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A smart emergency response system based on deep learning and Kalman filter: the case of COVID-19

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ABSTRACT

During an epidemic, the transportation of patients to emergency departments and the monitoring of their physiological parameters pose significant challenges in this critical scenario. Swift and efficient diagnosis has the potential to rescue the lives of these patients. The objective is accomplished through the utilization of deep learning to categorize information into emergencies, prioritizing its dispatch. In this article, we present a sophisticated emergency system that employs deep learning to swiftly transmit vital information from emergency patients to the hospital that can provide the highest quality healthcare for these individuals. The fusion method integrates data obtained and refined from patients' electronic medical records with data acquired by the wireless medical sensor network during the transportation phase. Subsequently, the process of choosing the parameters is employed as inputs to the learning model. The data gathered and educational outcomes, such as emergency notifications, are transmitted through Wi-Fi and 5G devices in our sophisticated system. The proposed contribution achieves a 98% accuracy with a runtime of 1.53 seconds. This discovery demonstrates the efficacy of our system, particularly in the context of epidemic situations such as COVID-19.

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1. INTRODUCTION

Effective management of global epidemics necessitates precise and comprehensive strategies, prompt emergency protocols, competent healthcare personnel, and essential medical apparatus. Insights gained from previous epidemics can be used to anticipate future situations and mitigate the complications of patient conditions and the loss of human lives. An essential component of emergency response is the implementation of ambulance services, which encompass various modes of transportation such as road and air. These preparations involve the allocation of resources, strategic planning, and efficient management of data pertaining to patients, hospitals (both those seeking assistance and those receiving patients), and the means of transport utilized for emergency interventions. Emergency resources are contingent upon various factors, including the type of outbreak, the geographical location, and the quantity of emergency cases. The availability and proximity of emergency resources may not always be adequate for efficient and prompt mobilization at the required location. The preservation of human life is of utmost significance in relief operations, such as during the coronavirus disease 2019 (COVID-19) epidemic. Emergency medical services administer initial medical assistance and pre-hospital care directly at the scene to patients in need. Services offer a restricted degree of medical care as a result of limited resources and other prevailing conditions.

During the acute phase of COVID, when patients require intensive medical care, they are transferred from their current location to a hospital or trauma center that can provide a higher level of care.

The primary difficulty in these circumstances lies in the promptness of patient transportation and the accessibility of timely medical assistance. Every instance of delay that affects response time results in disturbance, amplifies transportation expenses, and jeopardizes the lives of patients. This article presents a proposal for an intelligent emergency system (IES) that aims to offer robust and dependable medical assistance during emergency situations. The system relies on gathering data from various sources, including electronic patient medical records from the requesting hospital, which seeks to transport emergency patients to a receiving hospital that provides the highest quality healthcare. The records consist of physiological information obtained through wireless medical sensors while being transported in a control unit during each phase of travel, which may include ambulance or medical aircraft.

Emergencies require rapid response management capable of managing multiple resources to be effectively mobilized in the event of a potential emergency. Any delay could affect response time, increase transportation costs and put people’s lives at risk. However, there must be reliable and resilient medical support in an emergency with low delay.

