A SURVEY ON DIFFERENT MACHINE LEARNING ALGORITHMS IN EMERGENCY DEPARTMENT FOR PATIENT FLOW CONTROL

Pyelshak Yusuf[1], Fatima Umar Zambuk[2], Badamasi Imam Ya'u[3], Aminu Agabus[4] & [5]Mustapha Abdulrahman Lawal

[1]Department of Health Information Management, Plateau State College of Health Tech. Zawan,Nigeria

[2,3,5]Department of Mathematical Sciences, Abubakar Tafawa Balewa University, Bauchi, Nigeria

[4] Department of Computer Sciences, Nigerian Army University, Biu, Nigeria

ABSTRACT

The efficient management of patient flow control in emergency department (EDs) of a hospital is a critical aspect of delivering quality healthcare services. Overcrowding, long waiting times, and resource allocation challenges are common issues that EDs face on a daily base, leading to compromised patient care and increased healthcare cost. In recent years, machine learning techniques have emerged as a valuable tool for optimizing patient flow control in emergency departments, assessing their effectiveness and potential for addressing the aforementioned challenges. The survey presents a comprehensive analysis of diverse range of machine learning techniques implemented in emergency departments for patient flow management. The algorithm considered include but are not limited to, decision trees, random forest, support vector machines, neural networks, k-mean clustering and reinforcement learning. Both external and internal key factors influencing patient flow control, such as inter arrival time/patterns, triage process, bed allocation and resource optimization are examined in the context of each algorithms contribution and also highlight real–world case scenarios and research efforts that have applied machine learning techniques to address patient flow control challenges in emergency departments. By comparing the outcomes achieved by different techniques, and also providing insight to the strength and weaknesses of each of the approach, enabling healthcare administrators and practitioners to take informed decisions when selecting and implementing machine learning solutions. In conclusion, the study underscores the growing importance of machine learning techniques in revolutionizing patient flow management within the emergency department of the hospital. By shading light on the applicability and performance of various algorithm which will ultimately lead to the improvement of patient care, reduce patient Waiting time, Overcrowding and Resource Allocation.

Keyword: - *Emergency Department1, Patient flow Control2, Machine Learning Algorithm3, Simulation Model3*

1.0 INTRODUCTION

Healthcare systems are crucial for society, with the World Health Organization reporting a doubled average global health expenditure per capita from $480 in 2000 to $1111 in 2018. The COVID-19 pandemic was declared a global crisis in March 2020. (Ali & Kannan, 2022; Fattahi et al., 2023; Sohrabi et al., 2020; Ferreira et al., 2022). The global demand for hospital resources, particularly operating rooms, has surged due to the aging population and the need for increased attention and preparation in health-care systems. (Macario, 2010; van Oostrum et al., 2008). The first place of call is the emergency department of a hospital. ED are the backbone is a hospital facility.

Emergency departments (EDs) are crucial in healthcare, providing prompt medical care to patients with acute medical issues. Their operations and patient flow involve monitoring arrivals, triaging patients, delivering care, and admitting patients to the hospital or discharging patient from the hospital (Donaldson et al., 2021). Patient flow in the ED is influenced by factors like acuity, hospital bed availability, personnel availability, and operational constraints. Upon arrival, patients are registered and assessed using a triage system to ensure timely medical attention for life-threatening conditions. (FitzGerald et al., 2010). Medical experts assess patients' post-triage for treatment, using diagnostic studies and interventions. Effective patient flow management is crucial for enhancing care quality, minimizing wait times, and boosting patient satisfaction. Understanding factors like arrivals, triage, and treatment processes can help healthcare providers optimize patient flow processes (Jarvis, 2016).

1.1 Emergency department

An emergency department (ED) is a specialized hospital unit that provide immediate medical care to patients with medical conditions, injuries, or life-threatening situations, aiming to stabilize patients, provide critical interventions, and determine individual care levels. Below is an overview of the key aspects of an emergency department in a hospital:

Triage: When a patient arrives at the emergency department, they are evaluated and given a priority depending on how serious their illness is. This procedure is known as triage.

