



UNICO I+D Project
6G-DATADRIVEN-06

6G-DATADRIVEN-06-E6:

Architecture for data and AI use in emergencies: initial solution

Abstract

The integration of Artificial Intelligence (AI) and 5G/6G networks in enhancing emergency medical responses has increased in importance in the last years. This document highlights how these advanced technologies can significantly improve response times and efficiency through real-time data processing and AI-driven applications. It discusses the architectural framework for medical emergencies, employing AI and Machine Learning techniques for health monitoring and crisis detection. The document also addresses challenges such as data privacy and network reliability, advocating for ongoing research and cross-sector collaboration. Ultimately, it emphasizes the potential of these technologies in revolutionizing emergency services and improving public safety.

Document properties

Document number	6G-DATADRIVEN-06-E6
Document title	Architecture for data and AI use in emergencies: initial solution
Document responsible	Carlos J. Bernardos (UC3M)
Document editor	Pablo Picazo, Carlos J. Bernardos (UC3M)
Editorial team	Pablo Picazo, Carlos J. Bernardos (UC3M)
Target dissemination level	Public
Status of the document	Final
Version	1.0
Delivery date	31/12/2023
Actual delivery date	31/12/2023

Disclaimer

This document has been produced in the context of the 6G-DATADRIVEN Project. The research leading to these results has received funding from the Spanish Ministry of Economic Affairs and Digital Transformation and the European Union-NextGenerationEU through the UNICO 5G I+D programme.

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List of Acronyms

Artificial Intelligence (AI)

4th Generation (4G)

5th Generation (5G)

6th Generation (6G)

Machine Learning (ML)

Internet of Things (IoT)

3rd Generation Partnership Project (3GPP)

Work Groups (WG)

New Radio (NR)

E-UTRAN New Radio – Dual Connectivity (EN-DC)

Non-Line-Of-Sight (NLOS) Augmented Reality (AR)

Recurrent Neural Networks (RNNs)

Greater Node B - 5G New Radio Base Station (gNB)

User Equipment (UE)

Vertical Slicer (VS)

Service Orchestrator (SO)

mobile transport and computing platform (MTP)

monitoring platform (MON)

Network Function Virtualization -network services (NFV-NSs)

Long Short-Term Memory (LSTM)

Deep Learning (DL)

Recurrent Neural Networks (RNNs)

Long Short-Term Memory (LSTM)

Resumen Ejecutivo

El documento presenta un enfoque pionero para integrar las tecnologías 5G y 6G con la Inteligencia Artificial (IA) con el objetivo de mejorar las respuestas médicas de emergencia. Entre los puntos destacados se encuentran:

- **Integración Tecnológica:** Se destaca el papel de 5G y 6G en mejorar las aplicaciones de IA para emergencias, ofreciendo una transmisión de datos más rápida y una conectividad mejorada.
- **IA en Emergencias Médicas:** El documento describe una arquitectura propuesta para el papel de la IA en emergencias médicas, mostrando cómo el análisis de datos en tiempo real puede llevar a respuestas más efectivas.
- **Desafíos y Recomendaciones:** Aunque se reconoce el potencial de estas tecnologías, también se abordan desafíos como la privacidad de los datos y la confiabilidad de la red, recomendando una investigación continua y colaboración a nivel sectorial.
- **Impacto en los Servicios de Emergencia:** El documento concluye con el impacto significativo que esta integración tecnológica podría tener en los servicios de emergencia, posiblemente conduciendo a eficiencias que salvan vidas y una mejor gestión de la seguridad pública.

El resto del documento está redactado en inglés, de cara a maximizar el impacto del trabajo realizado en este proyecto.

