An Artificial intelligence application for Drone-assisted 5G remote e-Health

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Abstract

Artificial Intelligence (AI) algorithms are a growing research interest due to their ability to improve decision-making capabilities for promising applications in different economic sectors. The growing shift towards the Internet of Everything (IoE) environments brought by devices embedded with sensors that can share information brings immense opportunity for new applications. While these new applications thrive in resource-rich areas, i.e., capitals, neighboring cities that lack the resources and infrastructure to support them may be left behind. It is vital that new technologies can reach those who need them the most, especially healthcare-based. This article proposes an application (app)-based approach for long-distance patient monitoring and care. The app would serve as a platform of communication between patients and healthcare staff, where the latter can send standardized video footage or pictures to the former (e.g., their primary care doctor). This feature is enhanced with a Recurrent Neural Network algorithm as a validation tool for healthcare-related videos exchanged between patients and staff. Thus, the healthcare team does not need to check each video for validity, freeing their time for other activities.

Keywords:

Artificial Intelligence, Drone, 5G, e-Health, Remote, Application, RNN, IoD.

1 Introduction

The AI technology is a driving force in the market that has boosted the interest in developing new applications and supporting existing systems by improving their overall efficiency and scalability. However, AI is only one of the three main enablers of the novel healthcare framework, also known as Smart Healthcare. The latter consists of a new architecture for providing healthcare services with fifth-generation (5G) wireless technology, IoE, and AI.

The integration of the Internet of Things (IoT) paradigm promises to be a game-changer for companies. Nearly every sector of the economy can benefit from its connectivity. The healthcare industry is no exception, and with this paradigm slowly emerging in hospitals, a new concept called the Internet of Medical Things (IoMT) has emerged. The latter focuses on medical IoT applications having low network latency as its most important requirement [1]. On the other hand, 5G promises to deliver the cellular communication requirements necessary to support various applications. Prior wireless network capabilities are insufficient to support these applications with a high-speed connection, network scalability, and capacity [2]. The Internet of Drones (IoD) consists of infrastructures designed to control and exchange information between drones, users, and other IoT devices. We believe IoD can play a crucial role in e-Health. Despite the worldwide advancements made for Internet accessibility, there are still a number of locations that are deprived of the resources to support Smart Healthcare. Therefore, we believe drones can play an important role in providing assistance, as the IoD technology allows reaching new boundaries such as wide-area network coverage in networking and communication.

This article approaches how AI technology and the advancements made in wireless technology can benefit the healthcare system by reducing the burden of health care costs. We spotted that the strengths of AI in drone-assisted 5G remote e-Health had not been studied and emphasized so far. Therefore, the contributions of this article can be summarized as follows:

- It summarizes up-to-date solutions for innovative mobile communication technologies-enabled remote e-Health with their significant achievements and limitations.
- We propose an application that provides a communication channel between patients and doctors, where the latter can choose to communicate with the former remotely through videos.
- We developed a video validation mechanism to ensure that the patient's video is valuable and useful.
- We believe this system can reduce the burden of medical staff in hospitals by providing a remote general triage of patients.

The paper is organized as follows: Section II presents the concept and state-of-the-art applications of Drone-assisted 5G remote e-Health. Section III presents AI-based solutions proposed for remote e-Health environments. In Section IV, our proposed application is introduced. Section V, we discuss challenges and open issues. Section VI, we discuss future perspectives. Finally, Section VII presents conclusions.

2 **Drone-assisted 5G Remote e-Health: Concept and Applications**

2.1 ***Understanding Remote e-Health***

The Smart Healthcare environment has fostered the appearance of a new concept for providing healthcare, also known as remote e-Health. The latter can be defined as the hospital's ability to provide quality healthcare services through smart devices and networks to people either living in remote areas or distanced from the hospital that needs immediate medical care. This concept will result in a paradigm shift in how patients can access medical care, as most high-quality medical resources are present in big cities while individuals living in remote areas have difficulty accessing those resources.