Farooq and Ahmed [1] proposed in their work an institutional logic approach to understanding the resilience of helicopter-based medical services supply chain management in Norway. They say that emergency preparedness and response time are essential to conduct air ambulance operations. Lawner *et al.* [2] also specify in their work that the response time must be controlled to increase the chances of patient survival. Indeed, they examine the effect of the opening of an autonomous emergency service thanks to an examination of parameters such as the volume of ambulance calls, the response times of emergency vehicles and the delays of executions and their study give effective results such as the reduction of ambulance response times and out-of-service intervals. Borel *et al.* [3] proposed during the COVID-19 pandemic, a specific cell called “Dynamo” during the 1st wave at the Sorbonne to bring innovative solutions and free up places in resuscitation. Their solution has opened a flow between expert resuscitations and the new resuscitation units to transfer the requesting resuscitations to the host sites in Île-of France using private ambulances with the human and material resources of AP–HP of the University of Sorbonne. In the same context, Painvin *et al.* [4] conducted a comparative study in France between patients who underwent inter-hospital transfer during their stay in the intensive care unit and patients who did not during the COVID-19 pandemic. They showed that COVID-19 patients in intensive care initially hospitalized for respiratory failure and requiring inter-hospital transport had no higher mortality rates than locally admitted COVID-19 intensive care unit ICU patients. ThameezDeen and Sudhakaran [5] have implemented a new portable health-monitoring device based on a wireless sensor network. This device immediately detects the fluctuation in heart rate and immediately informs the people concerned of their location and the state of their health. It also keeps their temperature history, which makes it effective in the event of a pandemic. It prioritizes the health and safety of the user. All patient details are stored in the cloud and are monitored in real time using a device called ESP8266 that helps store collected data in the cloud and in case of emergency, a message will be sent to emergency numbers. Suleiman and Mahmud [6] offer an internet of things (IoT)-based healthcare architecture using wireless sensor networks, RFID and smart mobile, all interacting via a constrained application protocol (CoAP) on a low-power wireless personal network (6LoWPAN). This architecture has the ability to compress information over time and remotely access images, and quickly share information in geographic areas. Ali *et al.* [7] proposed in their contribution an intelligent health care surveillance system for the prediction of heart disease based on in-depth learning and fusion of information extracted from both sensor data and electronic medical records of patients. The system is evaluated using the Logitboost algorithm on cardiac disease data and compared to traditional classifiers based on fusion of characteristics, feature selection and weighting techniques. Their work fancies an accuracy of 98.5%.

Supriyanti *et al.* [8] used digital image processing techniques for COVID-19 screening, in particular they evaluate the surface area of white spots in patients' lungs. These white spots are an early indicator of the severity of lung damage from COVID-19. In this article the researchers use chest x-ray images as data for our study. The current experimental results show a success rate of 71.11%.

Nema *et al.* [9] are presented an intelligent knowledge-based system (KBS) designed to help patients with flu symptoms determine whether they are infected with COVID-19. In addition to providing a diagnostic function, this system makes it easier to quickly obtain medical assistance by alerting medical authorities via IoT. The information displayed includes patient details.

Gandhi and Singh [10] are working on reducing the mortality rate due to dysfunctions of the cardiovascular system and fatal heart attacks. They are proposed a model called "heart rate monitoring system (HMS)" based on miniature, portable, WBSN a wireless body sensor network, easily affordable, and accurate. This method can be used to regularly examine the heart condition in the hospital or at home to avoid or early detect any serious illness. In terms of heart rate monitoring, this system was designed to observe the extended spectrum of heartbeats and operated at the backend of the HMS.

Wei *et al.* [11] present a new algorithm for locating nodes in wireless sensor networks. Their approach relies on using the symmetric double sided-two way ranging (SDS-TWR) method to estimate the distance between the archor nodes and the unknown node, then applying the Kalman filter algorithm to optimize the obtained coordinates. The results of their experiments show that their algorithm significantly improves the accuracy of node positioning.

To manage excessive electrical energy consumption Hasan and Kadhim [12] use machine learning technology. They are developing a system that teaches consumers how to use electricity more efficiently, avoiding waste. This approach is part of a set of intelligent processes called efficient energy consumption management (EECM), which is connected to the IoT and uses Google Firebase Cloud to verify compliance with energy efficiency standards.

Recently, to monitor health and provide medical care, WBSNs have attracted great interest as a promising technology. For critical real-time medical use, it is essential to guarantee quality of service (QoS) in terms of delay and reliability. J. Bangash *et al.* [13] proposed a critical data routing (CDR) system that distinguishes sensory data into critical and non-critical data. In addition to managing data of varied nature. The results of this paper show that the proposed CDR system manages to transmit critical data within precise time frames and with maximum reliability, while limiting the temperature increase of body-integrated sensors.

