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Investigating the Components of Virtual Emergency Department

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Abstract. The prediction of the demography of Spain shows that Spain will experience an aging population soon. Aging is a condition of chronic disease resulting in overcrowding Emergency Department. Despite chronic diseases, Covid-19 became a serious issue for emergency Department staff and health care providers. All of these matters emphasized the importance of the Virtual Emergency Department which can provide faster and more affordable medical services while everyone can keep the social distance as much as possible. In this chapter, we investigated the role of IT in the healthcare system and the possible suggested solutions. We have studied the existing telemedicine, e-health, machine learning algorithms and in the end, their combination to built an integrated virtual emergency department to cover all the aspects. We have proposed a model for this integrated model and studied the possibility of success in each step including admission, triage, diagnoses, and clinical advice based on literature.

Keywords. Virtual Emergency Department, Smart Triage, Smart Diagnoses, Telemedicine, AI in Health Care System

1. Introduction

1.1. Importance of Virtual Emergency Departments in Pandemic

The main entrance to the health care system is the Emergency Department (ED), in which the quality of treatment directly affects the quality of the healthcare system. Overcrowding in EDs is a global multi-factorial issue causes (i) extended length of stay (LOS), and (ii) delay in medical care and treatment for chronically ill patients, frustration, and short-term mortality among patients. Our statistical analysis of the Parc Tauli Hospital's data set reveals that almost 70% of ED visits are non-urgent patients who do not need emergency care. Authors in [1] reported that 91.5% of patients who visited EDs within five days had mild or moderate symptoms.
Coronavirus (COVID-19) was first identified in China in 2019 and soon became a pandemic. Spain has undergone three outbreaks in the spring and fall of 2020, with the third wave in January 2021, which undermined the ED's response capability. The studies show that frequent visits of COVID-19 patients at Al4 or Al5 levels or patients with mild symptoms overwhelmed EDs and raised the risk of transmission.

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WHO on reports, on average, every person infected with COVID-19 exposes 2 or 2.5 persons. Besides the risk of exposure, Covid-19 affects the mental health of society widely. A survey indicates that 36% of the participants reported moderate to severe psychological impact, 25% impacted with mild to severe anxiety levels, and 41% showed depressive symptoms, and 41% felt stressed [2,3,4].

1.2. Contributions of The Virtual Emergency Departments Globally

Since the beginning of the pandemic, many countries began to strictly follow the evaluation, investigation, and implementation of the VED. For example, many EDs in Ontario use virtual follow-ups for discharged patients, virtual psychiatry consulting, and virtual appointments to the pediatric emergency department. The London Health Sciences Centre (LHSC) also opened an after-hour virtual "ED waiting room" integrated into their departmental electronic medical platform. SickKids in Toronto similarly rolled out virtual subspecialty consultations for children physically in the ED. The Virtual Emergency Department (VED) provides remote health services to non-emergency patients via video call using smart devices. The examination of this type of patient with long-distance care allows virtual clinical follow-up and consultation to provide care seekers with faster care services from home, eliminating travel time and ED wait times while maintaining social distance for pandemic management. The VED can also provide 24-hour service, which improves the healthcare system's efficiency and reduces LOS.

1.3. Motivation and Contribution

To the best of our knowledge, current studies are insufficient for presenting a comprehensive VED model with detailed modelling parameters. We recently proposed a comprehensive VED model validated using real-time data analysis from the Parc Tauli Hospital data set, with each stage of the ED elaborated separately. We use cutting-edge artificial intelligence classification and clustering algorithms to propose the method.

2. Materials and Methods

2.1. Traditional Process in ED

Patients visit ED by themselves or an ambulance. There are three main stages in the ED, including registration and admission, triage and then treatment. The patient's registration is followed by triage. The triage phase in ED specifies the treatment area (i.e., area A and B in Fig. 1). Patients with acuity levels (ALs) 1, 2 and 3 are assigned to Area A and stay in care-boxes during all hospitalization. Patients with ALs 4 and 5 belong to area B for receiving treatment. All patients in the admission and triage phases have the same nurses and healthcare staff. After triage, in diagnoses and treatment stages, separate doctors and assistant nurses serve at each Area while sharing the same test service resources such as laboratory test and X-Ray [5].