Emergency care: A variety of medical situations may be handled by the Emergency Department (ED), which including trauma, heart attacks, strokes, respiratory distress, severe infections, and more. This can also offer early evaluations, diagnoses, treatments, and stabilization to stop further deterioration.

Diagnostic services: The emergency department (ED) is furnished with cutting-edge diagnostic technology, including X-ray machines, CT scanners, ultrasound devices, and laboratory facilities, allowing for quick evaluation and diagnosis for knowledgeable patient treatment.

Medical Team: In order to provide prompt and appropriate treatment, the Emergency Department (ED) team, which consists of emergency doctors, nurses, paramedics, respiratory therapists, radiology technicians, and laboratory staff, collaborates with other healthcare professionals to provide timely and appropriate care to patients in the emergency department.

Specialized Units: Large hospitals feature specialized emergency departments (EDs), which cater to certain situations and age groups. Examples include intensive care unit, trauma centers, and pediatric emergency department.

Patient flow management: Using tactics like as EHRs and real-time data analytics, efficient patient flow in the ED is critical for maximizing resource utilization and lowering wait times.

Treatment Rooms and Observation Area: The Emergency Department (ED) is a medical facility that comprises treatment rooms and observation facilities for patients who need to be monitored for a prolonged period of time before being admitted or discharged.

Communication and Coordination: In the Emergency Department (ED), where medical teams work to ensure that patients get appropriate therapies, drugs, and expert consultations, effective communication and care coordination are critical.

Admission or Discharge: If a patient's condition is stable and can be handled in the outpatient department (OPD), they may be admitted to the hospital for additional treatment or released with follow-up instructions.

Education and prevention: To educate patients about their problems and avoid future crises, the emergency department (ED) offers rapid treatment, patient education, preventative programs, specialist referrals, and health and safety measures.

Above all, the emergency department is a critical component of the healthcare system, offering rapid, life-saving treatments to patients in critical need and functioning as a portal to the hospital.

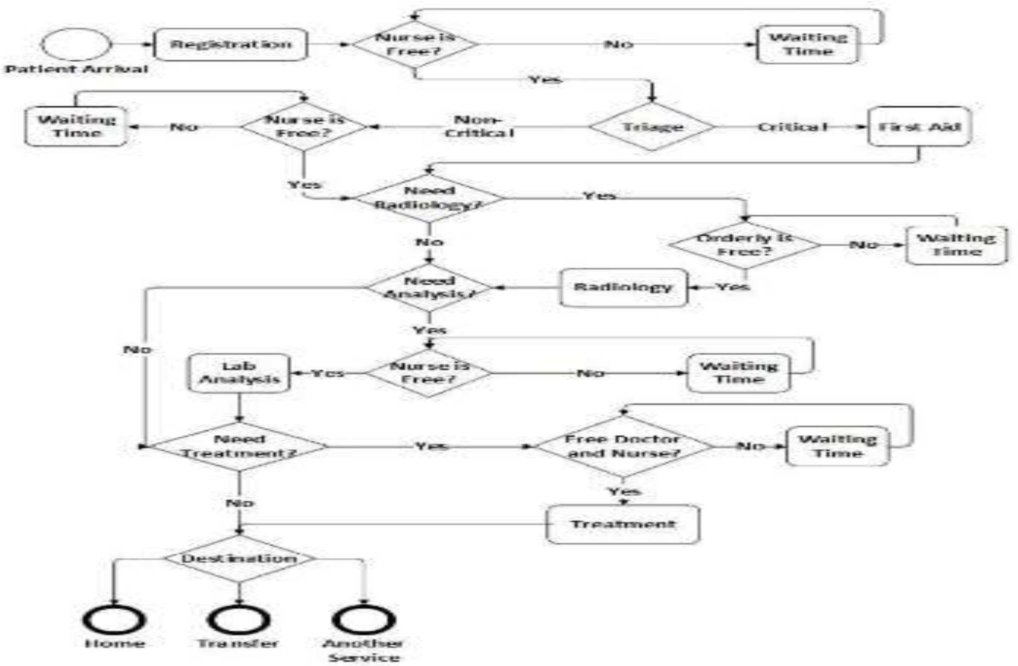

Fig -1: Depicts the flow of patients in an emergency department
(Source: Alenany & Cadi, 2020)

2.1 OVERVIEW OF OVERPOPULATION IN EMERGENCY DEPARTMENT

Emergency department (ED) overcrowding is a worldwide problem caused by rising demand for medical services and a scarcity of healthcare personnel. For example, a study found out that the number of ED visits in the United States increased by 27% between 1999 and 2013, from 102.8 million to 130.4 million (Center for Disease Control et al., 2013). Crowding is defined by the American College of Emergency Physicians (ACEP) as when the recognized demand exceeds available resources for patient treatment in the ED, hospital, or both. (Emergency Physicians et al., 2006).

