable device which can collect data from different sensors and send them to a cloud platform. The data are utilised for AR and health status notification. They also added a fuzzy-based Human Activity

Recognition (HAR) and tested different classes of data filters to reduce the volume of data sent to the cloud [45].

Chmielewski *et al.* present an application of non-invasive sensors for hosting data acquisition, filtering and analysis [46]. Selected data sources and signals are utilized to recognize and detect seizure symptoms in children. They constructed a system based on electromyography and inertial data which can be used for seizure detection. Hu *et al.* recently developed an IoT and blockchain-based healthcare system [47]. This system is mainly used for human activity recognition via monitoring vital/nonvital signals using wearable-sensors. This method is used to recognize an activity done by a patient which can be utilized as programmable alarms during a treatment period.

D. IDENTIFICATION AND AUTHENTICATION

As well as location tracking of targets through a mobile network, identification or authentication of personnel is another essential and possible outcome of the mobile network converged with IoT and LPWAN in terms of finding the intended and right target (soldiers or any other form of targets) amongst a group of individuals. Han [48] proposed a verification technology for hand-based personal authentication including two hand-based features, hand geometry and a user's palmprint where Positive Boolean Function (PBF) and the bootstrapping method adoption improved the performance. Beritelli and Serrano [49] decided to use Phonocardiogram (PCG) data to develop a system for identifying human as PCG is specific and unique to each person. They also proposed an individual identification study using analysis of cardiac sound frequency of 20 people. The two-loudest heart sounds detection algorithm proposed in this study played an active role in frequency analysis and signal matching phases and introduced a PCG sequence as a reliable physiological sign. Girish Rao Salanke *et al.* [50] proposed a novel approach to identify individuals using different and unique Photoplethysmography (PPG) signal of people in different states (stressed and relaxed) based on Mahalanobis distance between waveforms. They showed that PPG is a useful metric as it is impossible to be replicated easily compared to other biometrics such as the face, voice and fingerprint. Gui *et al.* [51] proposed an Electroencephalography (EEG) based framework to prove human identification and authentication. They not only decreased the noise level but also extracted some frequency features using ensemble averaging and low-pass filter, and wavelet packet decomposition respectively. Their classification method was derived from an artificial neural network which gave them 90 per cent accuracy of identifying authorised individuals. Spanakis *et al.* [52] analysed the voice acoustics and verified audio-visual identity for user authentication in the form of a face and voice recognition platform called SpeechXRays. They showed that a voice-and-face-recognition-based biometrics platform is sufficient for use as a valid and reliable entrance gate to sensitive data accessibility in the eHealth industry. Kacer *et al.* [53] used the FlexiGuar system as a base to develop a physiological data measurement system for air force staff in order to predict their physical and psychological situation. This system can measure body temperature, heart rate and acceleration simultaneously to contribute to the prediction of dangerous state identification for military staff. Su *et al.* [54] proposed an efficient and functional multimodal (multi-biometric) personal identification system exploiting finger vein and ECG signals in an integrative manner. Their system successfully achieved recognition accuracy and security evaluated by Receiver Operating Characteristic (ROC) and Equal Error Rate (EER) as two evaluation metrics. Aziz *et al.* [55] introduced a reliable, accurate and comparatively less expensive ECG based biometric authentication system through denoising raw ECG data and extracting interest regions from data using Empirical Mode Decomposition (EMD). Furthermore, they extracted some features including variance, skew, Shannon energy, occupied bandwidth and median frequency which were then classified using Support Vector Machines (SVM).

The human body possesses several traits and features which are almost universally present yet unique. Some of these traits, such as fingerprints, have been used historically for identification/authentication purposes in various applications [56]. Since each biometric trait has its own advantages and disadvantages, no singular biometric trait can meet the requirements of all applications. Some common biometric traits are briefly introduced below. The pattern of valleys and ridges on fingertips are defined as fingerprints. Fingerprints are one of the most reliable biometric traits for human identification/authentication, hence the prevalence of research papers and various applications which utilize this feature [57]. The convenient and non-intrusive nature of facial recognition methods has resulted in its popularity in many applications. The features used for recognition can include the eyes, eyebrows, mouth and nose shape [58]. The iris patterns of any two eyes are independent due to the epigenetic nature of iris patterns, and studies have found that even identical twins have iris patterns which are unrelated [59].

In conclusion, we found that an MIA can improve the longevity of battery power. Due to the computational limitations of devices however, such a system needs to be designed with efficiency in mind. Health data can be combined with biometrics to improve authentication and user identification. There is feasibility for ad-hoc networks to be used for military mobile health network purposes with various applications.

III. THE PROPSOED SOLUTION

This section describes the proposed solution, which includes the mHealth network to be emerged with IoT and LPWAN networks.

A. mHEALTH NETWORK USING MIA AND APPLICATIONS

The mHealth network refers to a collection of internetworking devices and systems architecture used for optimal collection, classification, and delivery of health information. The journey typically starts from the users/patients (capturing vital physiological signs), traversing across multiple

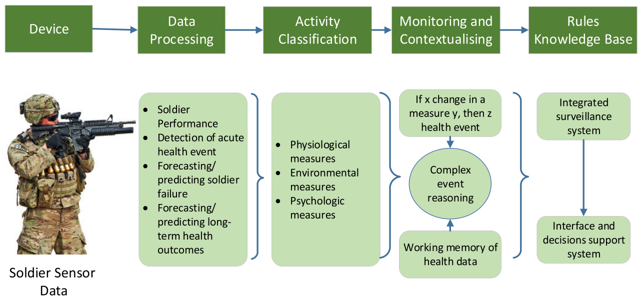


FIGURE 2. **Activity Recognition and Detection Support.**

platforms, hops and nodes across the internet as shown in Figure 3.

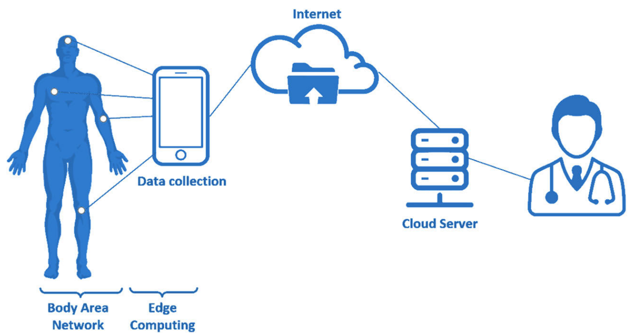


FIGURE 3. **mHealth Network.**

There are several technologies and protocols being used in the mHealth space, which are optimized for various segments of this end-to-end link, such as data capture, information management, user-centric device/sensor functionality, and protocol and data exchange. In this section, the focus is placed on the Body Area Network (BAN) segment shown in Figure 3. Other variants of BAN (xBANs), include Wireless Body Area Networks (WBAN), Body Sensor Networks (BSN), and Medical Body Area Networks (MBAN). Internet of Things (IoT) is the internet-aware feature of the xBAN devices, which requires these devices to have certain capabilities to not only route the health-driven data across the network efficiently but also provide bidirectional feedback to the user/patients from the cloud/internet stakeholders (e.g. remote doctors). The provisioning of mHealth devices with IoT capabilities has brought healthcare services closer to patients and users [60].