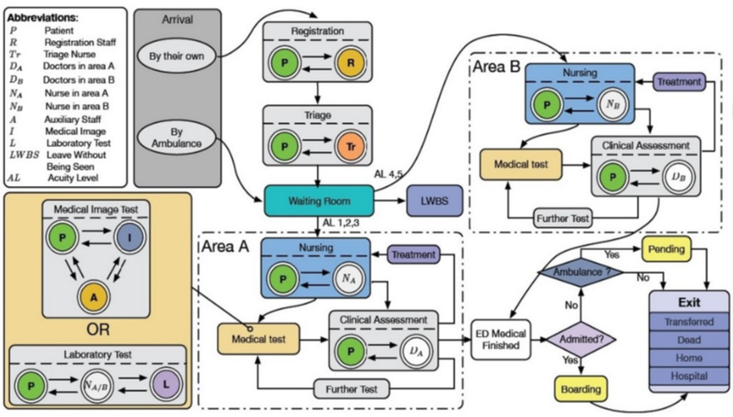

Figure 1. ED model modeled the actions and interactions between different elements of the system including patients, healthcare staff, and physical resources of ED. Urgent patient receive treatment in areas A and B were designed for non-urgent patients and have their own allocated staff [5].

2.2. Who Benefits from VED

The VED concept began with providing medical services to 1) rural areas with no access to the care system, 2) after-hours care needs, 3) chronic care monitoring, and 4) after surgery or post-acute passive monitoring. Participants in these four categories do not have life-threatening conditions. However, it has recently become a hot topic to provide virtual medical services to all types of patients. Patients with severe symptoms, on the other hand, should go to the nearest emergency department. The following are the life-threatening signs, according to Ontario Emergency Services: respiration problems, high body temperature, difficulty speaking or swallowing, neck stiffness or severe headache, fatal injuries, new or worsening seizures, possible broken bones (i.e., bones or joints look different, cannot put weight on injury), vomiting and inability to drink fluids, loss or change of vision, numbness or weakness of the face or body, inability to walk, new confusion or memory problems, pregnancy and labour problems, opioid pain medicine prescriptions or renewals

2.3. Non-Urgent Arrival Patients: Clinical Data Collection and Analyzes

The analysis of ED visits with varying acuity levels is required to clarify the importance and influence of VED on ED quality. This information revealed a correlation between the number of non-urgent arrival patients and ED saturation. A study shows that 30% of ED visits in USA are unnecessary, and it is preventable [6]. Another study reports that 67% of the visit to an ED in Iran are non-urgent patients [7]. However, statistical analyzes of clinical data collected from (Parc Tauli hospital) indicate that 70% of total ED visits are patients with ALs 4 and 5 (Table 1) [8]. In the triage step, patients are classified into five acuity levels (ALs) , where patients with ALs 1, 2, and 3 are considered urgent patients and prioritized to receive treatment and/or physical resources according to the Spanish triage system. Patients with ALs 4 and 5 are classified as non-urgent patients who have a lower priority to receive treatment and/or physical resources [9,10].

Table 1. Classification of patients visiting the ED based on their level of urgency (Spanish Triage System). The data represent 1 year of ED visits (collected from Parc Tauli Hospital in Sabadell/Spain)

Acuity Level	Type of Attention	ED Visits	Number of Visit
AL1	I-resuscitation	0.39	530
AL2	II-emergent	4.36	5,905
AL3	III-urgent	25.37	34,394
AL4	IV- less urgent	50.33	68,228
AL5	V-non-urgent	19.55	26,509