Other work uses data fusion in their health care systems as in [14] and [15], where Muhammad *et al.* [14] proposed in their work to merge medical data collected from several sensors. The main purpose of this fusion is to transform the data from erroneous sensors into good quality fused information. After the fusion treatment, the data is then, entered into a classifier to predict heart disease. Edgar *et al.* [15], introduced algorithms for automated recognition of human activities and actions. They use the supervised fusion method that focuses on the simultaneous processing of motion data received from videos acquired by portable sensors and a camera.

Not all health care systems in the aforementioned emergencies deal with the technologies of sending patient data during transport and changing related network devices in their systems. Thus, the medical IoT is a difficult domain due to network traffic patterns and various network devices. This makes it very important to select only the emergency and priority data are sent in order to ensure speed and reliability of sending over the network.

To address the problems mentioned above, our main contribution in this work is to propose an intelligent emergency system that collects patient data from different sources of information. The collected data are processed and merged using the Kalman filter and selection method in order to send only the emergency and necessary parameters during the transport phase. We propose two technologies, namely wireless access vehicular environment (WAVE) and 5G, in the data transfer phase, based on the deep learning to create emergency alerts. Our contributions are: i) filter the data measured by the sensors using the Kalman filter; ii) merge data collected from different sources (electronic medical record, wireless sensor network); iii) classify patient settings to create emergency alerts; iv) store merged data and learning outputs in a database called E-health data in the cloud; v) alert hospital by transmitting data via Wi-Fi and 5G devices along the transport between the requesting hospital and the receiving hospital; and vi) update patient information at each means of transport (road, air) during the transmission phase.

2. PROPOSED APPROACH: AN INTELLIGENT EMERGENCY SYSTEM: IES

Human life in rescue operations is very important. When the patient is in acute phase and needs intense medical care, the patient is transported from the hospital to another for many reasons (better level of care, inexistence of appropriate medical staff or appropriate equipment). In the face of an exceptional health crisis, the response and mobilization must be exceptional and all health staff must be mobilized.

In fact, to achieve these purposes, we propose the IES, showed in Figure 1, which is divided into different phases. The first phase is the collection of data from different sources, then the filtering of the data measured by the sensors using the "Kalman filter", which will be detailed in section 2. The third phase deals with the merging of the collected data and the application of the "Selection of features" method. Subsequently, the classification the patient's parameters are used to create emergency alerts. Finally, the merged data and alerts outputs in E-health data are stored and transmitted via Wi-Fi and 5G devices. We also propose to update the healthcare information during the transport. We detail in the following the proposed phases.