Executive Summary

The document presents a pioneering approach to integrating 5G and 6G technologies with Artificial Intelligence (AI) for improved emergency medical responses. Key highlights include:

- **Technological Integration:** It emphasizes the role of 5G and 6G in enhancing AI applications for emergencies, offering faster data transmission and improved connectivity.
- **AI in Medical Emergencies:** The document outlines a proposed architecture for AI's role in medical emergencies, showcasing how real-time data analysis can lead to more effective responses.
- **Challenges and Recommendations:** While acknowledging the potential of these technologies, it also addresses challenges such as data privacy and network reliability, recommending continuous research and sector-wide collaboration.
- **Impact on Emergency Services:** The document concludes with the significant impact this technological integration could have on emergency services, potentially leading to life-saving efficiencies and better public safety management.

1. Introduction

The advent of 5G and the emerging 6G technologies have the potential to revolutionize emergency response systems through the integration of Artificial Intelligence (AI). These advanced wireless networks offer significantly higher speeds, lower latency, and greater connectivity than their predecessors, enabling real-time data transmission and processing, essential for rapid emergency responses.

Enhancing emergency response times through the integration of 5G and upcoming 6G technologies AI represents a significant advancement in crisis management and public safety.

The implementation of 5G technology, as highlighted by [1], provides the necessary infrastructure for AI-driven applications in emergency scenarios. The low latency and high bandwidth of 5G enable rapid data processing and transmission, allowing AI algorithms to quickly analyze information from diverse sources like environmental sensors, surveillance cameras, and social media. This rapid analysis is crucial for assessing situations and optimizing emergency responses in real-time, particularly in natural disasters or medical emergencies.

As we look towards the future, 6G networks, expected to be operational by the 2030s, are predicted to take these capabilities further. Authors in [2] suggest that 6G will provide even higher data speeds and near-zero latency, facilitating more advanced AI applications. This could include the use of AI for real-time processing of high-resolution imagery from drones for accurate situational awareness during emergencies.

Furthermore, the extensive Internet of Things (IoT) connectivity anticipated with 6G could significantly enhance smart city infrastructure, enabling AI-datadriven automated emergency responses. AI algorithms could manage critical city functions, such as controlling traffic flows for emergency vehicles, as discussed by [3]. Such applications underscore the potential of AI in conjunction with 5G/6G to revolutionize emergency services and disaster management.

However, these advancements are not without challenges. As Nawaz et al. (2019) point out, issues such as data privacy, network reliability, and the development of robust AI models are crucial concerns that need addressing. The success of AI in emergency response via 5G/6G networks depends on overcoming these challenges through continuous research, development, and collaboration across various sectors.

As a result, the integration of AI with 5G and the forthcoming 6G technology offers a promising future for emergency response systems. This combination has the potential to significantly improve the efficiency and effectiveness of responses to crises, potentially saving lives and mitigating the impacts of disasters. The path forward involves addressing technical, ethical, and logistical challenges through a collaborative approach among technology developers, government agencies, and emergency service providers.

This document aims to provide a comprehensive exploration of the current landscape of AI/ML applications within 5G/6G networks. By delving into the status of these technologies, we seek to

unravel their potential in transforming various domains. Specifically, we will present a use case that illustrates the role of AI in addressing medical emergencies through 5G/6G networks. Furthermore, a proposed architecture for this use case will be outlined, showcasing the seamless integration of intelligent systems into critical scenarios. This document will also offer a summary of diverse Machine Learning (ML)/AI techniques applicable to the proposed architecture, providing valuable insights for further implementation.

2. AI/ML in next generation of 3GPP Networks

2.1. Related work

The integration of Artificial Intelligence (AI) and Machine Learning (ML) technologies marks a transformative phase in the evolution of 3rd Generation Partnership Project (3GPP) networks. From optimizing network performance to enhancing security, user experience, and resource management, the intersection of AI and 3GPP networks is shaping the future of telecommunications. This exploration encompasses key dimensions of network architecture, demonstrating the potential of AI/ML to revolutionize the way networks operate, adapt, and deliver services in an increasingly dynamic and complex technological landscape.

A study [4] emphasized the necessity of a 5G network, as opposed to a 4G network, to ensure high efficiency and rapid responses in a health monitoring scenario. Various technologies, in conjunction with 5G networks, aim to enhance health services. Specifically, works in [5],[6] focus on the application of deep learning and artificial intelligence (AI) to improve performance in heterogeneous networks, addressing health service enhancement in [7]. Additional studies [8],[9] propose solutions to enhance security in healthcare systems, with some focusing on multiple heterogeneous network settings [10].

