Smart Triage system for Patient Assignment after Disaster

Anjali Dongre, Neelam Netke, Ritika Rajput, Varsha Pardeshi

Department of Computer Engineering, SSBT Collage of Engineering and Technology Jalgaon, Maharshtra, India .

Abstract - The design and implementation of a system to automate patient handling and assignment to hospitals in mass disasters involving a large number of injured victims over a wireless network. In addition, the previously developed MEDTOC system is modified and enhanced to include location-aware features at the disaster site. as well as quick classification and assignment of patients to nearby hospitals. Patients are prioritized for medical care through a triage process. Manual systems allow for inconsistency and error. It proposes a novel system to automate accident and emergency centre triage and uses this triage score along with an artificial intelligence estimate of patient-doctor time to optimize the queue order. The optimal queue order is found using a novel procedure based on genetic algorithms. These components are integrated in a simple graphical user interface. Live tests could not be performed but simulations reveal that the average waiting time can be reduced by 48 minutes and priority is given to urgent patients. It is expected that chaotic mass-disaster situations can be more suitably controlled and stabilized by using the techniques from this project, thus saving more lives.

Keywords - Mass disaster, Location aware, triage, disaster site

I. INTRODUCTION

Machine Learning is a technique that allows computers to learn through programs that generalize behaviors from information or a set of patterns of data. Machine learning algorithms have existed for two decades, but recently, their application has become popular because of growth of power in computing and data storage. It is also important to indicate that there are several models for resolutions of problems in machine learning. In recent years, machine learning methods have been widely used in prediction, especially in medical decision making.

Triage is derived from the French term Trier which means "to select or choose / to choose or to classify", and it refers to a system that quickly evaluates the severity of each patient and indicates the best treatment depending on his/her condition. Usually triage is used in emergency department to screen patients before proceeding to any treatment. Triage is an important stage in the patient journey to ensure the best use of resources, patient satisfaction, and safety. Triage systems have also been found to be reliable in predicting admission to hospital, but are most reliable at extreme points of the scale, and less reliable for the majority of patients who fall in the mid points.

The design and implementation of a triage system to automate patient handling

and assignment to hospitals in mass disasters involving a large number of injured victims over a wireless network .System includes location-aware features at the disaster site, as well as quick classification and assignment of patients to nearby hospitals. In any mass-disaster situation such as a building collapse, earthquake, or flash floods, it is expected that many agencies would rush to aid the victims. Given the possible large number of victims, the situation can quickly become unmanageable, and chaos can reduce the chances to save lives. In addition, chaos can limit the ability of area hospitals to identify and treat the most critically injured victims in a timely manner. The triage service is a crucial part and only way to better distribute the resources of the hospitals process of categorizing patients to appropriate care level that medical needs. The decision process must take into consideration the seriousness of the patient's medical complaint.

II. RELATED WORKS

Using a range of clinical and demographic data relating to elderly patients, La Mantiana et al. [9] used logistic regression to predict admissions to hospital, and ED re-attendance. They predicted admissions with moderate accuracy, but were unable to predict ED re-attendance accurately. The most important factors predicting admission were age, Emergency Severity Index (ESI) triage score, heart rate, diastolic blood pressure, and chief complaint [9] (pg. 255). Baumann and Strout [20] also find an association between the ESI and admission of patients aged over 65. Boyle et al. used historical data to develop forecast models of ED presentations and admissions. Model performance was evaluated using the mean absolute percentage error (MAPE), with the best attendance model achieving a MAPE of around 7%, and the best admission

model achieving a MAPE of around 2% for monthly admissions. The use of historical data by itself to predict future events has the advantage of allowing forecasts further into the future, but has the disadvantage of not incorporating data captured at arrival and through triage, which may improve the accuracy of short term forecasting of admissions.

Sun et al. [8] developed a logistic regression model using two years of routinely collected administrative data to predict the probability of admission at the point of triage. Risk of admission was related to age, ethnicity, arrival mode, patient acuity score, existing chronic conditions, and prior ED attendances or admission in the past three months. Although their data showed the admission of more females than males, sex was not significant in the final model. Similarly, Cameron et al. [11] developed a logistic regression model to predict the probability of admissions at triage, using two years of routine administration data collected from hospitals in Glasgow. The most important predictors in their model included 'triage category, age, National Early Warning Score, arrival by ambulance, referral source, and admission within the last year' (pg. 1), with an area under the curve of the receiver operating characteristic (AUC-ROC) of 0.877. Other variables including weekday, out of hour's attendances, and female gender, were significant but did not have high enough odds ratios to be included in the final models.