To better understand the new remote e-Health paradigm, we must first understand the technologies that enable it, being 5G one of the main contributors. As previously stated, 5G is the new generation of wireless technology that promises faster transmission speed, lower latency, and reliable connectivity [3]. The network improvements are crucial for enabling e-Health applications. For example, the increase in transmission speed allows medical workers to properly assist patients through a high-quality live video feed in real-time and continuous stream without packet loss.

Figure 1 presents a four-layered healthcare architecture composed of healthcare, server, devices, and user layers. The lower layer, i.e., user, consists of the user's resources and parameters. The devices layer consists of AI-assisted monitoring and wearable devices. The server layer consists of Mobile Edge Computing (MEC) enabled Road Side Units, central and cloud servers. Moreover, the upper layer, i.e., healthcare, consists of smart hospitals, connected ambulances and medical staff.

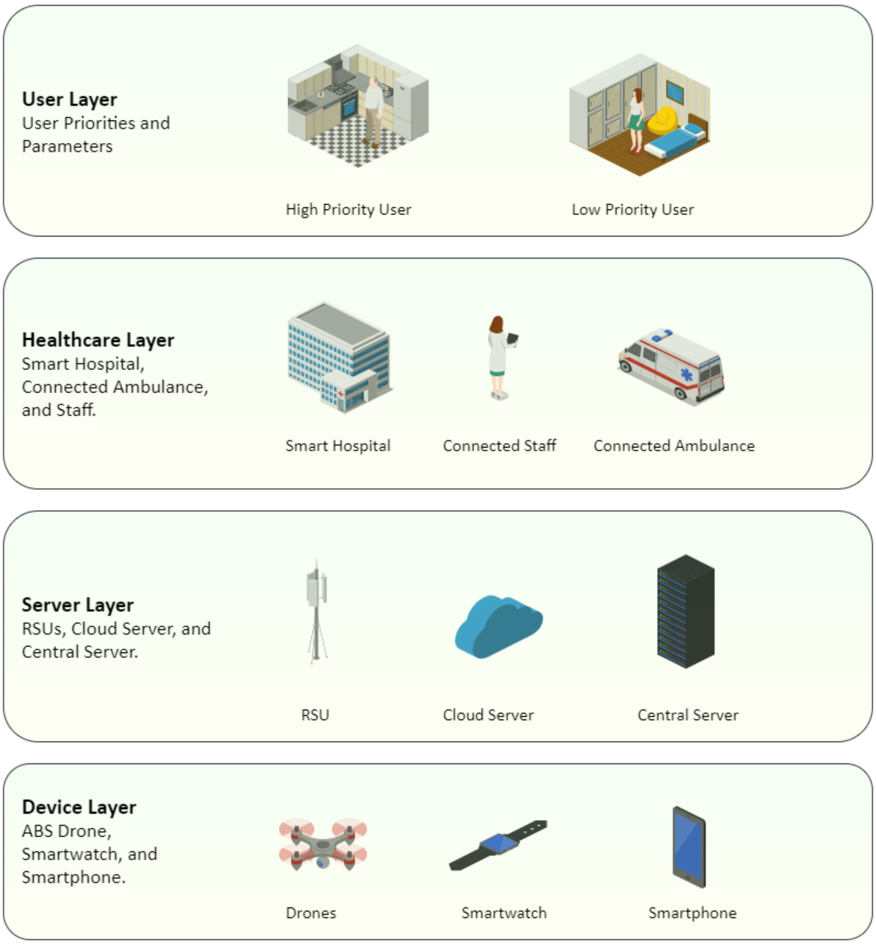

Figure *1*. An overview of the remote e-Health architecture and a representation of a remote monitoring framework.

Another great enabler of e-Health is the IoD paradigm. The following main capabilities of drones are useful for e-Health applications: freely navigate areas, connect to a cellular network, and perform computational tasks. These main characteristics, together with the 5G technology, enable new applications that were previously incapable. As Han et al. [3] described, with 5G and IoD, internetworking between drones and ground base stations (GBS) enables greater coverage. By working as flying and highly mobile nodes, they extend GBS communication reach.