According to Nazir *et al.* [60], applications of IoT in healthcare can be categorised into two main applications: Single health condition and cluster health (greater than one) conditions. The single main conditions are comprised of glucose level, blood pressure, blood oxygen level, body temperature and electrocardiography signal capturing.

The cluster condition applications are those dealing with the wheelchair, rehabilitation, and smartphone intervention healthcare solutions. The investigated IoT-based healthcare services included Ambient Assisted Living (AAL), Internet of mHealth Things (mIoT), mHealth Community Healthcare (mCH), and mHealth Paediatric Healthcare (mPH).

The interconnection of IoT devices, as well as systems and architectures belonging to the city infrastructure is often categorised as a Smart City. The Smart City Paradigm aims to manage devices and associated data to monitor and analyse the interactions of urban stakeholders efficiently. These include [61] people (smart citizens), smart energy, smart buildings (including homes), smart mobility (traffic and transportation), smart healthcare, smart infrastructure, smart governance, smart education, and smart security.

The communication protocols used to interconnect IoT-based devices and gadgets into the smart city communication grids include Radio-Frequency Identification (RFID), Near Field Communication (NFC), Low Rate Wireless Personal Area Network (LWPAN), ZigBee (and its longer-range/higher throughput variant; ZBee), and IPv6 over Low-Power Wireless Personal Area Network (6LoWPAN).

Military and defence applications fall within the domain of the smart city paradigm, and they belong to a specific class of high resilience devices and protocols that are expected to operate under harsh natural conditions (e.g. low visibility, high mobility, low bitrate etc.). Requirements for this class of applications are discussed further throughout this paper.

MIA is used to improve the accuracy and efficiency of the existing inferencing algorithm [7].

A two tier MIA is developed according to the following method:

1) Apply first inference algorithm (e.g. reduce 10,000 data points (DP) -> 1000 DPs)
2) Optimize (find more samples to reduce the gap between the original and sample data points) (e.g. 1000 DPs -> 1100 DPs)
3) Apply second inference algorithm (e.g. 1100DPs -> 300 DPs)
4) Optimize (find more samples to reduce the gap between the original and sample data points) (e.g. 300 DPs -> 320 DPs)
5) Finalise the sample DPs to calculate accuracy rates (AR) and savings rates (SR)

The real-time monitoring of personnel and equipment in the field is critical to ensure a successful military operation. Command centres are concerned with conducting efficient, precise and cost-effective warfare [14]. High value assets such as soldiers, military equipment and vehicles need to be monitored in real-time to enable precise manoeuvres in the field. GPS positioning systems have well-known, relatively simple applications to track the location of personnel and equipment. However, complexities are inherent in monitoring the physiological health of a soldier in the field. Real-Time Physiological Monitoring (RT-PSM) can be useful for medics and commanders to assess the physical and psychological health and wellness of a soldier [62], [63]. For RT-PSM to monitor and potentially forecast changes in health status, sensors will need to be worn or attached to the body of the soldier. Non-invasive, wearable, and tuneable electromagnetic multi-sensing systems have the potential to be used in soldiers. Electromagnetism (EM) is considered a leading technology in multi-sensor applications in health care and has been used for glucose monitoring [64]. EM sensors can be stretchy, adhering metallic devices that are able to radiate or receive EM waves. The types of sensors and number of sensors or monitoring devices will need to be determined based on the number of physiological measures that need to be collected [15] to allow the activity monitoring and decision-making system to make precise and clinically-relevant inferences about a soldier's health condition. Precision health is a concept used in medicine "*to enable a new era of medicine through research, technology, and policies that empower patients, researchers, and providers to work together toward development of individualized care*" [65]. Although technological advancements have enabled the collection of copious amounts of sensor data, the achievement of precision health for the public continues to be elusive [65]. Predicting or forecasting health-related outcomes requires unique algorithms determined by the desired outcome measures e.g. soldier's performance during training, during combat and long-term health outcomes such as chronic illnesses or suicide risk. The physiological data of a soldier may be vastly different on the battleground when compared to peace-time training [14], [66].

Based on the health and device data processed by the inference algorithm, an alarm can be raised by the smart device which sends an alarm to a server at a regional headquarter. To minimize false alarms, the smart device prompts for a confirmation prior to raising the alarm through a message display on the device. A timeout is applied such that if no response is detected within the time threshold, the alarm is raised automatically. A situation determination process is conducted by the pre-defined threshold table to determine whether the condition of the user would necessitate an alarm. Activity recognition is used to determine the posture or motion movement of the user to assist in determining the status of injury, level of consciousness or normal condition of the user. Management alarms are raised for sensors and device monitoring tasks such as low battery levels.

When a user is unresponsive to the confirmation message sent on the smart device, hardware devices may also be activated to aid rescue personnel to locate the user. The user may be equipped with some medical or emergency devices that can be operated remotely. Pre-programmed devices such as wearables may actuate automatically following the situation determination process without remote operation. Devices can include mHealth sensors for vital signs (heart rate, body temperature, respiration rate and blood pressure), AR sensors (such as accelerometers and gyroscopes) and smart devices with GPS. Personal equipment is connected to WBAN for management purposes to provide the status of battery level and availability. For a rescue operation, remote actuation may be fulfilled by triggering personal devices such as beacons to aid the physical rescue team in locating the injured personnel on the actual field.

B. IDENTIFICATION OF PERSONNEL USING BIOMETRICS

It is feasible to use biometric data of a soldier for identification purposes, which can be used to activate and deactivate weaponry equipment to prevent an adversary from acquiring and using them. As shown in Figure 4, biometric data can be extracted from two types of biometric traits, namely physiological traits such as the iris, fingerprints, and facial patterns and behavioural traits such as keystroke recognition and voice. There are seven properties of a biometric trait that determine whether it can be used for a biometric application with specific requirements [56]. These seven properties are:

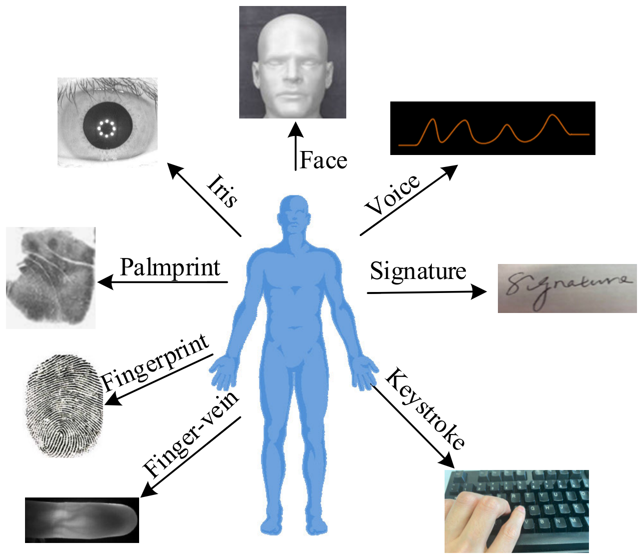


FIGURE 4. Examples of some physiological and behavioural biometric traits.