Various internal and external variables impact emergency department overcrowding, including:

Insufficient Hospital Bed Availability: According to Singer et al.'s 2009 research, limited inpatient bed availability may result in ED congestion, patient flow delays, and increased stress on healthcare workers.

Shortage of Healthcare Personnel: The staffing level and skill mix of healthcare personnel at Emergency Departments (EDs) are critical for timely patient care since they serve as the first entry point for most patient, despite limited insurance coverage. Di Somma et al., 2015.

Triage Process: Efficient and precise triage is vital for optimal patient prioritizing in the ED, ensuring that critical patients get early care based on their severity, despite possible delays for less urgent cases. Bullard et al., 2009.

Testing And Daignosis: The large number of patients awaiting test results might create delays in emergency care, extending stay time and influencing treatment choices in the ED. Miro et al., 2003.

Public Health Emergencies: Outbreaks, epidemics, and natural catastrophes may result in rapid increases in patient traffic, possibly exceeding emergency department resources and resulting in extended wait times and treatment delays. Hick et al. (2014).

The above mention factors and many other factors which include the number of patients admitted to other units within the hospital (Abraham et al., 2009), the number of patients waiting to be discharged (Solberg et al., 2003), the time from when the physician requests admission to the time of the beds assignment (Ospina et al., 2007), the proportion of the ED that is occupied by in-patients (Lucas et al., 2009) and the time or date of boarding (Falvo et al., 2007). This study focuses on overcrowding in ED wait times, which may contribute to extended wait times for low-acuity patients. (Cowan & Trzeciak, 2004). Overcrowding in emergency departments (EDs) is a complex issue that requires extensive research, expert panels, and surveys to identify its causes and develop effective solutions. This comprehensive body of information is crucial for effective healthcare service provision.

2.2 IMPACT OF OVERPOPULATION IN EMERGENCY DEPARTMENT

long patient waiting time: Overcrowding in emergency departments may result in delayed patient treatment, increased stress, and discontent among patients, resulting in a bad opinion of the quality of care offered. Derlet, 2002. Pines et al. (2008) found out that long wait times significantly increase the likelihood of a patient being dissatisfied and reporting lower ED satisfaction scores. Patients who are impatient are more likely to depart without receiving care (Derlet, 2002). According to research, the frequency of left-without-being-seen (LWBS) patient visits correctly reflects the amount of ED congestion.

It may result in poor patient outcomes: Ensuring quality care and timely emergency department intervention is crucial to prevent medical errors, reduce morbidity and mortality rates, and maintain patient satisfaction and trust in the healthcare system. (Arendt et al., 2003).

Overbaording on Hospital Resources: Overcrowding in emergency rooms may put a burden on hospital resources, impede efficient response, and degrade patient experience. (Derlet et al., 2014). According to the Center for Disease Control and Prevention (CDC), the average treatment time for all patients, excluding those with severe illnesses, is 90 minutes. (McCaig and Albert, 2014).

Decrease patient satisfaction: long wait times, overcrowding, and reduced attention in healthcare can lower patient satisfaction, decrease trust, and impact the hospital's reputation, potentially reducing patient volume and causing future care seekouts. (Derlet, 2002).

Financial implication: Overcrowding in healthcare facilities can lead to increased healthcare costs, resource utilization, and potential legal liabilities due to compromised care in the Emergency Department. (Schull et al. (2007).

Ambulatory service rerouting: Hospitals often redirect ambulances to other Emergency Departments due to high patient volume, causing temporary traffic pauses but also causing income loss. (Litvak et al., 2001). Pham et al. (2006) found that most ambulance patients require urgent medical attention, and delays may prolong the time to the emergency department.