Similarly, Peck et al. [12] developed three models to predict ED admissions using logistic regression models, naive Bayes, and expert opinion. All three techniques were useful in predicting ED admissions. Variables in the model included age, arrival mode, emergency severity index, designation, primary complaint, and ED provider. Their logistic regression model was the most accurate in predicting ED admissions, with

an AUC-ROC of 0.887. Perhaps surprisingly, this model performed better than triage nurse's opinion regarding likely admission. Using simulation models, Peck et al. [13] have shown that the use of the predictive models to priorities discharge or treatment of patients can reduce the amount of time the patient spends in the ED department.

III. PROPOSED SYSTEM

System provides a mechanism to integrate the patient data collected on site using vital motes and send it to hospitals using the cellular network. Vital motes are sensors that capture the vital signs of Patients and transmit them wirelessly to a nearby on-site computer. The enhanced system identifies the nearest hospitals to a mass-disaster location and automates the process of patient data flow and patient assignments. To the best of our knowledge, none of the existing patient-data communication schemes handle the patient assignment problem. Pre-assigning patients to most suitable hospitals can reduce the chaos and confusion in a triage room dealing with a mass disaster. A web portal is designed to let the authorized users obtain vital statistics about the overall disaster management scenario.

In the hospital, the received data are decompressed and segregated to be displayed to the physicians using machine learning algorithm. The client uses the GPS system for self-location. Based on its position, it searches for nearby hospitals using public data and connects to the server-side software in the nearest hospital. The position of the client is then transferred to the server to determine the disaster location. The server software attempts to establish connection with the server nodes in 2 to 5 additional nearby hospitals within 50 km. The paramedics attach vital motes to the patients, and the motes start sending the corresponding vital signs to the local client.

In absence of vital motes, the paramedics use color-coded paper triage tags. The six color codes include white (nonurgent), green (less urgent), yellow (urgent), red (emergent), blue (extremely urgent), and black (dead). Based on the available information, the server checks the queue and assigns a physician from a given hospital to a patient.

Next, the server notifies the client about the assignments for all the patients In system a disaster management algorithm is implemented at the client (disaster) side that finds the nearest hospitals and automates the process of patient data flow to the hospitals. In addition, algorithm at the server (hospital) side that assigns patients to nearby hospitals based on several factors including the distance, trauma rank and available capacity of the hospital. The GPS location of both i.e. disaster site and hospital will be calculated .Assigned hospital will be informed to send ambulance at the disaster site.

IV. ARCHITECTURE

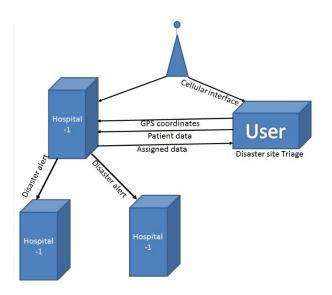


Figure 1: System Architecture

As information moves through software, it is modified by a series of transformations. Data Flow Diagram (DFD) is a graphical representation that depicts information flow and the transforms that are applied as data move from input to output. The basic form of a data flow diagram, also known as a data flow graph or a bubble chart. The data flow diagram may be used to represent a system or software at any level of abstraction. In fact, DFDs may be partitioned into levels that represent increasing information flow and functional detail. Therefore, the DFD provides a mechanism for functional modeling as well as information flow modeling. A level 0 DFD, also called a fundamental system model or a context model. The DFD Level 0 shows the abstract of the whole system.

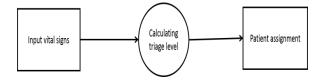


Figure 2: DFD Level 0

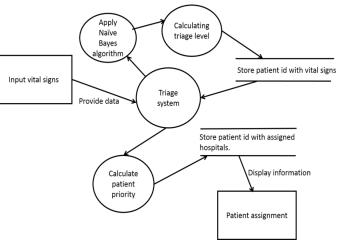


Figure 3: DFD Level 1

The Figure shows the level 1 DFD. The DFD level 1 shows some internal structure of the system also identifies data stores that are used by the major processes.