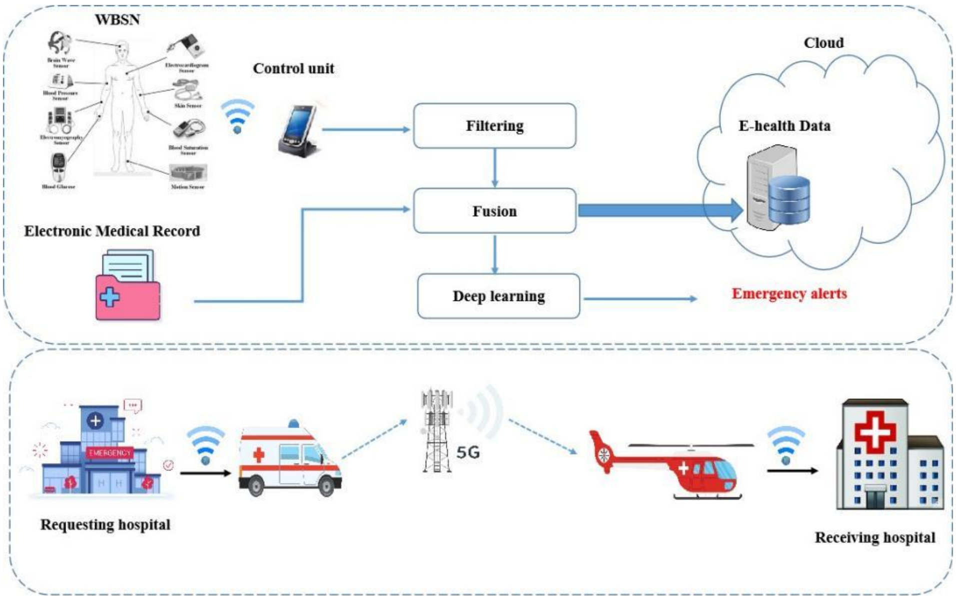

Figure 1. Intelligent emergency system

3. IES METHOD

3.1. Data collection

Our IES has two sources of information. The first source is the patient's electronic medical record (EM-record) stored at the original hospital that contains patient observation reports, medical history, smoking history, diabetes history and clinical examinations. The second source is collected from the WBSN based on medical sensors to collect physiological information related to patients in emergency. This network contains portable sensors that lead to personal devices. These sensors are characterized by their different transmission and detection capacities, computational power and storage [16].

The outputs of the sensors are transferred to a unit called a control unit, which has the role of collecting its physiological variations up to date in real time during the transport phase by means of transport of road and air emergencies. After collecting the physiological parameters of the patient in an emergency, our system transfers the information to the various devices are used as a gateway to collect and transmit these data for further treatment. At this level, data is transmitted via equipment supporting 5G and Wi-Fi.

During this phase, we noticed that there is redundant information and other information that is noisy by several effects such as interference related to the sensors and the network. Hence, the need to apply a filter. In this work, we propose the Kalman filter.

3.2. Kalman filter

The Kalman filter is a method that estimates the parameters of an intelligent system that evolves over time from the noise measurements related to the sensors. Our choice of this filter is based on several factors: its ability to predict and correct errors not only of the sensors but also of the model itself and its ability to determine the average error when estimating it. To use this filter, we need to model our system linearly to estimate noisy patient data [17]. The KALMAN filter is divided into two steps: prediction and update.

3.2.1. The prediction

This step is to take the previous estimate of patient data and error and predict the new parameters and error value based on our system modeling:

$$\hat{S}_k^+ = A.\hat{S}_k \tag{1}$$

$$\hat{P}_k^+ = A.P_k.A^T + Q \tag{2}$$

Where:
$\hat{S}_k^+$: the prediction of the current estimate from the previous estimate $\hat{S}_k$.
$\hat{P}_k^+$: the prediction of the error covariance matrix.

A : the matrix that links the previous state to the next state.
Q : the covariance matrix of the state noise.
Knowing that:

$$P_k = (H_k^T . \Gamma_k^{-1} . H_k)^{-1} \tag{3}$$

$$\hat{S}_k = P_k . H_k^T . \Gamma_k^{-1} . y_k \tag{4}$$

Where:
y_k : the measurement vector obtained by the sensors at the moment k.
$\hat{S}_k$: the vector of the parameters to be estimated.
H : the matrix linking the state to the measurement called the observation matrix.
Γ: the measurement noise covariance matrix.
P_k : the variance of the estimator (the Cramer-Rao bound).

3.2.2. The update

To account for the new measures, the prediction update is applied. This step will correct errors in our system:

$$K_{k+1} = P_k^+ . H_{k+1}^T . (R_{k+1} + h_{k+1} . P_k^+ . h_{k+1}^T)^{-1} \tag{5}$$

$$P_{k+1} = (I - K_{k+1} . h_{k+1}) . P_k^+ \tag{6}$$

$$\hat{S}_{k+1} = \hat{S}_k^+ + K_{k+1} . (y_{k+1} - h_{k+1} . \hat{S}_k^+) \tag{7}$$

With:
K_{k+1} : the gain of KALMAN at the moment k+1.
$\hat{S}_{k+1}$: the prediction to the state k+1.
P_{k+1} : the covariance of the error at the moment k+1.
h_{k+1}: the status matrix for the current measurement.
R_{k+1} : the noise covariance matrix.
I : identity matrix.
y_{k+1} : the measurement vector obtained by the sensors at the moment k+1.