2.3 Scheduling And Rescheduling Patients in Emergency Department

Using a hierarchical three-phase approach, patient scheduling in OTs distributes capacity into advance pieces. It schedules elective and emergency patients on a weekly, daily, and rescheduled basis to provide effective patient treatment. **Figure 2** shows a scheduling process flowchart, involving weekly, daily, and rescheduling phases. Phase 1 assigns OTs to surgery groups, while Phase 2 determines surgery timing and sequencing. Phase 3 involves rescheduling for emergency patients, potentially disrupting daily elective procedures.

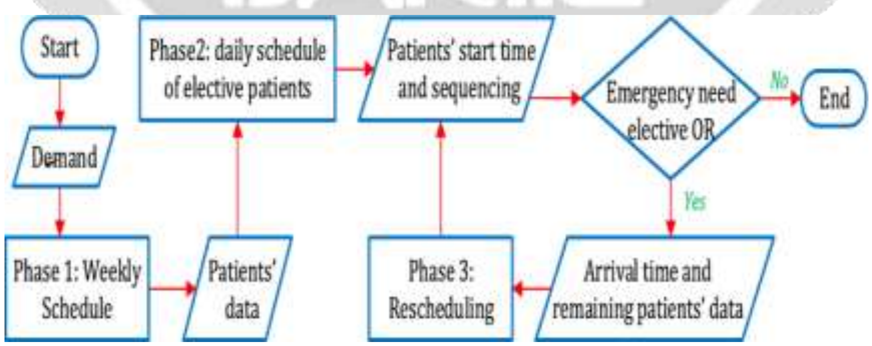

Fig -2: Scheduling process flowchart: (Alenany & Cadi, 2020)

2.4 Patients Flow Control in An Emergency Department

DPatient flow control in an emergency department is crucial for efficient healthcare delivery. It involves managing patient movement from triage to treatment, discharge, and admission. Effective patient flow management ensures timely and appropriate care, reduces wait times, overcrowding, and enhances patient satisfaction. Here are some key strategies and components for managing patient flow control in an emergency department.

Triage: Based on symptoms and medical history, the first evaluation of a patient's condition is classified as urgent, semi-urgent, or non-urgent, with appropriate treatment prioritized. "Emergency Severity Index (ESI): A Triage Tool for Emergency Department Care" by Gilboy et al. (2005).

Separation of flow: To minimize cross-infections and properly distribute resources, emergency departments often feature separate zones for various patient groups, such as trauma patients, pediatric patients, and those with less urgent problems. "Using Lean Six Sigma to Improve Emergency Department Patient Flow at an Academic Tertiary Care Hospital" by Durani et al. (2015).

Fast track and observation unit: For less severe patients, EDs offer "fast-track" sections, whereas observation facilities are utilized for patients who need more monitoring before admission or release decisions. "The Safety and Quality of Emergency Department Nurse Triage" by Fernandes et al. (2019).

Electronic Health Records EHRs: By sharing patient information, avoiding unnecessary testing, and assuring consistent treatment, digital record-keeping systems improve healthcare provider efficiency. The Use of Simulation to Determine Optimal Overcrowding Thresholds" by Boyle et al. (2010).

Clinical pathways and Protocols: For common illnesses such as chest discomfort and asthma, EDs adopt standardized procedures to guide therapy, limit care variability, and expedite care, lowering decision-making time. "The Safety and Quality of Emergency Department Nurse Triage" by Fernandes et al. (2019).

Scheduling and appointments: Appointments for patients with less urgent diseases are often scheduled in EDs, minimizing patient arrivals and simplifying flow management. The Use of Simulation to Determine Optimal Overcrowding Thresholds" by Boyle et al. (2010).

Bed management: Effective bed management is critical for patient flow, guaranteeing on-time admissions and discharges to avoid ED congestion. "Reducing Emergency Department Length of Stay by Simultaneous Bedside Registration and Testing" by Chan et al. (2013).

Collaboration and communication: Regular meetings or huddles with healthcare practitioners, including doctors, nurses, technicians, and support personnel, are essential for efficient patient flow and addressing difficulties. "Improving Emergency Department Patient Flow Through Collaboration with Inpatient Nursing Units" by Grafstein et al. (2009).