1) Uniqueness: this is the most important requirement for a biometric trait. The biometric traits that can be used for verifying individual identity must differ from one individual to another so that they can serve as that individual's unique identification (ID) [67].
2) Universality: biometric features should be universally present across most people. Very few people may not have certain traits in rare circumstances.
3) Permanence: the trait should be constant over a long period of time.
4) Measurability: a biometric trait should be easy to capture without demanding significant time and cost.
5) Performance: the recognition accuracy requirement imposed by an application should be met. To achieve this, a biometric trait should exhibit small intra-user variability and large inter-user variations. This means that features extracted from the same individual by multiple acquisitions should be similar, while features extracted from different individuals should be different.
6) Acceptability: individuals should be willing to use the trait in biometric applications.
7) Circumvention: it should be difficult for a biometric trait to be replicated.

TABLE 1. Comparison of some biometric traits in terms of seven properties (adapted from [56]) 'H' = high, 'M' = medium, 'L' = low.

Biometrics	Face	Iris	Finger print	Palm print	Keystroke	Signature	Voice
Universality	H	H	M	M	L	L	M
Uniqueness	L	H	H	H	L	L	L
Permanence	M	H	H	H	L	L	L
Collectability	H	M	M	M	M	H	M
Performance	L	H	H	H	L	L	L
Acceptability	H	L	M	M	M	M	M
Circumvention	L	H	H	M	M	L	L

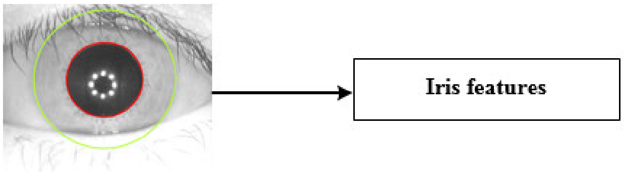


FIGURE 5. Extraction of the iris features from an iris image (adapted from [70]).

Several commonly proposed and used biometric traits have been outlined in Table 1 in relation to the seven properties. The iris has low acceptability, but can offer high universality, uniqueness and performance. In recent years, iris recognition has become an active scheme for personal recognition because of the high reliability and uniqueness that iris patterns can provide, especially when high recognition accuracy is required [68]. The human iris is the annular part between the pupil and the sclera, as shown in Figure 5, and is considered one of the most reliable biometric traits [69]. Military applications have strict security requirements and therefore require high recognition accuracy. Iris-based recognition systems usually outperform systems using fingerprints or face, thus in this paper, we present an iris recognition system as an example for showing how to perform personal recognition with the iris – this approach is based on [70].

Unique iris patterns can be extracted from the digitized image of the eye using image processing techniques and encoded into a feature vector, which can be stored in a database as the template. If a person wants to be authenticated by the iris authentication system, their eye image is first captured. Then a feature vector is extracted and compared with its claimed template in the database. If the similarity between them is larger than a predefined threshold, then a matching report is given and the authentication is successful [59]. To achieve highly accurate recognition of individuals, discriminative features in an iris pattern should be extracted. Generally, there are a few stages to extract the iris features, including segmentation, normalization, and feature encoding [59]. Specifically, in the segmentation stage, the actual iris region is isolated in a given eye image as shown in Figure 5. In the meantime, artefacts such as specular reflections within the iris region should be excluded with proper technique. In the normalization stage, the iris region is converted into fixed dimensions, such that even if two iris images of the same eye are captured under different conditions (e.g. various imaging distance, different eye positioning or rotation), features at the same spatial location can be extracted. In the feature encoding stage, from the normalized iris region, a number of feature encoding algorithms, e.g., wavelet encoding, Gabor filter, 1D wavelet, Haar Wavelet, Laplacian of Gaussian filter, can be used to extract iris features, which are used to perform intra-class matching (comparing iris images from the same eye) and inter-class matching (comparing iris images from different eyes).

In this study, the VeriEye SDK [71] is used to extract the iris features from the iris images. The feature vector extracted from each iris by the software includes 2348 integer values $I = [I(1), \ldots, I(i), \ldots, I(2348)]$, where i ranges from 1 to 2348 and each integer value $I(i)$ is in the ranging from 0 to 255. As in the method used in [70], each of these integer values is quantized with the following equation,

$$B_{I(i)} = floor(I(i)/S_{\Delta}) \tag{1}$$

where S_{Δ} is the quantization step size and is set to be 64 in this application; *floor*() is a function that rounds a value to the nearest integer towards minus infinity. By applying equation (1), the value of $B_{I(i)}$, can be 0, 1, 2, or 3, of which its corresponding binary representation is '00', '01', '10', or '11', respectively. By concatenating all the binary representations, e.g., $B_{I(i)}$, a binary feature vector F with a feature length of L=4696 bits can be produced from each iris image and can be used for matching. In the matching process, the similarity between the template feature vector F^T and the query feature vector F^Q is calculated by equation (2) as:

$$S = \frac{\sum_{k=1}^{L}(F^Q(k) - \overline{F^Q})(F^T(k) - \overline{F^T})}{\sqrt{\sum_{k=1}^{L}(F^Q(k) - \overline{F^Q})^2 \sum_{k=1}^{L}(F^T(k) - \overline{F^T})^2}} \tag{2}$$

where $F(k)$ represents the k$^{\text{th}}$ element of F and $\overline{F}$ is the mean value of F. Moreover, T represents template and Q represents the query. The authentication is considered successful if the value of S is greater than a predefined threshold.

Multi-factor authentication uses biometrics in combination with health data information to increase accuracy and security. Single-factor authentication is less secure and not ideal for a military application. For example, compromised biometrics for an individual could compromise access to potentially dangerous equipment and personal health information. The smart device holds the algorithm to determine personnel identification using a data set that includes predefined threshold data. In addition, it is necessary to have a safeguard that would override normal authentication procedures in an emergency, such as accessing restricted information by using a pre-recorded higher-level access password.

IV. DISCUSSION

There are two types of health data for experimentation: 1) Physiological data (e.g. vitals) and 2) Biometrics data (e.g. retina and fingerprint pattern.)