2.2. Standardization activities

3GPP's Release 18 is expected to include new standards and specifications for AI and ML. This includes enhancements for data collection focusing on use cases like network energy saving, load balancing, and mobility optimization, thereby leveraging the predictive power of AI/ML to enhance network performance and efficiency. In particular, several Work Groups (WG) are working on providing these enhancements to the next generation of 3GPP networks [11].

Improving data collection: Working Group (WG) RAN3 has finalized [12] (TR 37.817), a study aimed at improving data collection for New Radio (NR) and E-UTRAN New Radio – Dual Connectivity (ENDC). The focus was on three primary applications for AI/ML solutions:

- **Network Energy Saving:** This involves actions such as traffic offloading, coverage adjustment, and cell deactivation to conserve energy.
- **Load Balancing:** The goal here is to efficiently distribute the network load among cells or areas of cells in a multi-frequency/multi-RAT deployment, enhancing overall network performance by utilizing load predictions.
- **Mobility Optimization:** Ensuring satisfactory network performance during mobility events while selecting optimal mobility targets based on predictions of how user equipment (UEs) may be served.

AI for the New Radio Air Interface: WG RAN1 is focusing on AI and ML for the New Radio (NR) air interface. This includes enhancements in channel state information feedback, beam management,

and positioning accuracy, especially in challenging conditions like Non-Line-Of-Sight (NLOS) scenarios.

5G System Support for AI/ML Services: WG SA2 is working on architectural and functional extensions in 5G Systems to support AI/ML-based services. This includes studies on AI/ML operation splitting, model/data distribution, and federated learning over 5G Systems, aiming to provide a robust platform for AI/ML applications.

AI/ML in Media and Management: Studies are underway to identify interoperability requirements and constraints for AI/ML in 5G media services. Additionally, there's a focus on the management capabilities needed to support and coordinate AI/ML in 5G systems.

3. AI/ML in medical emergencies: Use case scenario

In the previous deliverable [18] we introduced the diverse applications of artificial intelligence (AI) in emergency scenarios. Our study identified three categories for AI implementation in emergencies, namely medical emergencies, locating lost individuals, and managing natural disasters. Building upon this foundation, the current deliverable delves into a more specialized domain by elucidating a specific use case of AI in emergencies. This use case makes use of the capabilities of 5G networks to enhance and optimize emergency response mechanisms, marking a significant advancement in the intersection of AI and emergency management.

Beginning with the considerations for improvement outlined earlier and considering the limitations imposed by the operational procedures of emergency response teams and the functioning of cellular networks, we have formulated the scenario depicted in Figure 1. The primary objective, deemed crucial by the emergency response team in Madrid, is to create a fully automated and tailored emergency response system.