V. CONCLUSION

The system describes the automated patient assignment to physicians in nearby hospitals in a mass-disaster situation. Ubiquitous cellular and GPS connectivity, as well as a smart computing infrastructure of hospitals are assumed. The patient assignment scheme will be developed as part of the overall triage system, which entails the disaster management with patient data transmission via the cellular network to designated hospitals. The patient assignment to hospitals is handled using several factors including the triage tags assigned by on-site paramedics to victims, the perceived trauma

rank of a hospital, the driving distance to the hospital from the disaster site, availability of appropriate number of the physicians in the respective hospitals. The design and implementation of a system to automate patient handling and assignment to hospitals in mass disasters involving a large number of injured victims over a wireless network.

REFERENCES

[1]R. Olson, J.A. Zubairi, A. Biliciler, A software framework for patient data handling in emergencies and disasters, in: Int. Conf. Collab. Technol. Syst., CTS, 2014, pp. 553–557.

[2] M. Muaafa, A.L. Concho, J. Ramirez-Marquez, Emergency resource allocation for disaster response: an evolutionary approach, in: Probab. Saf. Assess. Manag. Conf., PSAM12, 2014.
[3] Yunfei, H., and Ting, L., 2014, "Performance comparison of four triage—based patient flow interventions in the emergency department," International Journal of Collaborative Enterprise, 4(2), pp. 115-135.

[4] D. Malan, T. Fulford-Jones, M. Welsh, S. Moulton, Codeblue: an ad hoc sensor network infrastructure for emergency medical care, in: Int. Workshop Wearable Implant. Body Sens. Netw., 2004.

[5] San Pedro, J., Burstein, F., Cao, P., Churilov, L., Zaslavsky, A. & Wassertheil, J., Mobile Decision Support for Triage in Emergency Departments. Decision Support in an Uncertain and Complex World: The IFIP TC8/WG8.3 Organized in Italy, 2004. [6] Abad-Grau, M. M., Ierache, J., Cervino, C. & Sebastiani, P., Evolution and Challenges in the Design of Computational Systems for Triage

41(3): 432-441. 2008. [7] Jeffrey Leegon, BS, Ian Jones, MD, Kevin

Assistance. Journal of BiomedicalInformatics

Lanaghan, BS, and Dominik Aronsky, MD, PhD, "Predicting Hospital Admission in a Pediatric Emergency Department using an Artificial Neural Network" [8] Y. Sun, B.H. Heng, S.Y. Tay, E. Seow, Predicting hospital admissions at emergency department triage using routine administrative data, Acad. Emerg. Med. 18 (2011) 844-850. doi:10.1111/j.1553-2712.2011.01125.x. [9] M.A. LaMantia, T.F. Platts-Mills, K. Biese, C. Khandelwal, C. Forbach, C.B. Cairns, J. Busby-Whitehead, J.S. Kizer, Predicting hospital admission and returns to the emergency department for elderly patients, Acad. Emerg. Med. 17 (2010) 252-259. doi:10.1111/j.1553-2712.2009.00675.x. [10] G.M. Marres, L. Taal, M. Bemelman, J. Bouman, L.P. Leenen, Online victim tracking and tracing system (ViTTS) for major incident casualties, Prehosp. Disaster Med. 28 (2013) 445-453. [11] A. Cameron, K. Rodgers, A. Ireland, R. Jamdar, G.A. McKay, A simple tool to predict admission at the time of triage., Emerg. Med. J. 32 (2013) 174-9. doi:10.1136/emermed-2013-203200 [12] N. Esfandiari, M.R. Babavalian, A.M.E.

doi:10.1136/emermed-2013-203200 [12] N. Esfandiari, M.R. Babavalian, A.M.E. Moghadam, V.K. Tabar, Knowledge discovery in medicine: Current issue and future trend, Expert Syst. Appl. 41 (2014) 4434–4463. doi:10.1016/j.eswa.2014.01.011. [13] H.C. Koh, G. Tan, Data mining applications in healthcare, J. Healthc. Inf. Manag. 19 (2011) 65.