A. MIS OF IOT AND PERSONAL HEALTH DEVICES

The mHealth network provides a data inference system to reduce the frequency of data transfer and conserve battery power of sensor devices, which is critical in mHealth security. This has been further enhanced using MIS, which applies inference algorithms multiple times to increase the accuracy and efficiency by adding a process of optimization.

Health data combined with biometrics increase the accuracy of identification with multi factor authentication.

1) EXPERIMENT SCENARIOS AND APPROACH

This section describes the process of optimizing the data set and reducing data size through the application of the inference system. As previously stated, different inference systems such as applying variance rate, removing duplicate data and using beacons have been studied in various experiments and applications [7], [10], [11]. A practical inference system can extract a smaller volume of data, while ensuring that the gathered data continues to represent the original data set. In this study, the MIS could analyze the sensed data variance and compare it with predefined threshold measures. As health data will vary between individuals based on their age, gender, health conditions and status, the threshold is defined by a health practitioner who examines the user and defines a personal threshold.

Primary physiological data includes heart rate (HR), body temperature (BT), respiration rate (RR) and blood pressure (BP). HR is more amenable for experimentation and in providing a rich data set, as it can change rapidly and is sensitive to changes in the body and psychological state. Large quantities of HR values can be produced within a specific time; hence it has been chosen for use in the study's inference system.

The main objective of the inference system is to decrease the frequency of transmission in sensor nodes as well as to conserve battery consumption which is vital in military applications. Such an inference system can be implemented in military systems by not transferring unchanged or almost unchanged data and the data that does not affect the data analysis step. In this study, we use a MIA, including maximum and minimum points (relative extrema) of heart rate data points in each trend of heart rate data set, and optimize the sensed data set in two layers. The MIA can optimize the data set through different layers and steps to decrease the number of data samples from the original data set.

The MIA also uses beacons which are samples taken at set intervals to modify the distortion of inferred data as much as possible [7]. These intervals can be classified to the short and long interval for exercise mode based on every second, and for normal or non-exercise mode based on every minute, respectively.

The MIS developed in this study includes two inference layers consisting of four different steps to achieve efficiency with a high savings rate:

1) The first layer of the inference system extracts data from the original data set based on the maximum and minimum points and the 60-seconds beacons period. Figure 6 shows the real value in comparison to the inferred value graph, which is derived from applying the inference system.
2) The first layer optimizes the extracted data set from Step 1 by adding additional valuable data to the inferred data set to minimize the gap between the original and inferred data points. This process will increase the accuracy, however, will reduce the savings rate as a trade-off.
3) The second layer of the inference system extracts data from the previous inferred data set in Step 2 using a predefined variance rate. This step improves the savings rate; however, the accuracy rate will decrease.
4) The second layer optimizes the extracted data set from Step 3 by adding additional valuable data to the inferred data set to increase algorithm accuracy. This step improves the accuracy rate. As a result, the accuracy rate improves significantly whilst the savings rate is slightly reduced (as shown in Figure 7). The savings rate increased by 10.3% whilst the accuracy rate decreased by 0.91% against the baseline results as shown in Figure 7(a) and inferred results in Figure 7(d) using 1000 data points.

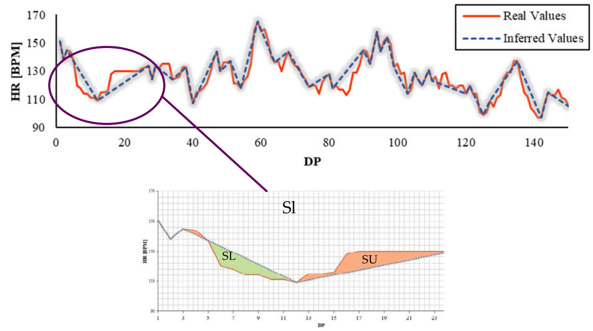


FIGURE 6. Graphical concept of SU and SL.

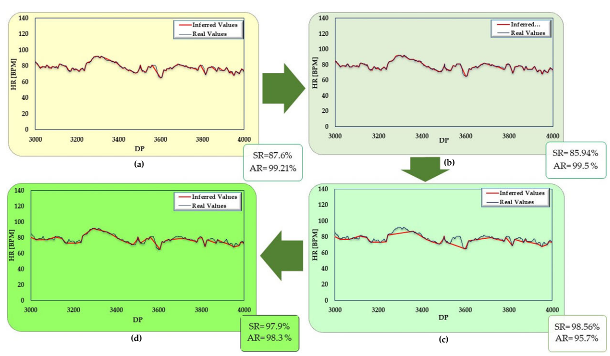


FIGURE 7. Progress trend of inference system after each layer of extracting data in a heart rate data set. (a) applying Max. and Min. points (b) extracting points with the specific gap between original data and inferred data graphs (c) applying variance rate between inferred data (d) extracting points with the specific gap between real data and inferred data graphs.

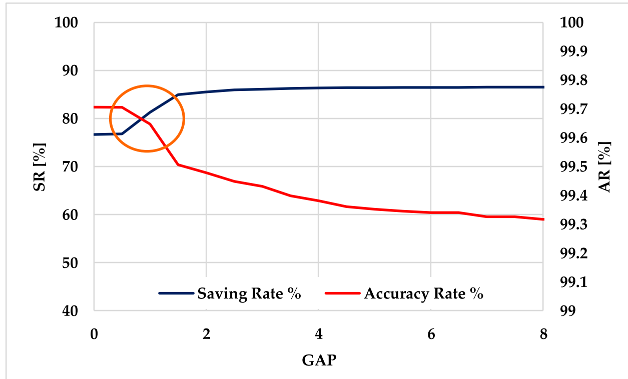
In the first layer of the inference algorithm, it compares a data point with a previous one; if there is a positive difference between those data points (i.e. increasing rate of HR), the MIA will continue comparing a data point with a prior one, until there is no sign of the increasing trend and a positive difference. This stopping point (relative extrema) will be transmitted as an inference value, and then the system continues with the same comparison. This system can transmit all the maximum and minimum points and covers all the time periods in this step. Then the first inference layer completes by applying beacons. Optimizing the inferred data resulted from the first inference layer is the next stage. To increase the accuracy of the inferred data, the MIA extracts more valuable and effective data points which were not extracted in the first layer of the inference algorithm. This optimization step includes a count of the maximum absolute differences between the original and the sample data in each and every period (S_l and S_u) and extracting those which are greater than a defined threshold (e.g. more than 2 per cent of real data points). The mentioned threshold should be the most optimized. The higher the accuracy and savings rates, the better and more optimized the threshold is. Furthermore, in this step, the AR and SR for different thresholds are calculated, and the most optimized one is extracted which lets the MIS achieve the best accuracy and savings rates as shown in Figure 8(a).