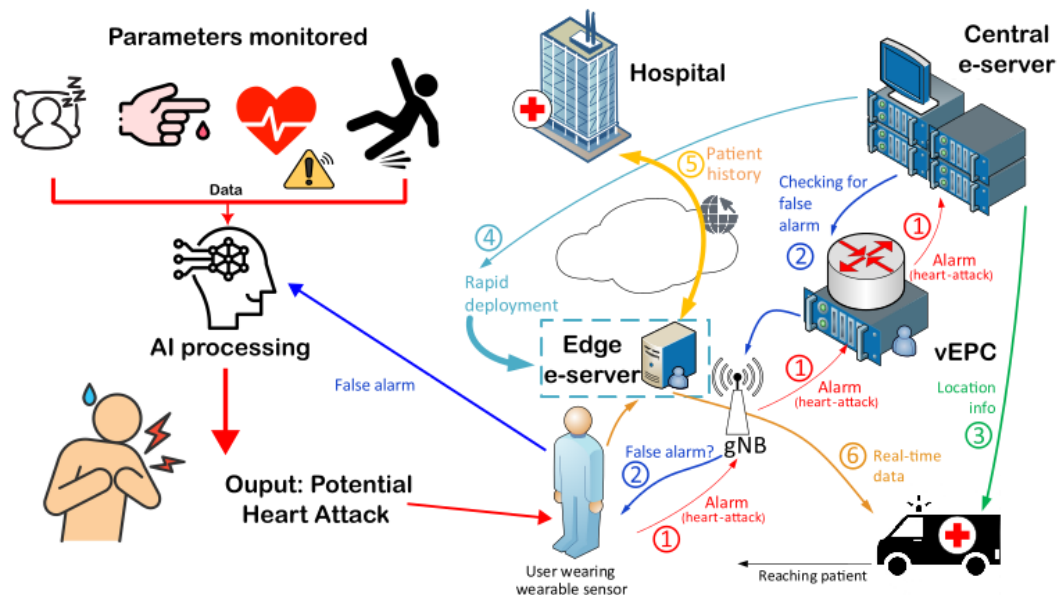


FIGURE 1: USE CASE SCENARIO FOR AI ASSISTED EMERGENCIES

To achieve our objective, we devised a straightforward scenario for which we developed a fully automated system, described in detail later. This scenario involves continuous monitoring of a patient's signs, such as abnormal sleeping, sugar in blood in case of diabetic, hearth pulse, or even fall detection. All these parameters are computed by AI/ML models that decide whether a potential emergency occurs. Several techniques can be applied to determine this and will be explained deeply in the next sections.

The system employs an Augmented Reality (AR) system deployed near the patient. To extend intensive health monitoring to a broader population, we leverage the extensive connectivity capabilities of 5G. A smart wearable, like a smartwatch, monitors various health aspects, detecting potential issues such as low blood sugar or, in our test case, a heart attack. While 5G enables direct

communication between wearables and a central cloud, in this early 5G stage, we assume connectivity via a mobile app reporting health status and location to a central cloud.

The Central eServer issues alarms to the user's mobile device if monitored data reveals a potential health issue, continuing emergency event processing. The system analyzes health issues, and medical records, and selects the most suitable emergency team based on factors like time and required skills. The deployed emergency team can be cancelled by the user if it's a false alarm. If cancelled, the AI/ML model will learn for further alarms not to consider those scenarios as alarms.

Our system can deploy an AR service for the emergency team, enhancing care quality by displaying geolocation and health information from the patient. To ensure a high-performance, stable, and durable AR service, the system requests the deployment of an emergency Edge eServer closer to the emergency location. This Edge eServer hosts the AR service and patient health data, automatically deploying in minutes as the emergency team approaches. The edge application establishes a connection with the team, guiding them with an AR-marked pathway streamed to the doctor's AR headset.

The edge application also acquires the user's health records, presenting them in real-time on the doctor's AR headset alongside live sensor data from the user's wearable. Additionally, the AR headset facilitates live video streaming to a remote medical team, offering specialized support if necessary. This capability significantly enhances the efficiency of paramedic teams, enabling faster triage and real-time feedback to the hospital. Consequently, this reduces the door-to-balloon time, thereby increasing the likelihood of saving lives.

While the use of AR technology in emergency situations has been proposed previously, it is the advent of 5G that makes widespread adoption by emergency response teams feasible. This feasibility is attributed to the low latency requirement between the AR device and the AR server, a condition that 5G adequately satisfies. As demonstrated later in this article, previous mobile networks, such as 4G, lack the low latency necessary for optimal AR experiences. Our 5G-based solution has the capability to dynamically instantiate an Edge eServer near the emergency location and adapt the mobile network infrastructure, ensuring a low-latency path to the newly deployed Edge eServer. Achieving this may necessitate a network service federation involving different operators to meet the requirements of the AR service specifically designed for emergency scenarios.

4. AI/ML in medical emergencies: Use case architecture

We designed a platform equipped with dynamic and adaptable management capabilities to automatically deploy diverse and heterogeneous services, meeting the specific requirements of various vertical industries. These services can be simultaneously instantiated across a collaborative infrastructure that incorporates diverse resource types in computing, storage, and networking, extending across multiple administrative domains.