3.3. Data fusion

The data collected from the control unit and electronic patient records are merged and stored in a single database' E-health data. These data existing in the control unit are the outputs of the sensors, such as electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), heart rate, blood pressure, respiratory rate, blood glucose, oxygen saturation and cholesterol levels. While medical record data are patient-related information such as age, gender, history (diabetes, blood pressure, and stroke), old clinical exams (computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, ECG, and EEG). The data fusion from different sources, previously described, is physiological information, collected from sensors and stored in electronic medical (EM)-record as represented in Figure 2.

We deploy a control unit that saves physiological information from WBSN sensors periodically. This collected data is then transferred to the coordinator to merge it with the information existing in EM-record. A set of smart devices with Wi-Fi or 5G technology are used, including mobile phones or medical devices as coordinators. Let be S={S_1, . . S_m} the set of parameters collected by the sensor and Γ={μ_1, . . μ_m} the corresponding weights, where $\sum_{i=0}^{i=m} u_i$=1. In addition, ER={$er_{1...}$, ern} is the set of parameters saved in electronic medical record (EMR) and £={α_1 , . . ,α_n} is the corresponding weights such that $\sum_{i=0}^{i=m} \alpha_i$ =1. Assuming these are the sensor values after filtering by Kalman filter, the system output is calculated following (8).

$$\hat{O} = (S_1 u_1, \ldots\ldots S_m u_m, er_1 \alpha_1, \ldots\ldots., er_n \alpha_n\} \tag{8}$$

To simplify, we suppose that the weights are equiprobable for all the information, i.e. μ (1/m), for information from the sensor and i.e. α (1/n) for information from the digital elevation mode (DEM). The data received at the control unit is entered into an updated configuration in (1) for data fusion. Feature selection is of paramount importance, because it helps to avoid the problem of over-fitting and to reduce the variance of the training model. In this paper, we work through correlation-based feature selection (CFS) [18]. In addition, we base on the calculation of a score based on the correlation to predict the importance of the features.

The selection of the correlation function 'FeatureSelectionParameter' described in Algorithm 1 finds the best features for the prediction task. This correlation operates on an underlying importance score in (9) that figures the usefulness of the features in predicting the response. The importance score is used to select the most significant features.

$$\text{Score } S_i\ \mu_i = \frac{mC_{r-f}}{\sqrt{m+m(m-1)C_{f-f}}} \tag{9}$$

With:
- Score S_i μ_i: score of a parameter collect.
- C_{r-f}: correlation response-feature.
- C_{f-f}: correlation feature-feature.