2.2 *Applications*

Table 1 shows the network capabilities of 5G compared to the previous generation and how it enables applications that form the structure of future Smart Healthcare frameworks such as telesurgery, remote patient monitoring, connected ambulances, and wearable devices.

2.2.1 *Telesurgery*

Telesurgery is the process of performing medical surgery remotely when specialized medical personnel is not available at the current medical facility. According to Gupta et al. [4], telesurgery works as a master-slave system where the master domain uses interfaces and various commands to control the robot responsible for operating. The authors provided an in-depth look into the 5G-enabled telemedicine environment and proposed a state-of-the-art architecture for telesurgery. They also outlined the key challenges for telesurgery into five main categories: ultra-low latency, ultra-high reliability, security and privacy, high communication cost, and latency in multi-user haptic communications.

2.2.2 *Remote Patient Monitoring*

Remote Patient Monitoring systems are an application of IoMT systems enhanced by 5G technology. In these systems, the healthcare providers monitor the individual's vital signals remotely and potentially monitor their actions through a camera and AI algorithms that can identify when a person is in jeopardy, e.g., having a seizure. However, some privacy concerns need to be addressed before such applications can come into fruition. Chen et al. [5] proposed a secure and efficient patient monitoring framework called SRM to accomplish data security. They utilized Intel Software Guard Extensions (SGX), besides creating a "heartbeat" mechanism to address the limitations of the SGX architecture.

2.2.3 *Connected Ambulances*

Connected Ambulances are a new technology that has been driven by the advancements in MEC environments, which is another enabling technology of 5G. MEC networks enable numerous applications that require low latency by shifting the computational resource load from the traditional central processing server to servers located in base stations at the edge of the network. MEC technologies promise to bring numerous advantages to Vehicle-to-Everything (V2X) communications. As a result of the dynamic environment of moving vehicles, the applications in V2X networks require a reliable connection with ultra-low latency to provide better service for users. Lin et al. [6] proposed a solution for optimizing MEC network delay in healthcare applications using Blockchain to guarantee the authenticity of the information provided. They used an Abbreviated Injury Scale to determine the user's priority based on the injury's criticality.

2.2.4 *Wearable Devices*

A promising form of IoMT application comes in Wearable Devices (WD). These are devices that continuously monitor the individuals' vital signals such as temperature, respiration and heart rates, blood pressure, physical activity, sweat, and emotion. The ability to measure these parameters with high precision and reliability opens opportunities for numerous applications that can assist the medical staff in acting proactively and make decisions for patients that may not be subject to immediate medical service [7]. A. Kos and A. Umek [8] discussed the benefits that WD, combined with real-time patient monitoring, can accomplish in a rehabilitation scenario. The data collected provides beneficial information for both parties, the swimmer can use it to analyze his physical capabilities and performance, and the therapist can analyze the swimmer's tiredness and overall vital signals.

Table 1. Performance comparison of 4G vs. 5G and Drone-assisted 5G remote e-Health applications. It showcases how 5G improvements enable several applications that were unviable with 4G technology.

Metrics	Performance comparison	
	4G	5G
Peak data rate	1 Gbit/s	20 Gbit/s
Latency	10 ms	>1 ms
Area traffic capacity	10 Mbit/s/m2	10 Mbit/s/m2
Bandwidth	At least 100 MHz	At least 100 MHz
Mobility	0 km/h to 350 km/h	0 km/h to 500 km/h

3 AI Solutions for Remote e-Health

The efforts of developing faster and more reliable communication networks are going to have a profound role in improving the healthcare system. However, another critical tool for state-of-the-art Smart Healthcare is AI. AI algorithms aim to solve some of the challenges faced by IoMT applications such as data privacy, energy consumption, big data analysis, and patient health prediction. Table 2 presents a comparative table highlighting each approach's advantages and disadvantages.