2.4. *General Model of VED*

VED follows the same steps as ED but using remote infrastructure technology for monitoring. A telemedicine setup will require basic infrastructures such as an internet connection, a video platform, smart devices, and telecommunication technology support. Patients seeking medical care or recommendations log on/into a hospital webpage/app to start a virtual visit from their own device. After the connection, the patient would be (i) registered, (ii) triage, (iii) diagnosed and (iv) treated/advised by an automatic system or online medical staff. If necessary, prescriptions or lab tests is organized, and the patient is redirected to an in-person emergency department or an appointment with a primary care provider. Figure2 shows the different stage of VED which each stage has been elaborated as follows:

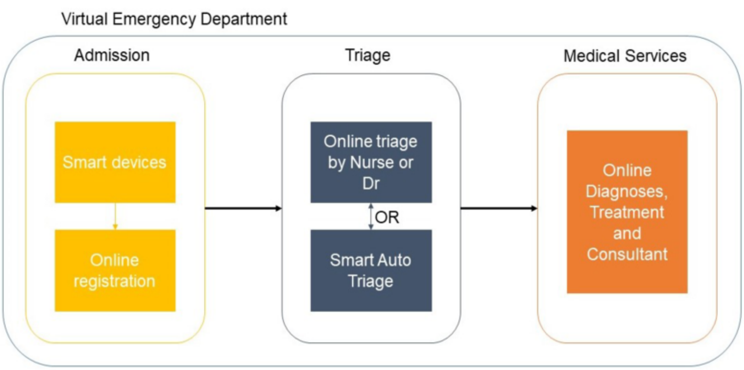

Figure 2. ED is composed of three main sub-model including admission, triage and medical services (diagnoses, treatment, consultation, medical test and so on)

2.4.1. *Registration*

When a patient enters an ED, he/she must be admitted to ED and stays in the waiting room. There are patients frequently visiting ED, usually without an appointment. However, they should be admitted every time. Managing the registration is a solution to optimize the time-efficient service providing. Online registration helps care providers manage patients' entrance and organize the less/non-urgent visit in not-hectic time. It also reduces there-admission and waiting room time. To do online registration, a smart device and internet connection are needed. Patients themselves or their families can easily connect to the website or app, sign up and enter some information such as personal data, historical medical data, and fill up the pages with current symptoms and signs of the patient requesting the visit.

2.4.2. Virtual Triage

The triage stage starts after collecting health information from patients or his/her family. This information is acquired by answering a few questions about the health status. The questions such as how quickly your symptoms developed, how long you have had them, and whether they have changed recently are also asked to rectify the degrees of urgency [12,13]. Virtual triage could be implemented through (i) attending physician virtually and remotely; (ii) an artificial intelligence platform and automate smart model such as machine learning algorithms. Some patients, especially older people, use VED to be monitored after surgery. For such a purpose, the quantity of the vital signs such as electrocardiogram, heart rate, blood pressure, respiration rate, blood oxygen saturation, blood glucose, skin perspiration, body temperature, motion evaluation, cardiac implantable devices, and ambient parameters are required. Wearable Health Devices (WHDs) help them measuring these parameters and transfer them to the medical staff for real-time and remote health tracking.

2.4.3. Online Clinical Service

The next step after the successful triage is the diagnosis. The system could automatically assist the system, live communication type - involving a physician - or a non-real-time consultation. Generally, the type of implementation depends on several factors, such as the severity and type of disease and patient willingness. A non-real-time option includes the clinical analysis, result of the medical test, and medical recommendation. The result is sent as a text message or an email to care seekers.

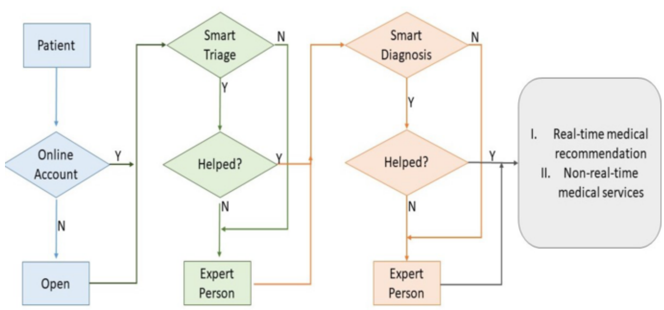

Figure 3. VED model is merged of automated model through (machine learning algorithm) and telemedicine
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3. Importance of Artificial Intelligence in VED

In emergency department studies, the use of AI-based solutions and platforms is rapidly increasing. As a subset of AI, Machine Learning (ML) has grown in popularity in medicine. As a result, its classification algorithms are employed in prediction, triage, and diagnosis. These algorithms contribute to decision-making, whether independently or minimize the uncertainty of medical staff in manual working.