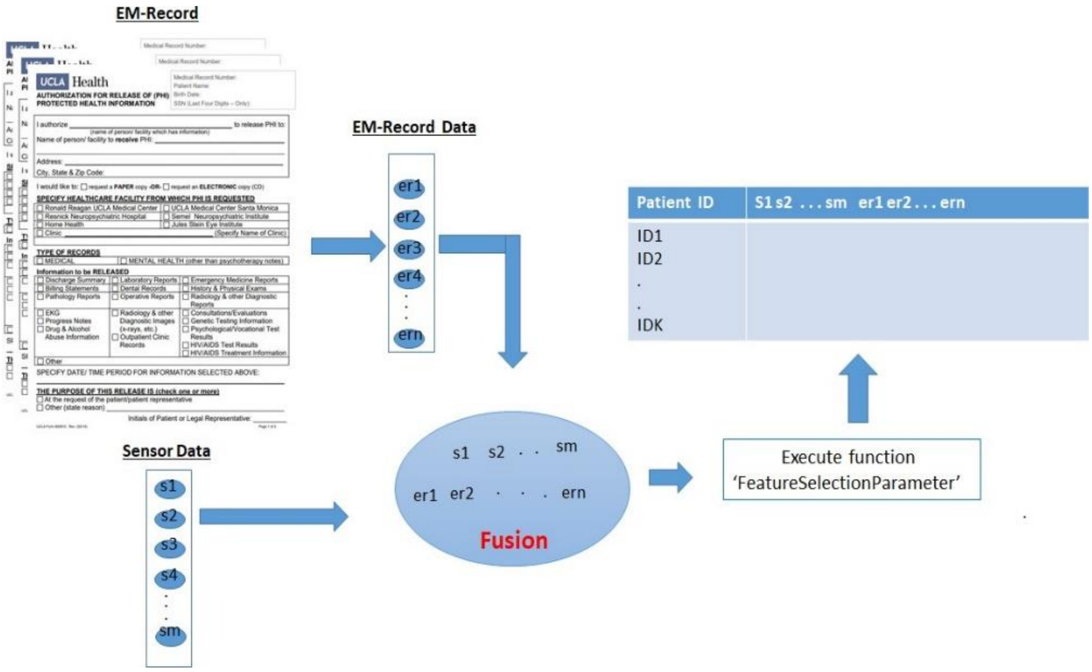

Figure 2. Data fusion

Algorithm 1. Feature Selection Parameter
```
D: dataset (WBSN)
Si µi: feature set
1: function FeatureSelectionParameter (D, Si µi)
2: for i=1 to m do
3: compute importance scoreSi ui by (9)
4: end function
```

3.4. Learning

After the parameter selection phase, the output is the patient database as shown in Figure 2. This database is used in the learning phase to create emergency alerts sent to the receiving hospital department. The creation of these alerts is based on the priority level of the information sent first. In fact, physiological data in emergency takes the priority value '1' and the other parameters take the value '0'. So, learning in our healthcare system helps classify the necessary and higher priority information based on multiple entries collected through EM-record and WSN sensors during patient transfer.

To achieve our goal, we used the hybrid algorithm 'convolutional neural network-long short-term memory (CNN-LSTM)' as a learning algorithm. Our choice is based on several factors: its simplicity, its speed, its low memory cost and its effectiveness in classifying medical signals [19]. The target learning output is the information priority level. It can be either equal to 1 that is to say the information is in emergency and gives a patient health alert; otherwise it is equal to 0.

The epidemic treated in this work is COVID-19; indeed, the patient transferred to the receiving hospital is fueling this viral virus [20] in order to find better health care. Learnings data are the parameters extracted in the post-merger selection phase that are represented as follows:

– Identifier: unique identifier.
– Age: the person's age in years.
– Gender: the person's gender (1=male, 0=female).
– HR: heart rate.
– ECG related physiological signals.
– Oxygen saturation.
– Temperature.
– Heart disease (0=no, 1=yes).
– COVID (non COVID=0, COVID=1).
– Hypertension: 0 if patient does not have hypertension, 1 if patient has hypertension.
– Glucose level: mean blood glucose level.
– Ever married: (no=0 or yes=1).
– Type of residence: (rural=0 or urban=1).
– BMI: body mass index.
– Smoking status: (formerly smoked=1, never smoked=0, smoked=2).
– Stroke: 1 if the patient had a stroke or 0 if not.

Learning output: priority level: 1 if information is urgent or 0 otherwise.

3.5. Sending the data

In our system, data is delivered via devices (WAVE) and shared via 5G between the means of mobile emergency transport. The two routes of communication between the hospital and the emergency vehicles are the ambulance and the plane. This indicates that these various technologies are supported by emergency transit media.