3.1 Remote Patient Monitoring

AI algorithms promise to be extremely important in assisting remote patient monitoring applications. Harb et al. [9] proposed a patient monitoring scheme that utilizes big data analytics to achieve three features: emergency detection, adapting sensing frequency, and real-time patient health prediction. First, they utilized a periodic patient monitoring model and an early warning score to determine the patient's criticality level. Then, they used a simple linear regression algorithm to find patterns for emergency detection. Next, they categorized the level of risk of that patient, and lastly, they make use of a "long short-term" memory prediction algorithm for predicting the patient's progress.

3.2 *Pathology Detection*

Pathology Identification is another hot topic in the Smart Healthcare researcher area. It is an application that employs ML algorithms for pattern identification in x-rays, electroencephalogram (EEG) signals, and magnetic resonance imaging (MRI) scans. Amin et al. [10] proposed a cognitive Smart Healthcare framework that utilizes Deep Learning (DL) algorithms for pathology detection from EEG signals and improves decision-making while monitoring the patient's condition in real-time. The initial data collected by the EEG sensors are first sent to the cognitive system to process and decide the next course of action. Next, the data is sent to the DL algorithm for pathology detection. Then, the cognitive system receives the overall result from the DL algorithm to make final decision making on emergency response.

3.3 *Risk Prediction*

Assessing and predicting risk is an integral part of the new Smart Healthcare framework, through ML algorithms researchers believe they can accurately identify symptoms of depression and other mental illnesses by observing the individual's behavior and language. J. W. Baek and K. Chung [11] proposed a Deep Neural Network (DNN) for predicting depression risk using multiple regression. They believe they can predict the circumstances that can lead to depression. First, the proposed model goes through a regression analysis to find any correlation between variables. Then, the data goes through the DNN for feature extraction and data classification, and lastly, the model compares its findings with other models for performance analysis.

Table 2. A comparative table highlighting the advantages and disadvantages of AI-based solutions for remote e-Health.

Topic	Publication	Approach	Advantages	Disadvantages
Telesurgery	[3]	An architecture for telesurgery that includes traditional networks and 5G technology.	The inclusion of 5G technology improves the quality of service and quality of experience to users.	Lacks support for long-distance telesurgery applications because of latency issues.
Remote Patient Monitoring	[4]	A remote monitoring framework that utilizes Intel SGX to provide information security.	Bypasses the complexity of problems related to encryption software by providing a hardware-based solution.	Requires BIOS support of Intel SGX to function.
	[8]	A remote monitoring mechanism based on emergency detection, adapting sensing frequency, and real-time risk prediction.	Low cost and energy-efficient solution for remote monitoring frameworks.	Scalability issues.
Connected Ambulances	[6]	A resource allocation algorithm based on the user's priority levels through a Blockchain consensus protocol.	Improves end-to-end latency issues in MEC healthcare applications.	Simulation results do not take into account resource-rich and -poor users.
Wearable Devices	[7]	The use of WD in combination with real-time therapist feedback to enhance the user experience.	Provides extremely useful information for both the user and the monitoring party.	Does not take into consideration the necessity for data privacy.
Pathology Detection	[9]	A cognitive healthcare framework that utilizes smart sensors for data collection and decision-making through DL.	A DL algorithm handles the pathology detection problem and then notifies the medical staff, which can be important for reducing the medical staff workload.	Does not take into account the user's data privacy.
Risk Prediction	[10]	A depression risk prediction system using a DNN model to predict situations and environments that contribute to depression occurrence.	Takes into consideration the data received and the environmental context before making a decision.	Does not present a real-life simulation and applicability.

4 A Drone-assisted Remote Patient Monitoring Application

A requirement was to understand how to help people living in remote and distant locations of healthcare infrastructure, besides monitoring and providing information via a mobile application to healthcare professionals about patients. With this in mind, the proposed application aims to provide videos of breathing exercises and to monitor if patients are performing the exercise as prescribed. Please note that many post-COVID patients need to perform such breathing exercises.