Although this inference system can result in a reasonable accuracy rate, it may not demonstrate satisfactory savings results in certain data sets, particularly where there are expected to be large and frequent fluctuations in values. In these volatile data sets, it is likely to generate a large number of maximum and minimum points, and subsequently a relatively large number of extracted data points resulting from the first inference layer as shown in Table 2.

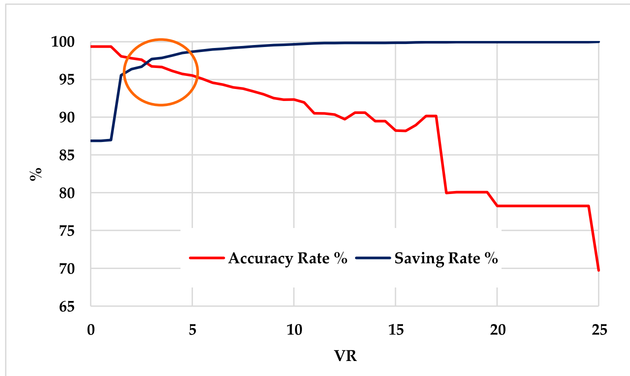
TABLE 2. Savings and Accuracy Rates in different layers and steps for low and high fluctuation data set.

Low Fluctuation Data set					
Parameters	HR Original Data	First Inference	1st layer optimization	Second Inference	2nd layer optimization
			Gap = 2.5%	VR=3%	Gap = 7.5%
DP	11288	1400	1587	163	237
Savings (%)	-	87.6	85.94	98.56	97.9
Accuracy (%)	-	99.21	99.5	95.7	98.3
High Fluctuation Data set					
Parameters	HR Original Data		Gap = 6%	VR=13.5 %	Gap = 15%
DP	4292	1921	2013	305	330
Savings (%)	-	55.24	53.1	92.9	92.3
Accuracy (%)	-	98.6	98.94	92.3	93.5

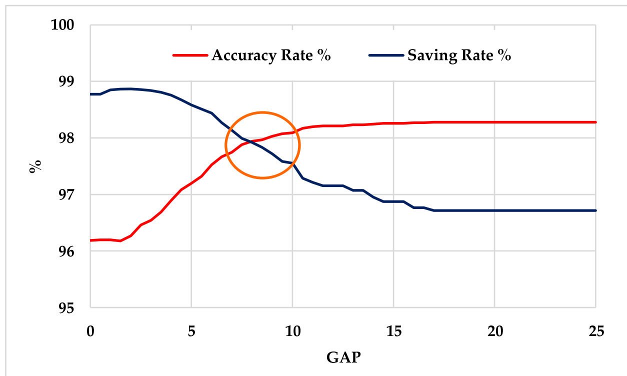
The first layer of optimization is applied to improve the accuracy. In this stage, the gaps between original and inferred values are monitored. Between each two inferred points, a point with a maximum gap between two plots is selected and if the gap is above a defined and optimized threshold, this point will be extracted as a new inferred point, and added



(a)



(b)



(c)

FIGURE 8. Sensitivity analysis of savings rate and accuracy rate for low fluctuation data set for the purpose of optimization, (a) finding the optimized percentage of the gap in the first layer of optimization, (b) finding the optimized VR in the second layer of inference system. (c) finding the optimized percentage of the gap in the second layer of the inference system.

to the inferred data set. This layer has a notable impact on the accuracy of MIS, which is shown in Figure 7(b) and Table 2.

Although these two steps result in an excellent accuracy of MIS, the total number of inferred points are unsatisfactory (Table 2). Therefore, the third step is applied. In this step, the second inference algorithm named variance rate (VR) can be implemented. The VR algorithm compares the variance between two consecutive data resulting from the two previous steps, including every minimum and maximum data point against the data set from the first optimization step.

In this layer, if a point passes the predefined threshold, it is extracted as an inference value. By applying the VR algorithm, the inference algorithm can avoid the unchanged or nearly unchanged data point from the last stages (Figure 7(c)). The mentioned predefined threshold of VR in this study is optimized variance rate, which could result in the best accuracy and savings rates. In this step, different AR and SR based on the different VR are calculated, and the best VR related to the highest AR and SR will be chosen. This VR is shown in Figure 8(b) where two lines intersect each other. In the last step, an optimization process like the second step is applied to the inferred data. This is done to increase the accuracy of the system (Figure 7(d)). The VR can be adjusted based on the different requirements, situations and applications. The complete inference system is shown in the algorithm in Figure 9.

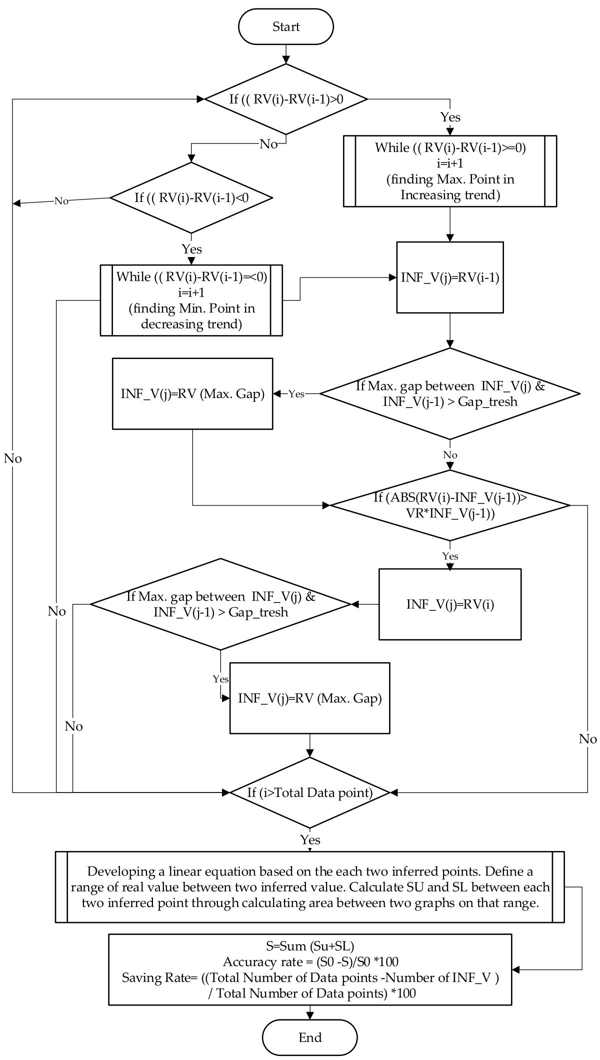


FIGURE 9. Algorithm of Inference system including detecting Max and Min Points, detecting points with Max Gap and VR between extracted data points.