3.5.1. WAVE: wireless access vehicular environment

Patient information collected during the data collection phase is sent via WAVE between the requesting hospital and the ambulance. For that, we used the same technology between the plane and the receiving hospital. WAVE is an improvement of Wi-Fi, it currently considered the promising technology for wireless medical networks. It aims to support interoperability and robust security communications in a vehicular environment, the frequency band for WAVE is equal to 5.825-5.850 GHz, with a bandwidth of 10 MHz per channel. Its network coverage actually reaches 1,000 m, much higher data transfer rates (between 6 and 27 Mbps in theory) [21], [22]. The WAVE standard provides a single mode of communication called the WAVE short message protocol (WSMP) mode, which allows the exchange of messages in a fast-changing, low latency, radio frequency (RF) environment. This Protocol is used to facilitate communication between vehicles and enhance safety [23], [24].

3.5.2. 5G

Updated patient physiological data and emergency alerts are transferred between the ambulance and the aircraft via 5G. This technology provides very high speeds of up to 10 Gbit/s to support the growing use of mobile internet, broadband above 6 GHz while increasing network density and low latency equal to 1 ms [25]. The communication between these means of transport is of type vehicle to vehicle (V2V). These types of communications have more stringent performance requirements for the communication layer, with some use cases requiring ultra-reliable communication links and maximum end-to-end latency of 100 ms or less [26], [27]. The communication in our system between the ambulance and the plane is established via the network through the interfaces, according to the standard ISO 17419 [28]. The interfaces use uplink and downlink to implement vehicle-to-vehicle communication [23] as illustrated in Figure 1. According to 3GPP, these interfaces have the capability to transfer 20 GB of data per second, from the base station to a device connected to the network, and half the way back [29]. The data is sent in 802.11 [30], [31] standard ethernet frames as shown in Figure 3.

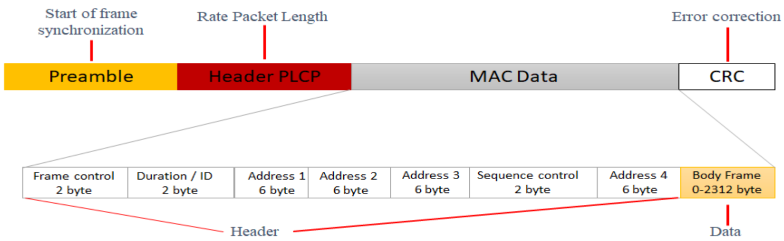

Figure 3. Data sending frame format

4. RESULTS AND DISCUSSION

In our work, we use learning to create emergency alerts based on the priority level of the information in order to send it first and avoid network overload when sending this critical data. Since any delay in sending may affect the health of patients in the case of epidemics, such as COVID-19. To do this, it is necessary to use a robust algorithm to achieve our goal. All our simulations are run based on data that has undergone all the necessary pretreatments mentioned above. Our contribution based on the use of CNN-LSTM to classify urgent and non-emergency information when transporting patients between the requesting hospital and the receiving hospital while taking into account updates of physiological data acquired during the transfer.

4.1. Performance metrics

Our algorithm gives as performance metrics: the confusion matrix (CM) measuring the quality of system where each row corresponds to an actual class. Each column corresponds to an estimated class represented in (10) and accuracy (ACC), to measure the proximity or remoteness of a given set of observations in relation to their real value, represented by (11).

$$\text{CM}=\begin{matrix} TP & FP \\ FN & TN \end{matrix} \tag{10}$$

With:
TP: true positive is the number of information correctly detected (urgent and not urgent).
FP: false positive is the number of non-emergency information detected as urgent.
FN: false negative indicates the number of urgent information classified as non- urgent.
TN: true negative indicates the number of urgent information correctly classified.

$$ACC = \frac{(TN+TP)}{(TN+TP+FP+FN)} \tag{11}$$

4.2. Experimental results

In our contribution, we vary the learning rate to indicate the speed at which the coefficients of our algorithm evolve. We initially choose 20% as a learning rate until we reached a maximum rate equal to 80% as shown in Figure 4. This variation indicates the performance of the used learning algorithms and the confusion matrix used to determine if there is a wrong categorization in the learning. Our algorithm is developed with anaconda navigator, which is based on Python 3. The used samples in the training for the training and test data sets are stored on our machine. The CNN-LSTM algorithm is one of the most suitable algorithms for the classification of physiological data of the human body and the detection of alerts. In fact, it is effective in terms of runtime, even with a large number of neurons and a large volume of data sets, as shown in Figure 4.