4.1 Drone-assisted Network

Drones would have a pivotal role in providing temporary network coverage for users in low resource areas in cases of remote patient monitoring. Montero et al. [12] showcases how drones can act as aerial base stations (ABS) to provide network coverage in emergency situations, and proposes a device positioning mechanism for drones called PERCEPT. We believe a similar approach can be taken advantage of by Smart Hospitals, where drones can supply low resource areas with connectivity, often complementing GBS. By doing so, they act as an ABS. The stable and reliable connection provided by ABS enables remote e-Health applications, hence no longer being strictly required for the GBS to the main source of network coverage. For instance, remote patient monitoring and telesurgery also benefit from ABS in disaster recovery, emergency, or even a scheduled situation. Connected Ambulances can also be assisted by drones, where the latter can be used as Road Side Units (RSUs), enhancing vehicles' connectivity.

4.2 *The Mobile Application*

Figure 2 shows the flow of the mobile application (app) for its two user profiles, namely the patient and health professional user profiles. The healthcare user is responsible for sending videos, e.g., breathing exercises (Step 4), and analyzing the videos recorded and sent by patients that perform it (Step 5). DL will replace the last step after a large number of videos have been uploaded and verified by the healthcare professional. The patient-user has a list of the exercises that it must perform. The list tells among the returned videos by the user, the ones that already have been evaluated as a valid performance (Step 2). It is the patient's responsibility to record the videos performing the exercises received by the healthcare user (Step 3) and upload the videos to the app.

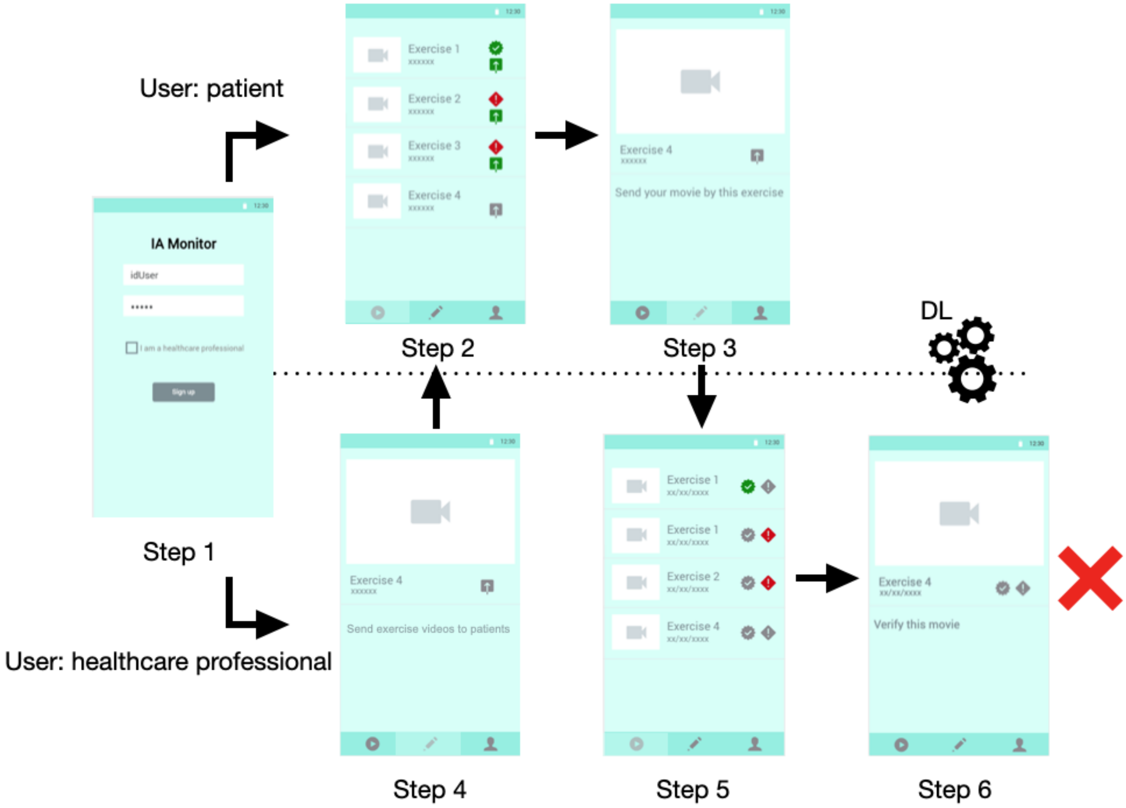

Figure 2. The flow of the mobile application.