The quality of output data transmission from the inference system is analyzed using three indices, including Efficiency Rate (ER), Savings Rate (SR) and Accuracy Rate (AR) of which terminology are defined as below [7]. The ER equation is shown in (3):

$$\text{Efficiency Rate (ER)} = \frac{(No.of\ Sensed\ data - No.of\ Transferred\ data)}{No\ of\ Transferred\ data} \times 100 \tag{3}$$

SR shows the data size reduction rate through the inference system and is shown in (4):

$$\text{Savings Rate (SR)} = \frac{(No.of\ Sensed\ data - No.of\ Transferred\ data)}{No\ of\ Sensed\ data} \times 100 \tag{4}$$

The smaller the volume of data transmitted from the original data set, the less battery consumption that can occur resulting in greater energy efficiency.

The AR shows the amount of produced and transmitted data accuracy using the inference system and is shown in (5):

$$\text{Accuracy rate (AR)} = \frac{S_0 - S}{S_0} \times 100 \tag{5}$$

where S_0 = Area beneath original DPs and S = sum of differences which refers to the sum of the gaps between the transferred data and sensed data plots and:

$$S = S_u + S_l \tag{6}$$

S_u shows the area of gaps where the inferred values are less than the original ones, whilst S_l shows areas of inferred values that are higher than the original values.

$$S_u = \sum_{k=2}^{n} Snu, \tag{7}$$

where Snu = area differences between general values and inferred value between inferred value k and k-1 in the cases that the inferred values are less than the original.

$$\text{Similarly, } S_l = \sum_{k=2}^{n} Snl, \tag{8}$$

Legend:

- DP = Data Point
- i = Data point calculator
- RV = Real Values
- INF_V = Inferred Values
- S0 = area beneath the real value graph
- SL = area of differences between two set of data in each pair of data in which inferred data is higher than original data
- SU = area of differences between two set of data in each pair of data which inferred data is lower than original data
- S = Sum of all SU & SL
- VR = Variance rate

- Gap_tresh = Specified threshold for gap between real data graph and inferred data graph

where *Snl* = area differences between general values and inferred value between inferred value *k* and *k-1* in the cases that the inferred values are less than the original. The graphics of S_u and S_l are depicted in Figure 6. Higher values of total area gaps refer to greater distortion in comparison to the original data set, and lower values of S in (6) imply a better accuracy rate in the inference system.

The smaller the differences, the closer the extracted sensed data set is to the original data set. Therefore, these figures can determine how accurate each inference is with different amounts of VR, while the decreased number of extracted data points can be defined as efficiency. Zero gaps between plots prior to and after applying a VR ($S = 0$) would represent the original data completely with no distortion [5].

2) EXPERIMENT METHODS AND DATASET

Data set: Two data sets from the University of Queensland Vital Signs Dataset was used in the experiment, which included vital signs such as heart rate, SpO2 (oxygen saturation), NBP, ETCO2 [7].

Experiment: This study applied a novel MIA on two different data sets used for our experiment. One of the data sets had a lower fluctuation of values, whilst the other had higher fluctuation over a specific time interval. The developed MIA was applied to the high fluctuation data set with 4292 valid HR data points, and the lower fluctuation data set with 11288 valid HR data points. Changes of AR and SR resulted from the different number of VRs are shown in Figure 10. Matlab R2019b was used to develop the MIA for coding and visualization with graphs.

3) RESULTS AND ANALYSIS

The results of applying the multi-layer inference system are shown in Figure 10. This figure shows the saving rate and accuracy of the inference system in the VR percentage range. VR=0 represents applying relative extrema inference layer and beacons without using VR inference layer. Figure 10(a) shows the results of the inference system applied to the low fluctuation data set. This study aimed to reduce the size of data points (more than 90%) with an acceptable accuracy rate of more than 90%. An optimized inference system is defined as the system resulting in a savings and accuracy rate of greater than 90%. It can be inferred that the closer these values are to 100%, the better the results are to be expected. The optimum accuracy and savings rate would ultimately be adjusted and defined based on the requirements of the end user.

Graphical distortions of inferred values against original values in VR=0 and VR=3% are depicted in Figure 10(a). This subgraph shows the heart rate along with the 500 data points. As it is demonstrated, VR=3% is the optimized point which has an acceptable savings rate and accuracy rate. VR=3% is extracted as the optimized VR based on Figure 8(b).

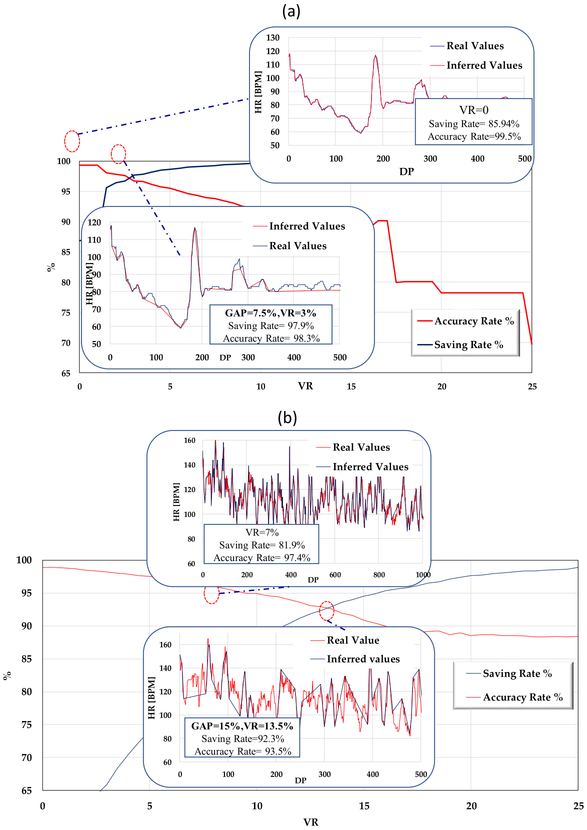


FIGURE 10. Savings rate and accuracy rate graphs after application of the inference system to (a) low fluctuation data set (b) high fluctuation data set. X-axis represents the variable rate and Y-axis represents Savings and Accuracy rates.

Figure 10(b) shows the savings rate and accuracy rate of the MIA with different VRs applied and all four steps of the MIS on more volatile data set. Graphical distortions of inferred values against original values in VR=7 and VR=13.5% are depicted in Figure 10 with 1000 and 500 data points respectively. As it has been shown, VR=13.5% is the optimized point which has optimized savings and accuracy rates resulting from applying the MIA. According to the subgraphs (a) and (b) in Figure 10, it can be deduced that the increase of VR reduced the accuracy rate while increasing the savings rate. Based on this trend, it can be inferred that with a smaller VR, the degree of accuracy provided by MIA is more significant. In contrast, the degree of accuracy is lower at the higher levels of VR.