Discharge Planning: In the emergency department, early discharge planning promotes effective follow-up treatment, freeing up resources for incoming patients and promoting efficient care. "The Impact of Hospital Discharge Planning on Reducing Readmissions" by Mistiaen et al. (2006).

LP systems are designed with the ability in analyzing the actual nature of the sensitive data as well as the surrounding context. They also have the ability in providing protection of critical information at the different levels of data state, which are data-in-use (which uses an endpoint protection), data-in-transit (that makes use network monitoring) as well as a data-at-rest (which uses data classification). Lastly DLP have the ability in protecting the confidential data through various policies and rules execution responses, such as notification, data auditing, active blocking, data encryption and data quarantining. This makes DLP systems to be proactive and dedicated, which makes it different from the conventional security mechanism such as Intrusion Detection Systems (IDS), firewalls and Virtual Private Networks (VPNs). The convention security technologies have less dedication in terms of the content of the data they are protecting..

3.1 OVERVIEW OF CONCEPTS APPLIED TO PATIENTS FLOW CONTROL IN EMERGENCY DEPARTMENT

In emergency rooms, researchers have used queueing theory and reinforcement learning to improve patient flow and reduce wait times. A few of these investigations are analyzed below

3.2 Wait time prediction models

Queues arise in all service industries, including healthcare, when demand exceeds system capacity. Waiting psychology has been widely researched. According to LARSON (1987), waiting is a bad experience that causes emotions of sadness, irritation, and worry. Researchers are looking on methods to lessen the harmful impacts of excessive wait times, and many service providers are increasingly warning customers of expected delays.

Hospitals use a variety of strategies to notify patients of ED wait times, such as alerts, billboards, and smartphone applications. With more people searching for ER wait times on Google, prediction algorithms are attempting to understand how previous data might be utilized to lower wait times. Historical data may be used to determine seasonal patient arrival trends in the emergency department and enhance operational decision-making to avoid congestion. To analyze patient wait times, forecasting methodologies such as time series analysis, queuing theory, and discrete event simulation are utilized. The author compares traditional rolling average and multiple regression algorithms for usage in the emergency department.

3.3 Machine Learning Algorithms

By analyzing complicated data patterns, machine learning algorithms are being used in hospital emergency departments (EDs) to improve patient care, optimize resource allocation, and assist decision-making.

Predictive Analysis for Patient Flow: Machine learning algorithms can forecast patient arrival patterns, wait times, and ED occupancy, allowing administrators to allocate resources and personnel more efficiently. "Predictive Modeling of Emergency Department Patient Flow" by A. W. Kaminsky, et al. (Annals of Emergency Medicine, 2008) - This study uses machine learning to develop predictive models for ED patient flow.

Triage and Patient Severity Prediction: By predicting patient acuity and severity based on clinical data, machine learning may improve patient prioritizing by automating the triage process. "A Machine Learning Approach to Triage Decision Support" by M. Bai, et al. (Artificial Intelligence in Medicine, 2018) - This paper presents a machine learning approach to support ED triage decision-making.

Resource Allocation and Staffing: For more effective resource usage, machine learning algorithms may improve staff scheduling, resource allocation, and bed management. "A Machine Learning Approach to Predicting Patient Bed Requirements in an Emergency Department" by J. S. Hwang, et al. (PLOS ONE, 2018) - This study applies machine learning to predict patient bed requirements in the ED.

Patient Disposition Prediction: Machine learning models may forecast patient admission, discharge, or transfer, allowing for better resource allocation and decision-making. "Predicting Hospital Admission at Emergency Department Triage Using Machine Learning" by S. Lee, et al. (PLOS ONE, 2018) - This research focuses on predicting hospital admission using machine learning at ED triage.

Early Warning System: Machine learning algorithms can detect early signs of patient deterioration, thereby informing healthcare providers and enabling timely interventions. "Machine Learning Predictive Analytics for Acute Patient Deterioration: A Scoping Review" by S. Gong, et al. (Journal of Medical Internet Research, 2020) - This review explores the use of machine learning for predicting acute patient deterioration.