Step 6 refers to the verification of the videos sent by the patient. This step will need to assist the process of learning the algorithm that will recognize the patterns of the videos. With the high number of videos received by the application, this step becomes more and more obsolete, being replaced by the DL-based recognition.

4.3 ***DL Training***

DL algorithms have demonstrated to be particularly useful at pattern recognition exercises in computer vision [13]. For this experiment, the training was carried out from images captured from videos recorded simulating breathing exercises. The dataset formed by these videos received a check informing whether they were performing the exercise correctly or incorrectly.

The well-designed structure of RNN is an ideal way of processing sequence data [14]. The LSTM network for binary classifiers was applied, which is one of the recurrent neural network (RNN) models. Here, we build a two-layer LSTM network for each category to learn the temporal dynamic of videos based on features generated by the last layer. The dataset used for training consisted of 46 videos. Based on it, the long short-term memory (LSTM) training model is used. For the learning process, it was necessary to generate sequences of images from these videos. By dividing them into frames, 11,237 images were generated and used in the DL training process.

Consequently, the dataset has videos transformed into images generated from frames of the video in sequence. If the medical team and patients continuously use the application, there will be an increase in the number of videos, which will increase the accuracy of the model's training.

In Figure 3, it is possible to verify the variation in accuracy and loss during training and model validation. One may conclude that for a dataset under construction, more videos are necessary. Consequently, more with input data, the accuracy of the model will improve.

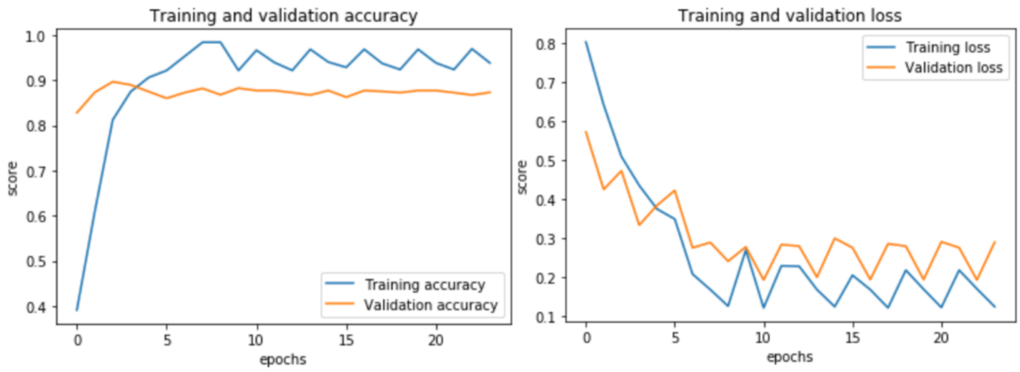

Figure 3. The accuracy and loss of model training and validation.

4.4 *Analysis*

After training the model using videos with both the correct execution of the exercises and incorrect exercises, it was possible to have good results with the validation of the model. Figure 4 shows the correct image of the exercise and the tests performed with two different videos. It is possible to see that the algorithm's answer is correct.