As shown in Table 2, the data size was significantly reduced after applying the MIA. As it is evident in this table while applying the first layer, a high level of accuracy will be obtained; the savings rates were not tolerable in data sets with high fluctuation. After applying the second layer, the savings rate improved to an acceptable level. The accuracy rate decreased but remained satisfactory. By showing the savings and accuracy rates in one plot, points with acceptable savings and accuracy rates can be extracted. In Figure 10(a), the inference system with VR=3% is one of the optimal points to choose as it has a savings rate of 97.9% and an accuracy rate of 98.3%.

Optimized values in high fluctuation data set are merely different. As shown in Table 2, the first inference layer (with Max and Min points and beacons) has a 55.2% savings rate and a 98.6% accuracy rate. The first layer of the optimization (detecting points with a max gap) is applied to improve the savings rate, and the result is shown in Table 2. It is clear that VR=13.5% is one of the best points within the inference system to choose as it has a 92.3% savings rate and 93.5% accuracy rate based on the Gap=15% in the second layer of optimization. Achieving a higher accuracy rate is possible at lower savings rates. For the purpose of optimization in the low fluctuation data set, AR increased by about 0.3% and 2.6% after applying the first and second layers of optimization respectively. Regarding high fluctuation data set, this number increased by 0.3% from 98.6 in the first layer of the inference system to 98.94 in the first layer of optimization, and around 1.2% from 92.3 to 93.5%, which is a notable level of optimization in this range.

Additionally, by applying the MIS in two tiers, the system resulted in a 97.9% savings rate and 98.3% accuracy rate for the low fluctuation data set. These figures were 92.3% and 93.5% for savings and accuracy rate respectively for the high fluctuation data set. In comparing these two data sets, the results show that while the low fluctuation data set with a relatively lower VR can achieve the optimized results, a more volatile data set with greater fluctuations requires a higher VR implementation to obtain high accuracy and savings rates.

In summary, the MIA reduced data samples by 97.9% while maintaining a 98.3% accuracy against existing methods using 2-layer inferencing. Additional layers can be applied as required depending on the size of the dataset, for example an electronic health record whose dataset may be large.

When compared to a single layer inferencing algorithm [7], MIA shows significant enhancement for accuracy and savings rates, whilst it is not fully comparable for the inferencing variables may be different. For example, a single layer inferencing algorithm showed results with 89.7% and 93.7% for accuracy and savings rates, whilst MIA demonstrated 98.3% and 97.9% respectively.

B. BIOMETRICS

The study of an iris recognition system is considered for the measurement of physiological characteristics in identity recognition.

The performance of the iris recognition system was evaluated on a publicly available database (CASIA-IrisV3-Interval [72]) in which there were 2639 iris samples in the size of 320 × 280 pixels collected from 395 different eyes. Only the 1332 left iris samples from this database were utilized for input into VeriEye SDK for feature extraction. Feature extraction for 179 samples failed, and thus these samples were excluded from progressing through the experiment. A total of 1153 (=1332-179) samples were included in the experiment to evaluate the system performance through the following three metrics: false acceptance rate (FAR): the proportion of times the system grants access to an unauthorized person, false rejection rate (FRR): the proportion of times the system fails to grant access to an authorized person, and the equal error rate (EER): the value when FAR and FRR are equal. In the experiment, the feature vector extracted from the first iris image of each eye is compared with the rest of the iris images of the same eye to calculate the FRR, while the feature vector extracted from the first iris image of each eye is compared with the feature vector extracted from the first iris image of different eyes to calculate the FAR [70].

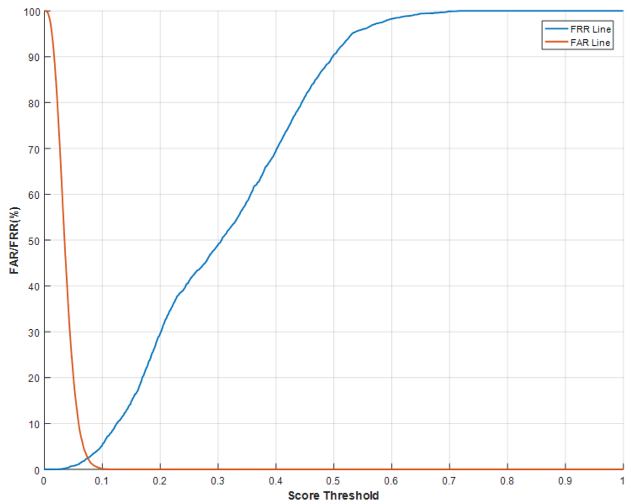


FIGURE 11. **Performance of the iris recognition system, EER=2.54%, when M=1.**

As there is possible iris rotation during the iris image acquiring process, shifting of the obtained binary string in the matching process is essential to obtain satisfactory performance. In this experiment, the template feature vector is not shifted, but the query feature vector will be shifted left or right up to M=1, 4 and 7 bits, similar to [70]. After each shifting, a similar score is calculated between the template feature vector and the generated query feature vector. In this way, a set of 2M+1 score is calculated by using equation (2), and the maximum score is considered as the similarity score between the two compared iris images. After the matching process is run on the whole database, the Receiver Operating Characteristic (ROC) curves of the system is generated with the calculated similarity scores and is shown in Figures 11 - 13. These figures show that with an increasing similarity threshold, the FAR reduces, while the FRR increases. The crossing point of the FAR and FRR lines is the EER. It can be seen that when M is set to be 1, the EER is 2.54%, while the EER=0.22% when M increases to 4 or 7. Even if the EERs are the same, there is a greater computational cost when M=7 than when M=4 as more template and shift query feature vectors have to be compared.

The FAR and FRR can be configured by adjusting parameter settings; in this way, the system security level can also be adjusted. The lower the FAR, the higher the security of the system as the proportion of false users wrongly accepted is less; however, a lower FAR means a higher FRR, which

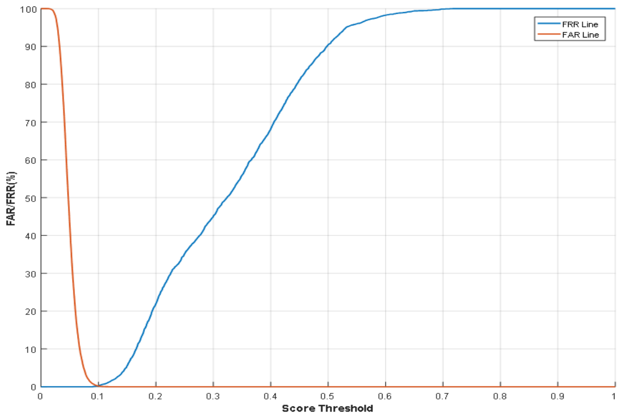


FIGURE 12. Performance of the iris recognition system, EER=0.22%, when M=4.