3.1. AI-based Solution in Triage

The Spanish triage system, which is similar to the Canadian system, is known as the Emergency Severity Index (ESI), and it is a five-level emergency department (ED). The triage algorithm divides patients into five clinically relevant groups ranging from 1 (most urgent) to 5 (least urgent) (least urgent). The classification is determined by acuity and resource requirements. Figure 3 [14,15] represents the algorithm.

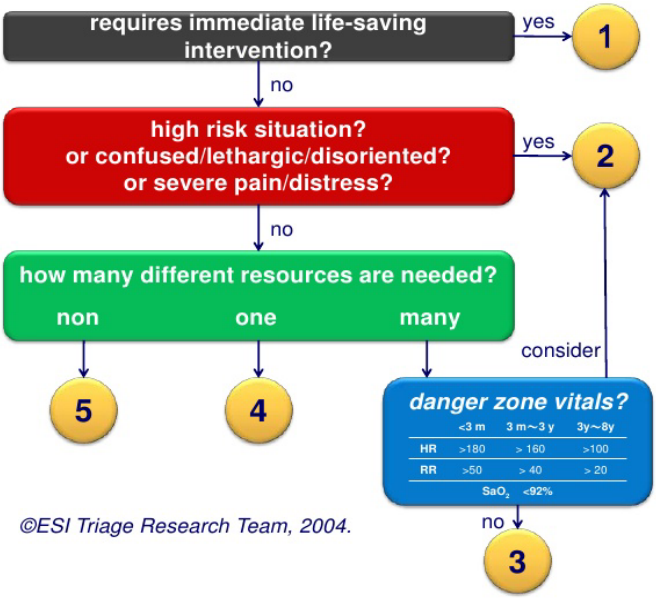

Figure 4. Canadian(similar to Spanish) triage system classifiys the patient in five categories based on their severity and need of resources. [14]

A team from Harvard Medical School investigated machine learning prediction models using routinely available ED triage data. They have collected data from the ED component National Hospital and Ambulatory Medical Care Survey (NHAMCS) between 2007 and 2015. 70% of triage data was used for training as predictors (e.g., demographics, triage vital signs, chief complaints, and comorbidities), and the remaining 30% of ED data was used for the test. As the reference model, a logistic regression model based on ESI data had been developed. The clinical outcomes were split into two categories: critical care and hospitalization. In this study, they assessed each model's predictive performance, using the Area Under the receiver-operating-characteristics Curve (AUC) and net benefit (decision curves). The AUC is a measurement to evaluate a classifier's ability to distinguish between the positive and negative classes; the higher the AUC, the better the performance of the model. Decision curve analysis with the key concept net benefit also is a method to measure prediction models and diagnostic tests. In both outcome predictions (critical care and hospitalization), all four machine learning models outperformed the reference model. The result of the study is shown in the Table2:

A research team in Korea has investigated the different machine learning models to predict the Korean Triage Acuity Scales (KTAS) levels. This team collected a data