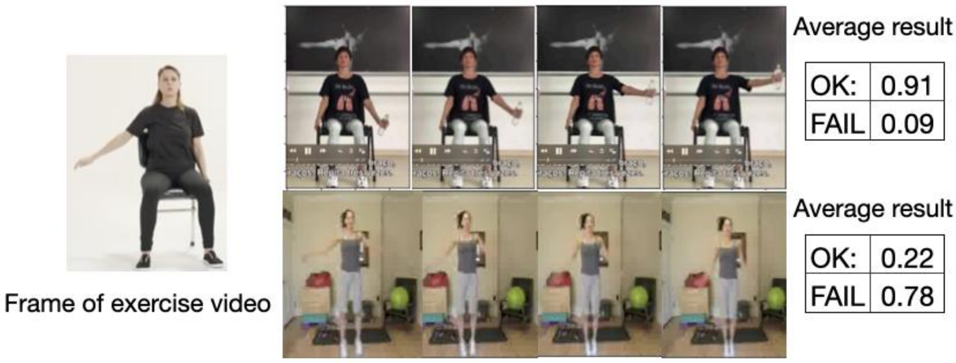

Figure 4. Validation of the exercise and the tests performed with two different videos.

We believe enhancing a healthcare application with an image training algorithm can help reduce the burden for healthcare staff in handling the app. In the case someone has breathing problems, he/she could contact his/her personal healthcare professional through the app, in this case the professional could ask the patient to record a simple breathing exercise and have the video sent to him/her once completed. The algorithm would be responsible for validating the exercise performed.

5 Challenges and Open Issues

The development of IoT technologies combined with AI approaches and Drone-assisted 5G networks has brought forth exciting prospects for future Smart Healthcare frameworks with changes to how individuals can access quality service remotely and how medical staff interacts with patients. Emergency use cases for telemedicine in this new framework are of great importance and establish requirements for such situations [15]. Our proposed framework aims to introduce these new technologies into the healthcare system. However, some challenges and open issues have to be addressed.

5.1 *Datasets*

An Activity-based Dataset, one of the challenges many researchers face when developing their machine learning algorithm, is identifying the right dataset that would ensure the algorithm is working as intended. The video validation algorithm required multiple videos to be used as the standard during training, which is difficult given that most commonly available datasets are directed towards labeled images for supervised training. As such, identifying usable videos is a difficult task since they have to be of good quality and supervised by a professional. Data collection is another key issue in healthcare-based approaches because of sensitive user information.

5.2 *Machine Learning*

Although ML algorithms show great promise for improving Smart Healthcare, these algorithms are usually limited. They are designed to perform a particular task utilizing pre-determined parameters. Therefore, ML algorithms lack generalization and can only be used to fulfill a specific task. Generalizing the scope means the algorithm can be utilized in many different areas, such as data analytics, while also performing the intended purpose. Although we are confident that our proposed algorithm fulfills the role we expected, we understand that a more generalized approach could be more beneficial for future users. However, that goes beyond the scope of this paper.

6 Future perspectives

The integration of Drone-assisted 5G networks and ML algorithms in modern hospitals is inevitable. However, to accomplish a Smart Healthcare system, a need for better datasets from hospitals is vital. We believe it would be of great benefit for all Hospitals to standardize their data collection practices. Each hospital has its approach in how and what data is collected, creating a discrepancy between information quality and credibility. If data collection in hospitals followed a more research-based approach, we believe it would be easier for researchers to approach issues and propose solutions faster and more reliably.

7 Conclusion

This article introduces the Smart Healthcare paradigm by presenting technologies such as AI and Drone-assisted 5G networks, which have the potential to drastically improve the quality of life of healthcare workers and enhance the healthcare system's service. Moreover, we highlight promising applications and solutions for this state-of-the-art environment relevant to the e-Health and mobile health environments. We also introduce our remote e-Health application. Finally, we believe that our proposed scheme can improve communication between healthcare providers and patients, make it easier for individuals to seek quality healthcare service, and reduces the burden on healthcare infrastructures.

We expect modern hospitals to fully integrate with state-of-the-art technology thanks to the developments made in IoT research. We expect that the research achievements made in Drone-assisted 5G and AI development research to be the driving force behind countless applications in the healthcare system and assist medical staff in providing better and faster service. Unmanned Aerial Vehicles, also commonly called drones, are receiving increased popularity following the growth of wireless communications. We expect them to integrate into future healthcare services where they can assist the medical staff following a major accident and natural disasters by locating the injured or providing telemedicine services when necessary.

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