From the Figure 4, we find that accuracy increases with increasing learning rate and our algorithm reaches its maximum accuracy, which is equal to 98% with a maximum learning rate of 80%. Thus, we notice that training accuracy coincides with validation accuracy. This confirms the performance of the CNN-LSTM algorithm in emergencies. For this learning rate 80%, we have CM=$\begin{matrix} 239 & 3 \\ 4 & 74 \end{matrix}$, that is FN=4, which represents the number of patients detected as non-urgent then who are in emergency and this number is minimal before TP=239, which are correctly detected hence the effectiveness of our algorithm. These results are sent in the data fiels found in the MAC data fiels in the frame shown in Figure 5. The massage sent in our system is of this form shown in Figure 5.

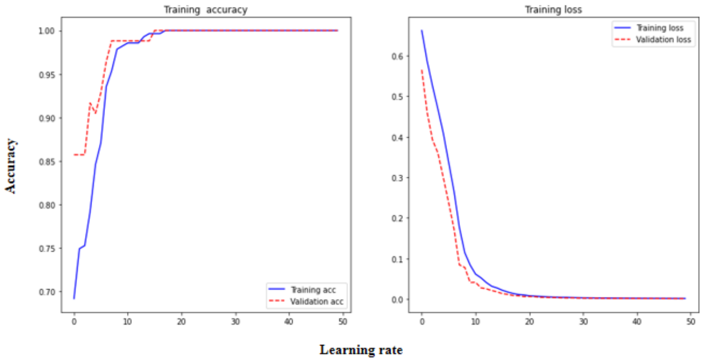

Figure 4. Training accuracy and training loss as a function of learning rate for CNN-LSTM

ID patient	*Personal Data*	*Emergency alert*	*Priority class (0,1)*

Figure 5. Alert message format

The execution time in our intelligent system is defined by the process time noted T_p, which is represented by (12).

$$T_p = T_D + T_{DL} + T_A \tag{12}$$

With:
T_D: the time of collection of patient data (EM record data and sensors data).
T_{DL}: learning run time.
T_A: the time for sending emergency alerts.
In our work, the overall process time of our system is equal to 1.53 s, which is interesting when considering emergencies, traffic in routes and transportation speeds of used vehicles.

5. CONCLUSION

In this paper, we proposed a new architecture for transporting emergency patients to a receiving hospital in order to provide the best possible health care. This architecture is built around a smart system called IES, which enables the fusion of medical data from WBSN and EM-record. In the parameter selection phase, we used CNN-LSTM on data selection to generate emergency alerts based on the priority level of information that may be urgent in order to send those in emergency first and avoid overloading the deployed system. All of this data is sent to Wi-Fi and 5G devices along the patient transport route between the requesting and receiving hospitals. COVID-19 is the practical case we've chosen for this article. The selection of learning parameters based on physiological data related to this virus, which has a potentially lethal impact on human lives. In this global epidemic, each delay in intervention can have an impact on patients' health and even increase their risk of death. Our contribution yields performance results in terms of accuracy that exceeds 98% and a confusion matrix that detects the fewest false negative rates in comparison to true positive rates. In our proposed health system, the turnaround time is 1.53 s. We intend to use other methods of fusion and selection of medical data in future work, increase the number of records in our dataset, and then test other learning algorithms to compare with the one used in this article.

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