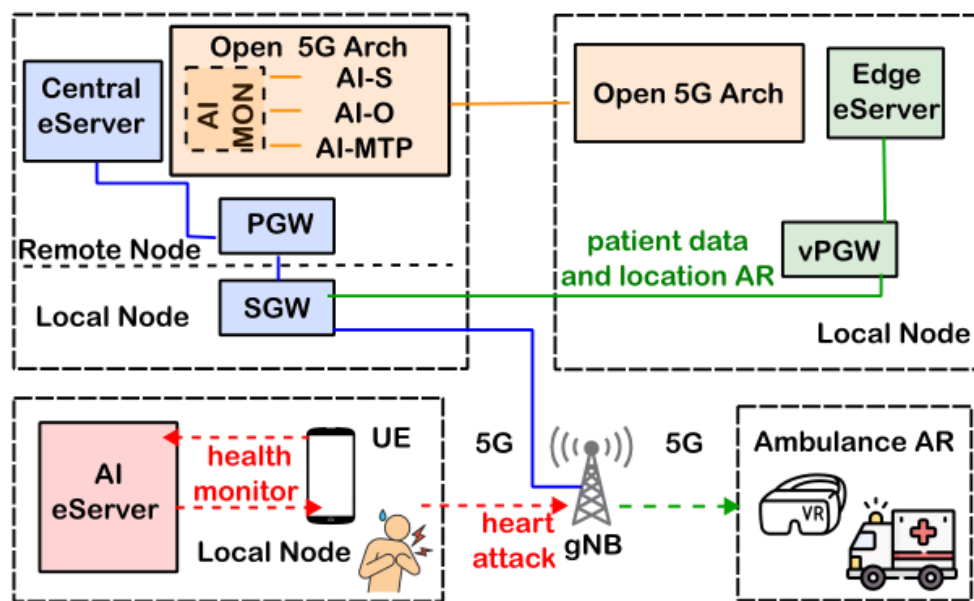


FIGURE 2: ARCHITECTURE OF THE SYSTEM PROPOSED

AI eServer

The AI eServer emerges as a central component, diligently tracking and analyzing user health parameters in real-time. By harnessing the power of AI/ML algorithms, this server operates on a remote platform, delving into the intricacies of health data to identify potential issues and proactively predict emergencies. In the event of a critical health event, the AI eServer performs a dual role: first, it triggers immediate alerts to the User Equipment (UE), typically a mobile phone, or smart watch, ensuring swift communication of the emergency to the user. Simultaneously, the AI eServer seamlessly interfaces with a gNB (5G New Radio Base Station), a pivotal element in our interconnected architecture, to alert the sanitarian system.

This integration with the gNB signifies a critical enhancement in our emergency response mechanism. Through this connection, the AI eServer not only notifies the user but also ensures that the sanitarian system is promptly informed, initiating a rapid and coordinated response. This orchestrated approach, as described in the subsequent paragraphs detailing our system architecture, guarantees that the right parties are alerted in real-time, maximizing the potential for immediate and effective

intervention. In essence, the AI eServer's multifaceted functionality adds a layer of intelligence to our health monitoring system, reinforcing its commitment to user safety and well-being.

Open 5G Architecture

The open 5G architecture consists of four primary building blocks: the Slicer (AI-S), the Orchestrator (AI-O), the mobile transport and computing platform (AI-MTP), and monitoring platform (AI-MON).

The AI-S serves as the initial point of access for vertical industries, facilitating the creation and management of network slices. **The AI-O** is responsible for overseeing end-to-end orchestration and lifecycle management of NFV-network services (NFV) based on the available resources (compute, storage, and network) provided by the underlying **AI-MTP**. This transport stratum controller integrates fronthaul and backhaul networks, as well as computing and storage resources located in multiple NFVI-Point of Presence. The **AI-MON** supplies metrics to the open platform, enabling it to respond and make decisions to adapt to network conditions while adhering to service-level agreements embedded in the NFV-NS request.