Table 2. Result of AI solution in triage

Outcome and Model	AUC (Area Under Curve)
Critical care outcome	
References model	0.74 (.072- 0.75)
Lasso regression	0.84 (0.83 – 0.85)
Random forest	0.85 (0.84 – 0.87))
Gradient boosted decision tree	0.85 (0.83 – 0.86)
Deep neural networking	0.86 (0.85 – 0.87)
Hospitalization outcome	
References model	0.69 (0.68 – 0.69)
Lasso regression	0.81 (0.80 – 0.81)
Random forest	0.81 (0.81 – 0.82)
Gradient boosted decision tree	0.82 (0.82 – 0.83)
Deep neural networking	0.82 (0.82 – 0.83)

set from a single emergency department of a tertiary university hospital from November 2016 to June 2019. They classified the data into three types of (i) only structured data, (ii) only text of nursing triage notes, and (iii) a mix of both structured data and nursing triage notes. The data set was analyzed to develop Logistic regression, random forest, and XG-Boost and predict the KTAS level [16]. The models with the highest AUROC (Area under the receiver operating characteristic curve) were the random forest and XGBoost models trained on the entire dataset obtained the highest AUROC (Area under the receiver operating characteristic curve) (AUROC = 0.922, 95% confidence interval 0.917–0.925 and AUROC = 0.922, 95% confidence interval 0.918–0.925, respectively). The result (Table3) demonstrates that machine learning can strongly predict the KTAS level at triage, which provides us with many possibilities of uses [16]. Another study [17] collected the

Table 3. Result of AI solution in Korean triage acuity scales

Model	AUROC
Logistic regression(clinical data)	0.8812
Logistic regression (text data)	0.8595
Logistic regression (all data)	0.9053
Random forest (all data)	0.9220
XGBoost (all data)	0.9220

information from different ML models in triage and compared each algorithm's accuracy with others. These algorithms include Decision Tree, Support Vector Machine, Random Forest, Naïve Bayes Classifier, and Bayesian Network. The comparison of accuracy is shown in Table 4.

The abilities of artificial intelligence and machine learning techniques can be used in medicine. Especially, these techniques may have a significant contribution in emergency medicine and some critical issues, including disease prediction, admission or discharge prediction, and patient triage. By early prediction and diagnosis of high-risk diseases such as AKI, Sepsis, pneumonia, and contagious diseases such as influenza, necessary interventions can be performed more rapidly in ED to prevent multiple disease progression complications. Different machine learning algorithms such as Logistic regression,

Table 4. Different models used in machine learning-based triage systems

Model	Accuracy
Decision tree	84.0%
Support vector machine	84.0%
Random forest	AUC: 0.73 – 0.92
Naive Bayes classifier	Accuracy: 87.9%
Bayesian network	Accuracy:86.9%

Bayesian network, deep learning have been deployed with high accuracy ranging from 70% to 90%.

3.2. AI-based Solution in Diagnoses

Using AI and ML classifiers such as Fuzzy Logic System, Decision Tree, SVM (support vector machine), K-nearest neighbours (KNN), PNN (probabilistic neural network), and RBFNN (radial basis function nueral network) facilitates predicting various diseases, such as Parkinson's disease, liver disease, heart disease, breast cancer, and lung cancer. The result especially, the prediction of cancers with the slightest uncertainty, have been admissible [18]. Many ML algorithms, including Naive Bayes classifier (gaussNB), LDA (linear discriminant analysis), KNN, quadratic discriminant analysis (QDA), SVM (nu-SVC), MLP1, linear SVM (LinSVM), Random Forest, logistic regression, and C-SVC as a type of SVM (called SVC) have been tested under the same condition in a study [19,20]. MLP1 is a multilayer perception algorithm with one hidden layer that the hidden layer included a maximum of 200 neurons. In the end, the nu-SVM algorithm gained the best accuracy with 93.08% and the highest F1-score rate of 0.9151 In another study, the accuracy of ML in detecting some of the most important diseases have been compared. The diseases in this study are acute kidney injury (AKI), chronic obstructive pulmonary disease (COPD), and asthma, urinary tract infection (UTI), Sepsis and influenza. We summarize the results in Tables 5-8.

AKI: Many types of research investigated the detection, prediction, and diagnosis of AKI. They have been applied different methods and models to discover the most precise algorithm. In these studies, the algorithm such as Multinomial naıve Bayes (MNB), L1-/L2- regularization, SVM, Logistic Regression (LR), Random Forest (RF), Gradient Boosting and Decision Tree (GBDT), support vector machines, Gradient Boosting Machine, Deep learning, and architecture knowledge-guided deep learning was used to design the model. The best result of each study is shown in Table 5.