Resource Demand Forecasting: In educational institutions, machine learning can effectively forecast resource demand for critical services such as imaging or laboratory testing. "A Machine Learning Approach to Estimate Patient Demand for Emergency Department Services" by J. Kang, et al. (Journal of Medical Systems, 2016) - This research applies machine learning to estimate patient demand for ED services.

3.4 Simulation Modeling

In healthcare, simulation models are used to monitor patient flow, optimize resource allocation, and improve operational efficiency, assisting administrators in finding bottlenecks. Below explain some selected applications of simulation models in ED management.

Patient flow analysis: By altering staffing numbers, triage methods, and treatment processes, simulation models may assist detect bottlenecks in the ED, improve patient flow, and minimize congestion. "A Discrete-event Simulation Model of Patient Flow in an Emergency Department" by H. L. Almogy, et al. (Journal of Medical Systems, 2010) - This study presents a simulation model to analyze patient flow in an ED and suggests strategies for reducing waiting times.

Resource Allocation: By modeling numerous situations, simulation models assist healthcare managers in evaluating optimum resource allocation, recognizing shortages, and planning capacity growth. "A Simulation Model for Resource Constrained Scheduling of Patient Admissions" by C. R. Ramsey, et al. (Health Care Management Science, 2005) - This study proposes a simulation model to optimize patient admissions and resource allocation in an ED with limited resources.

Testing Operational Changes: Simulation models provide a safe environment for testing operational changes and regulations in the actual emergency department, reducing patient care risks and allowing data-driven decision-making. "Use of Simulation Modeling to Optimally Design an Emergency Department in a Large Hospital" by J.

Kang, et al. (Journal of Healthcare Engineering, 2015) - This study uses simulation modeling to design and optimize the layout and processes of an ED.

Disaster Preparedness and Surge Capacity: Simulation models help analyze surge capacity, resource demands, and the ED's ability to manage higher patient loads during large-scale catastrophes or pandemics. "Modeling and Simulation of Emergency Department Crowding" by R. C. Chin et al. (Academic Emergency Medicine, 2006) - This article discusses the use of simulation modeling to study ED crowding and assess the impact of interventions.

3.5 A combination of simulation modeling and machine leaning algorithm

Because of their capacity to improve decision-making processes and maximize resource utilization, simulation modeling and machine learning algorithms are becoming more popular in healthcare operations. Machine learning allows computer systems to learn from data.

In healthcare operations, simulation modeling and machine learning approaches are used to improve patient flow, resource allocation, and scheduling, ultimately improving patient outcomes and lowering costs. Shi et al. (2021) optimized ED patient flow using a simulation model and machine learning approaches, resulting in shorter wait times and increased efficiency. Rangaraju et al. (2021) utilized a simulation model to enhance emergency department staffing and scheduling, and machine learning techniques to predict patient acuity levels.

Tucker et al. (2022) created synthetic patient data for cardiovascular disease risk prediction using UK primary care data and investigated techniques for producing it using publicly accessible cancer registry data. Mitre.org's Synthea patient generator provides synthetic patient data that is equivalent to clinical quality metrics and may be utilized for deep neural network learning.

Table -1: Summary of related Studies

Author (s)	**Title**	**Methods**	**Limitation**
Shi, L., Dai, Y., Tang, L., & Wang, X. (2021)	Optimizing emergency department patient flow with a combined simulation and machine learning approach.	Random forest algorithm and Simulation Model	The study used historical data to train the machine model, which may not capture changes.
Rangaraju, S., Ramanathan, R., & Gaur, P. (2021)	Optimizing emergency department staffing and scheduling using simulation and machine learning.	Random forest and k-nearest neighbors (k-NN)	did not consider other factors that may affect patient flow and waiting times, such as bed availability and diagnostic testing
Kim, H., & Cho, M. (2020)	A simulation-based machine learning approach for bed allocation and patient discharge prediction	Gradient Boosting Decision Tree (GBDT) algorithm.	Use data from a single hospital and focus only on bed allocation and patient discharge
Li, Y., Li, X., Li, Y., Li, X., & Li, Y. (2021)	A machine learning-based simulation approach for hospital inpatient service system optimization	A hybrid simulation model that integrates agent-based modeling and system dynamics	
Zha, Y., Li, S., Li, Y., & Li, Y. (2020).	A simulation-based optimization method for patient flow and scheduling in a chronic disease management center.	A data-driven approach using machine learning algorithms	Did not account for the impact of external factors, such as patient arrival patterns and seasonal fluctuations, on emergency department operations
Zolfaghari et al. (2021),	Improving emergency department patient flow: Combining simulation modeling and machine learning approaches.	Simulation model combined with a random forest algorithm (waiting reduction time 25.5%)	The sample size of the study was relatively small, which may impact the statistical power and reliability of the results.