Additional network services

As previously discussed, the Open 5G Architecture enables the deployment of network services that extend across multiple administrative domains, referred to as Network service federation (NSF) [13]. This capability is facilitated by the AI-O, which can orchestrate composite NFV. The NSF feature proves crucial for implementing the 5G personalized eHealth emergency system precisely when and where it is needed, as illustrated in [14].

Consider a straightforward example: a city municipality's emergency services have a contractual agreement with a 5G operator to supply patient monitoring and edge emergency NFV, along with communication services used by all emergency teams. The operator deploys most of its core network components and the monitoring NFV (in blue in Figure 2) in a remote cloud location due to operational considerations, such as not imposing stringent latency constraints. In the event of an emergency, the Central eServer requests the instantiation of an edge emergency service (in green in Figure 2) connected to the monitoring NFV-NS near the emergency location. A placement algorithm (in the AI-O) [15][16][17] is responsible for determining the placement of the Edge eServer based on location constraints, information about the availability of local computation resources, and latency constraints of the AR application. The placement algorithm calculates these factors efficiently.

5. Data generated and ML techniques integration

In the realm of health monitoring systems, the fusion of machine learning techniques with diverse health data promises an innovative approach to emergency detection. Leveraging supervised, unsupervised, and deep learning methods, we aim to harness the intricacies of health parameters such as heartbeat, fall detection, sleep patterns, and blood sugar levels. Supervised learning, with its reliance on labelled datasets, allows the system to discern patterns indicative of potential emergencies based on instances of both normal and emergency scenarios. Unsupervised learning, devoid of labelled datasets, detects anomalies in inherent data structures, aiding in the identification of emergent patterns. Deep learning, particularly adept at handling complex data, employs neural networks to automatically extract hierarchical features, contributing to a nuanced understanding of health dynamics.

5.1. Supervised learning

Medical emergencies, such as heart attacks, stroke, and seizures, demand rapid and accurate assessment to ensure timely intervention and improve patient outcomes. Supervised learning, a powerful branch of machine learning, holds immense potential to transform emergency care by enabling real-time identification and analysis of critical health data.

In supervised learning, the model is trained on labelled datasets, where each instance is associated with a known outcome. For health data, such as heartbeat, fall detection, sleep monitoring, and blood sugar levels, labelled datasets comprising instances of both normal and emergency scenarios are crucial. The model learns to identify patterns indicative of potential emergencies based on this training data. For instance, it can recognize abnormal heart rate patterns, sudden changes in activity consistent with a fall, disruptions in sleep patterns, or irregular blood sugar levels.

True emergencies and false alarms play a pivotal role in refining the model's accuracy, as they contribute to the learning process, allowing the model to distinguish between normal variations and actual emergencies. As the model encounters more data, it continuously refines its ability to detect and differentiate between normal and emergency situations, enhancing its overall reliability.

The integration of supervised learning into medical emergency settings offers several compelling advantages:

1. Early Detection and Intervention: By analyzing real-time physiological data, supervised learning algorithms can detect subtle changes that may signal an impending emergency, enabling prompt intervention and potentially preventing severe complications.

2. Improved Diagnostic Accuracy: The ability to analyze vast amounts of data and identify patterns that may be overlooked by human experts enhances the accuracy of emergency diagnosis, leading to more targeted and effective treatment decisions.

3. Personalized Risk Assessment: By analyzing individual patient data and medical history, supervised learning models can stratify patients based on their risk of specific medical emergencies, allowing for personalized preventive measures and targeted monitoring.

4. Resource Optimization: By accurately identifying and prioritizing genuine emergencies, supervised learning can help healthcare providers optimize resource allocation, ensuring that critical attention is directed to those in greatest need.

The implementation of supervised learning in medical emergencies is not without its challenges. One key concern is the need for high-quality, well-labelled datasets that accurately represent the diversity of patient populations and medical conditions. Additionally, ensuring the robustness and generalizability of models across different healthcare settings and populations is crucial.