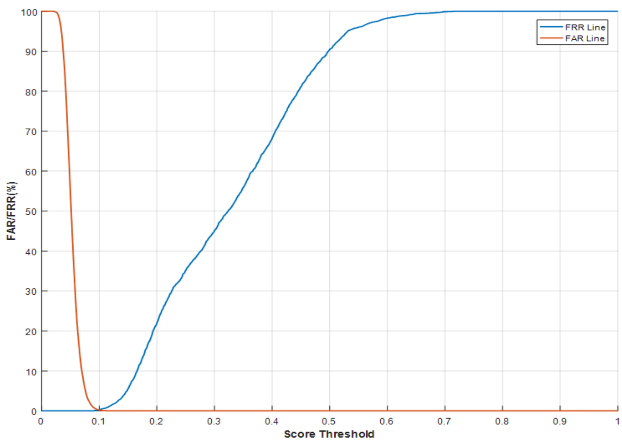


FIGURE 13. Performance of the iris recognition system, EER=0.22%, when M=7.

means the system will be less convenient as the proportion of wrongly rejected users is higher. Therefore, there is a balance between system security and user convenience, and the acceptable standard for each should be carefully considered and designed in the practical application of the biometric authentication system.

V. CONCLUSION

In this paper, a general wireless body area network-based framework was constructed to assist soldiers in emergency situations such as in field operations. The proposed framework includes various military network applications. Multi-factor authentication has been enhanced using health data and biometrics for personnel identification. Multilayer inference algorithms have been used to improve the accuracy and efficiency to reduce power consumption. Results showed that the second inference layer improved with further savings rate of dataset increased by 10.3% whilst accuracy rate decreased only by 0.91% comparing to the first layer inference algorithm, which has already improved savings and accuracy rates. As the accuracy trades off with efficiency due to the nature of data points which play a key role in calculating the rates, future study is needed to improve both rates to minimise the impact of data points to the inferencing algorithm.

TABLE 3. Multilayer Inference Algorithm.

```
clc
clear
close all
Data=xlsread('uq_vsd_case14_trenddata.CSV');
%%Read the data set excel from computer memory
Data_Valid(:,1)=Data(:,1);                %extracting
time and HR data
Data_Valid(:,2)=Data(:,2);
Data_Valid(any(isnan(Data_Valid), 2), :)=[];
%deleting NAN cells

HR=Data_Valid(:,2);                       %Heart Rate
[BPM]
[rsize,csize]=size(HR);
No_D=rsize;                               %Number of
Data
VR_gap=0.15;
VR=0.017;                                    %Variance
rate
for c=1:1:No_D
    DP(c,1)=c;
end
i=1;
Inf_D=0;                          %first pointS(t)of
original data
Inf_D(1,1)=i;                          %first
pointS(t)of original data
Inf_D(1,2)=HR(1,1);
c11=1;                                 %inferred data
counter
c_i(1)=1;
i=2;
S=0;                                       %Sum of Area
Gap
SL=0;                                      %Sum of
areaS(t)of inferred valueS(t)that are higher than
the original valueS(t)
SU=0;                                        %Sum of
area of inferred valueS(t)that are lesS(t)than the
original
while i<=No_D
        if HR(i)-HR(i-1)>0

     while  HR(i)-HR(i-1)>0
          i=i+1;
                if i>=No_D
          break
                end
      end
      i=i-1;
[c11,Inf_D,c_i]=
gap_detection(c11,i,Inf_D,c_i,HR,VR_gap); %Max.
Gap point detection function
       c11=c11+1;
       c_i(c11)=i;
       Inf_D(c11,1)=i;
       Inf_D(c11,2)=HR(i);
     else if HR(i)-HR(i-1)<0

      while  HR(i)-HR(i-1)<=0
          i=i+1;
                if i>=No_D
          break
                end
      end
      i=i-1;
[c11,Inf_D,c_i]=
gap_detection(c11,i,Inf_D,c_i,HR,VR_gap);
       c11=c11+1;
       c_i(c11)=i;
       Inf_D(c11,1)=i;
       Inf_D(c11,2)=HR(i);
```

TABLE 3. *(Continued.)* **Multilayer Inference Algorithm.**

```
          else if i==No_D % The last point
[c11,Inf_D,c_i]=
gap_detection(c11,i,Inf_D,c_i,HR,VR_gap) ;
       c11=c11+1;
       c_i(c11)=i;
       Inf_D(c11,1)=i;
       Inf_D(c11,2)=HR(i);
             end
         end
        end
i=i+1;
 continue
 end
No_D2=c11;
       DP2=Inf_D(:,1);
       HR2=Inf_D(:,2);
       i=2;
    Inf_D2(1,1)=Inf_D(1,1);                   %first
pointS(t)of original data
    Inf_D2(1,2)=Inf_D(1,2);
    c12=1;                                  %inferred
data counter
    c_i2(1)=1;
while i<=No_D2
     if    abs(HR2(i)-HR2(i-1))>(VR*HR2(i))
%Variance rate
          [c12,Inf_D2,c_i2]=
gap_detection(c12,DP2(i),Inf_D2,c_i2,HR,VR_gap);
       c12=c12+1;
       c_i2(c12)=DP2(i);
       Inf_D2(c12,1)=DP2(i);
       Inf_D2(c12,2)=HR2(i);

         else if i==No_D2 % The last point
       c12=c12+1;
       c_i2(c12)=DP2(i);
       Inf_D2(c12,1)=DP2(i);
       Inf_D2(c12,2)=HR2(i);
             end
         end
i=i+1;
 continue
end
for p=2:1:c12
    c1=p;
    [SU,SL,c1,c_i2]=
Sum_differences(c1,i,Inf_D2,c_i2,HR,SL,SU); %
Function of Area difference
end

S=SU+SL;            %Total Area difference
SD=abs(SU-SL);   %Absolute Difference of SU and SL

SR=(No_D-c12)/No_D*100 ;         %Savings Rate
S0=trapz(DP,HR);                      %Area under
real data plot
AR=(S0-S)/S0*100;                %Accuracy rate AR
```

The alarm notification module can raise an alarm when the integrated sensor devices with activity recognition system monitors the status of the situation programmed with a predefined threshold level. Additionally, the actuation module will take corresponding operations to assist the user and rescue team members based on specific circumstances. It is envisaged that the solution can provide real-time monitoring and actuation features with embedded mHealth devices and wearables using LPWAN networks. In future studies, centralizing the power supply and battery types across equipment used by soldiers should be considered to maximize compatibility across all equipment. Lightweight security measures need to be implemented for LPWAN, due to its computational and battery power constraints. Enhanced sensors and devices should be considered to minimize power consumption and to improve security. For example, smart hydrogel biomedical sensors can be implanted on the hand or wrist for capturing health data and identification of personnel.

APPENDIX

See Table 3.

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