Table 5. prediction and diagnosis of AKI

Algorithm	Result
Boosted ensembles of decision trees	AUC; 0.72 – 0.87
Logistic regression	AUC: 0.77
Gradient boosting machine	AUC: 0.73 – 0.97
Deep learning	Accuracy: 99.1%
Logistic regression	AUC: 0.74
Binary logistic regression	Sensitivity: 96.6% Specificity: 95.7%

Influenza: is an infectious disease affecting many people every year, and it can cause epidemics due to its contagious nature. Two different studies have been performed: natural language processing and different classifiers were used in a combined manner. In the second one, seven classifiers, including Naïve Bayes, Bayesian network with the K2 algorithm, Efficient Bayesian Multivariate Classification, Artificial Neural Networks, Logistic Regression, SVM, and Random forests were applied, and the results were compared with each other. The first study reports a Bayesian network classifier (naïve Bayes) with an AUC of which was 0.79 and showed the highest value among the nine experiments. Moreover, in the second one, Bayesian (naïve base) showed better performance with an AUC of about 92-93%.

Table 6. Influenza – algorithm with highest AUC

Algorithm	AUC
Bayesian Classifier	0.92-0.93
Bayesian network classifier (naïve Bayes)	0.79

Sepsis: A machine learning-based method has been proposed for the prediction and diagnosis of Sepsis, which can improve patients' treatment procedure. Using a gradient tree boosting algorithm, three levels of Sepsis are detected. Features used in this method include values of 6 vital signs in EDs, general wards, and ICU, and, eventually, the Area under the ROC value for Sepsis and severe Sepsis are 0.92 and 0.87, respectively. Applying SVM to a bag of words is more effective than other methods, and the AUC values for test and train data are 0.86 and 0.89, respectively.

Table 7. Sepsis: algorithm with highest AUC

Algorithm	Accuracy
Gradient tree boosting	AUC: 0.87-0.92
Support vector machine	AUC: 0.86

COPD and Asthma: Asthma condition and COPD exacerbation in EDs has been assessed in different studies using different machine learning methods such as Lasso regression, random forest, and boosting, and deep neural network, Gradient-Boosted Decision Tree, Naïve Bayes, and some models have been developed based on available data. The models with the best results are presented.

Table 8. COPD and Asthma: The most accurate result

Algorithm	Result
Random forest	C-statistic: 0.84
Logistic regression	Accuracy: 89.1%
Naïve Bayes	Accuracy: 70.7%
Tree-based decision model	AUC: 0.83

UTI- To predict UTI, seven machine learning algorithms including Random forest, extreme gradient boosting, adaptive boosting, elastic net, support vector machine, logistic regression, and neural network. Results showed that among the mentioned algorithms, the XGBOOT algorithm provided the best efficacy with an AUC of 0.90.

4. Discussion

In order to reduce pressure on ED and enhance its performance, several solutions have been suggested. Some solutions incorporate patients by redirecting them to different wards, increasing resources (e.g., physicians, nurses, and physical resources), and applying operational research methods. Nevertheless, those methods can not only solve the problem of budget but also social distance issues for communicable diseases such as Covid-19 stay unchanged. It has been reported proximately, the average cost of a VED per visit is about $40 to $50, while the average estimated cost of in-person acute care is $136 to $176 [30].