Despite these challenges, the potential benefits of supervised learning in medical emergencies are substantial. As research and development continue, we can expect to see increasingly sophisticated supervised learning models integrated into emergency care settings, leading to more timely, accurate, and personalized care for patients facing critical medical situations.

5.2. Unsupervised learning

In the dynamic realm of medical emergencies, prompt identification and treatment are crucial for improving patient outcomes. Unsupervised learning, a distinct branch of machine learning, offers a valuable approach to emergency care by uncovering hidden patterns and anomalies within unlabelled health data.

Unlike supervised learning, which relies on labelled datasets, unsupervised learning algorithms delve into unlabelled data, seeking to identify inherent structures and patterns. This method is particularly well-suited for medical data, where labelling every instance may be impractical or infeasible.

Clustering techniques, a cornerstone of unsupervised learning, play a pivotal role in emergency care. By grouping similar data points together, clustering algorithms can effectively identify clusters of normal patterns, representing the expected range of health parameters. Any deviation from these established clusters can then be flagged as a potential emergency, prompting further investigation.

The ability to detect emergent patterns that may not be explicitly labelled in the training data is a key advantage of unsupervised learning in medical emergencies. This capability enables the identification of novel and unforeseen patterns, potentially leading to the discovery of new risk factors or early warning signs for various medical conditions.

Integrating data from true emergencies and false alarms further enhances the model's ability to distinguish between normal and emergency states. True emergencies provide valuable insights into the characteristics of actual medical events, while false alarms help refine the model's ability to filter out normal variations and focus on genuine emergencies.

Unsupervised learning offers several compelling benefits for medical emergency care:

1. Pattern Recognition: By uncovering hidden patterns in unlabelled data, unsupervised learning algorithms can detect anomalies and potential emergencies that may not be readily apparent to human experts.

2. Novel Discovery: The ability to identify emergent patterns can lead to the discovery of new risk factors or early warning signs for various medical conditions, potentially improving preventive measures and early intervention strategies.

3. Adaptability: Unsupervised learning models can adapt to new data as it becomes available, continuously refining their ability to detect and differentiate between normal and emergency situations.

Reduced Reliance on Labeling: Unsupervised learning eliminates the need for extensive labeling of data, which can be time-consuming and costly, particularly in the context of medical data.

The integration of unsupervised learning into medical emergency settings holds immense promise for improving patient care. As research and development continue, we can expect to see increasingly sophisticated unsupervised learning models integrated into emergency care systems, leading to the early detection and prompt intervention for a wide range of medical emergencies.

5.3. Deep Learning

In the fast-paced and critical environment of medical emergencies, accurate and timely diagnosis is paramount for ensuring optimal patient care. Deep learning, a subfield of machine learning, has emerged as a powerful tool for medical emergencies, offering the ability to analyze complex health data, uncover intricate patterns, and provide real-time insights for prompt intervention.

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, specialized architectures within deep learning, are particularly well-suited for analyzing time-series health data. These networks possess the unique ability to capture dependencies and trends over time, making them ideal for processing data streams such as ECG recordings, blood pressure readings, and sleep patterns.

Deep learning models excel at automatically extracting hierarchical features from diverse health parameters, enabling them to learn complex relationships between various physiological signals. This capability allows deep learning systems to identify subtle patterns that may signal an impending emergency, even in the presence of noisy or incomplete data.

Training deep learning models for medical emergencies involves exposing them to large datasets of labelled instances, encompassing both emergency and non-emergency scenarios. The inclusion of data from actual emergencies and false alarms is crucial for ensuring that the model generalizes well to diverse scenarios and can effectively distinguish between normal variations and genuine medical emergencies.