Cao, D., Wang, L., Guo, Y., & Yang, L. (2021).	Optimizing emergency department operations using simulation and machine learning.	Simulation model and a random forest algorithm (waiting times by 27.3%, and improved ED efficiency by 18.7%.)	Did not explore the impact of staffing levels or other operational factors on emergency department efficiency

3.6 Related Work on ED Management

James W. T. (2023) investigates the estimation of patient waiting times in emergency rooms, emphasizing the need for more precise and nuanced projections to increase patient satisfaction and decrease abandonment. To produce probabilistic predictions from huge patient-level data sets, a quantile regression forest machine learning technique was utilized, extracting predictor parameters such as calendar influences, demographics, staff count, ED load, and patient condition severity. The proposed method enhances wait-time estimates by constantly updating and altering predictions based on patient and ED-specific data, resulting in more accurate probabilistic and point forecasts.

Various approaches, including machine learning and systems thinking, have been used to anticipate ED wait times, as proven by Kuo et al. (2020) and Stagge (2020).

Arha (2017) and Curtis et al. (2018) used machine learning algorithms to forecast wait times for low-acuity patients in the emergency department, taking into account parameters such as arrival, service completion, and examination. Studies on patient waiting time before treatment use quantile regression, but this study uses multi-DL optimization strategies and extracts new predictors from patient joining, queue waiting time, and departure time. Because of long wait times and congestion in many hospitals throughout the globe, the number of emergency department visits in the United States is growing year after year (Di et al. 2015).

According to the National Center for Health, 145.6 million individuals visit the ED each year, with rising visits and wait times. Since 2015, the Canadian Institute for Health Information has documented considerable growth. These problems might be addressed by evaluating ER efficiency. (Rasouli et al. 2019). By tracking patient arrival times, some hospitals utilize queuing models to enhance staff allocation. (Kaushal et al. 2015; Sasanfar et al. 2020). Predictive models are critical in the medical business for anticipating patient wait times utilizing past data and efficiently handling seasonal arrival and wait times. (Ruben et al. 2010; Cai et al. 2016). Electronic Health Record EHR data is critical for uncovering hidden healthcare concerns and improving queuing systems, especially in predictive models for future behavior analysis. (Eiset et al. 2019).

Machine learning approaches were used in the research on queuing behavior projection, however their time series analysis on queue data prediction study is faulty. (Srivastava 2016; Stagge 2020). According to Dong et al.'s 2019 research, ED waiting time is an important aspect people evaluate when selecting their medical care provider. The previously released data assists in operational choices targeted at minimizing wait times and congestion in the Emergency Room. (Abir et al. 2019).

Kroer et al. (2018) and Meersman and Maenhout (2022) investigated capacity allocation for elective and emergency patients to decrease wait times and OR and overtime expenditures.

For allocating COVID-19 patients and speciality teams, Arab Momeni et al. (2022) offered a mixed-integer mathematical programming technique, while Wang et al. (2016) employed a discrete simulation model.

Tuwatananurak et al. (2019) used a 15,000 surgical case data set to predict patient surgery duration using leap Rail, a customized machine learning algorithm.

Fairley et al. (2019) forecasted PACU time using machine learning, resulting in lower holdings and cost reductions. Schiele et al. (2021) combined ORs and units to schedule master operations. Shuvo et al. (2020) created a deep reinforcement learning strategy.

Luo and Wang (2019) used machine learning algorithms to identify canceled procedures, with the random forest model proving to be the most successful, allowing preventative actions to be taken to lower cancellation rates. To forecast surgical cancellations at West China Hospital, Luo et al. (2016) used machine learning approaches such as boosting, Bayesian additive regression trees, and random forest.