4.1. Utilizing Telemedicine to Support VED

While not identical, telehealth, telemedicine, m-health, e-health, and Miot (Medicine Internet of things) terms, they may be used interchangeably. Telehealth is the distribution of both Health Resources and Services Administration such as video conferences, videophone for consultation, home monitoring of patients, robotic surgery, treatment via digital instrument, live feed and application combinations [21,22]. Telemedicine is a subgroup of telehealth limited to only long-distance clinical services such as diagnosing and monitoring patients. E-health is defined as a healthcare practice supported by electronic processes and communication, including internet medicine and all virtual things related to medical and services that can search, find, and understand the health information by using electronic sources to solve a health problem [24]. MHealth (mobile health) uses mobile communication devices, such as mobile phones, tablet computers and wearable devices (e.g. smartwatches), for health services, information, and data collection, which is a sub-segment of e-health. It uses information and communication technology (ICT), such as computers, mobile phones, to provide health services and information [25]. The Internet of Medical Things (IoMT) merges medical devices and applications to obtain accurate diagnoses, fewer mistakes and lower costs of care. IoMT allows patients to send their health information to the physician to follow up and prevent chronic illnesses [26]. With the different definitions, all of these could be used in the proposed VED via electronic, smart, communication and mobile or wearable devices and technology to provide virtual and accurate health care services. Some programs and applications such as Jefferson Health, Mount Sinai, Kaiser Permanente, Cleveland Clinic, Providence have been developed and allow clinicians to see patients at home. Doctors and nurses can provide medical recommendation, Triage through web-conferencing, automate triage, monitor the patients in ICU, making the medical decision by accessing the specialist, giving consultations, permitting the patient to schedule a video visit on demand, and even provide the possibility for clinicians to work from home [27]. At present, coordinating of the testing system, pharmacy, insurance and payment regulation, and coherence among all the components are parts of unsolved issues [28]. The average number of VED visits per patient is 1.3 visits/year. Unfortunately, not many types of research have been conducted to investigate an integrated VED objectively. VED allows health care is timesaving for both staff and patients and less costly with minimum touch, and, in many cases, more effective than other health care options. Specifically, it can be important for patients with less of an emergency condition who are transmitters and can impose a significant burden on EDs.

4.2. VED Vision: from Testbed to Real Application; Requirements

No telemedicine program and application can be conducted overnight, but all the discussed researches and studies represent that partially VED is implemented and used in some countries and EDs for some particular type of diseases successfully. However, a central, allied, and integrated healthcare system is missing to unify all the sub-models and types of diseases. The existing systems already helped the care seeker and giver with faster clinical services, but still, it does not provide them with all needs of patients. To fulfill all the requirement, the entire existing sub-segment incorporating automated and/or online initial intake, triage, diagnoses, treatment, monitoring via video, web, phone, smart, and/or wearable devices should be concatenated and then unified with transport and ambulance system management, pharmacies delivery system and insurance and finance department. Despite Internet and electronic devices, a secure database is needed.

4.3. Problem and Limitation of VED

The health care system requires the collection and massive storage of personal health information. It may be sensitive and potentially embarrassing. Thus, medical data protection is one of the concerns of both caregivers and care seekers. Insecure data could lead not only to data breaches but also to fatalities in people relying on medical devices. Clinicians also need to rely on technology when ensured security and fully compliant with privacy laws. Besides, both caregivers and care seekers have to be trained for using the virtual system. However, the VED is unable to test and examine patients and might cause a delay in treatment. VED relies on the technology of measurement and data. Therefore, the methods' performance depends not only on the efficiency of the algorithm but also on data quality and conditions of implementation. The structure of data (supervised and unsupervised) and medical reports may significantly impact the results.

5. Conclusion

A model had been designed and developed to integrate existing sub-segment models and merge an intelligent automatic system with telemedicine and mhealth. The proposed model has studied the possibility and probability of success in each sub-segment according to related researches. Machine learning is highly recommended to triage, diagnose and decision-making especially for for most common diseases. In general, the machine learning model methods were superior in predicting critical care, triage, and diagnoses, thereby achieving better clinical care and optimal resource utilization.The system can ease self-care management, accelerate the clinical services, and organize self-quarantine while in-person visits become the last option. Decreasing the non-urgent visit also provides the urgent visit with a better quality of medical services and result in patient satisfaction. The smart algorithms minimize the failure while caregivers making decisions. VED enable people from different locations to have the equal access to the healthcare system and connect to specialist easier. However, the uncompleted data and shortage of information have significant implications on the accuracy of all studies. Therefore, no definitive answer is gained about the most accurate method.

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