The integration of deep learning into medical emergency settings offers several compelling advantages:

- 1. Enhanced Pattern Recognition:** Deep learning models can capture intricate patterns and relationships in complex health data, enabling them to detect subtle anomalies that may signal an impending emergency.
- 2. Real-time Insights:** Deep learning systems can analyze data streams in real-time, providing continuous monitoring and real-time alerts for potential emergencies, enabling prompt intervention.
- 3. Improved Generalizability:** The ability to learn from large datasets ensures that deep learning models generalize well to diverse patient populations and clinical settings.
- 4. Personalized Risk Assessment:** Deep learning models can analyze individual patient data and medical history to stratify patients based on their risk of specific medical emergencies, allowing for personalized preventive measures and targeted monitoring.

As research and development continue, deep learning is poised to revolutionize medical emergency care. With its ability to handle complex data, uncover hidden patterns, and provide real-time insights, deep learning has the potential to significantly improve patient outcomes and reduce the burden of medical emergencies.

TABLE 1: PROS AND CONS OF ML METHODS

Technique	Pros	Cons	Considerations
<i>Supervised Learning</i>	<u>Predictive Power:</u> Excel at making predictions for specific outcomes, providing actionable insights for decision-making.	<u>Overfitting:</u> Prone to overfitting, leading to poor performance on unseen data.	<u>Human Biases:</u> Reflects the biases present in the labeled data, which can perpetuate inequalities.
<i>Unsupervised Learning</i>	<u>Adaptive Nature:</u> Continuously learns from new data, adapting to changing patterns and trends.	<u>Exploratory Analysis:</u> Uncovers hidden patterns and relationships in data, providing a deeper understanding of underlying structures.	<u>Anomaly Detection:</u> Effectively detects outliers and anomalies in data, facilitating anomaly-based monitoring and detection of deviations from normal behaviour.
<i>Deep Learning</i>	<u>Feature Extraction:</u> Automatically extracts hierarchical features from raw data, reducing the need for manual feature engineering.	<u>Scalability:</u> Handles large and complex datasets efficiently, making it suitable for big data applications.	<u>Representation Learning:</u> Captures complex relationships and representations of data, enabling the modelling of abstract concepts.

6. Conclusions and next steps

In the modern era, wearable devices have permeated our lives, continuously monitoring an array of health metrics, including sleep patterns, heart rate, step count, and electrocardiograms. Individuals managing chronic conditions are at the forefront of embracing these monitoring tools, incorporating patches for glucose measurement, connected insulin pumps, and wearable blood pressure monitors. The advent of 5G technology, with its emphasis on massive machine-type communications, is poised to seamlessly integrate these devices with eHealth services provided by public or private entities. These services will leverage the cutting-edge capabilities of AI and ML techniques to enable continuous monitoring, promptly detect anomalies, and initiate appropriate actions, fundamentally transforming emergency healthcare delivery.

This study delves into a practical application showcasing the transformative impact of 5G on emergency services in Madrid. The implemented service aims to elevate healthcare quality through two primary mechanisms: firstly, by significantly reducing the time required to identify emergencies, eliminating dependence on human witnesses and their potential for delays or errors. Secondly, by providing location and health-related data to emergency teams in real-time, the service facilitates more efficient triage using augmented reality technology, enabling first responders to make informed decisions on the go. Additionally, real-time data is seamlessly transmitted back to hospitals, with AI/ML techniques playing a pivotal role in emergency detection, further enhancing the speed and accuracy of response.

These innovative services leverage the advanced features of 5G, encompassing not only high-bandwidth and low-latency connectivity but also the orchestration, federation, and dynamic instantiation of virtual functions at the network's edge. This edge-computing approach ensures that critical data processing and analysis occur closer to the source, minimizing latency and enabling real-time decision-making. The incorporation of AI/ML techniques further enhances the efficiency and accuracy of the entire system, making significant strides toward the future evolution of emergency services.

The Madrid-based case study serves as a compelling example of how 5G and AI/ML are revolutionizing emergency healthcare. By enabling continuous monitoring, prompt anomaly detection, and real-time data sharing, these technologies are poised to reduce response times, improve patient outcomes, and save lives. As 5G networks continue to expand and AI/ML techniques become more sophisticated, we can expect to see even more transformative applications emerge, transforming the landscape of emergency services worldwide.

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