Erekat et al. (2020) and Zhao et al. (2019) employed data mining approaches to estimate surgery cancellations, resulting in cost reductions and more efficient robotic surgery scheduling. Machine learning models were helpful in OT scheduling.

3.7 Conceptual Review of Random Forest in ED Management

Random Forest is a very successful high-performance strategy that can handle binary, continuous, and categorical data types and is extensively utilized in a variety of industries. (Klassen, M., Cummings, M., and G. Saldana, 2008).

Random Forest is a resilient, efficient, and dynamic model that can handle binary, categorical, and numerical data. Its unique ability to handle missing data makes it an excellent option for quick and efficient model creation. Ho, T. K. (1995). Random Forest is an ensemble learning-based supervised machine learning approach for classification and regression that incorporates many classifiers to enhance model performance.
Random Forest is a classifier that use numerous decision trees on a dataset to improve predictive accuracy by taking the average of each tree's predictions into account. (Ga, o, D., Zhang, Y.-X & Zhao, Y.-H. (2009). Gao, D., Zhang, Y.-X., & Zhao, Y.-H, 2009). The Random Forest approach, as shown, employs a greater number of trees to improve accuracy and limit the danger of overfitting.

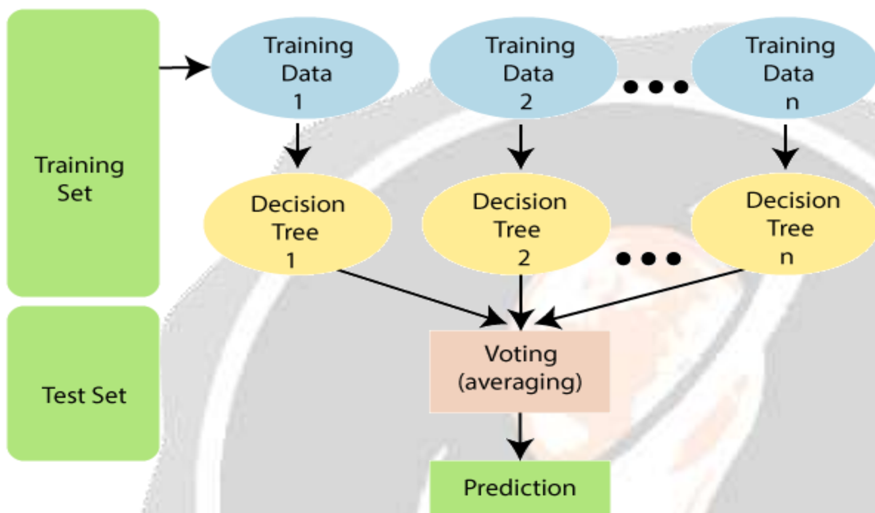

Fig -3: The Random Forest Method. (leo Breiman and Adele Cutler 2021)

Random Forest classifiers use many trees to predict dataset classes, with some trees correctly predicting the result and others incorrectly. (Ho, T. K. 1998).

1. There should be some actual values in the feature variable of the dataset so that the classifier can predict accurate results rather than a guessed result.
2. Each tree's predictions must have extremely low correlations.

The Random Forest algorithm is recommended for a variety of reasons as stated below.

<="" li="">

1. It takes less training time as compared to other algorithms.
2. It predicts output with high accuracy, even for the large dataset it runs efficiently.

It can also maintain accuracy when a large proportion of data is missing.

3.8 Nature of the Random Forest Algorithm

Random Forest is a machine learning system that builds a random forest by mixing N decision trees in the first phase and then makes predictions for each tree. (A.-L. Boulesteix, S. Janitza, J. Kruppa, and I. R. König, 2012). The Working process can be explained in the below steps and diagram:
Step-1: Select random K data points from the training set.
Step-2: Build the decision trees associated with the selected data points (Subsets).
Step-3: Choose the number N for decision trees that you want to build.
Step-4: Repeat Step 1 & 2.
Step-5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes.
The following example will help you understand how the algorithm works:

Example: Assume there is a dataset with multiple fruit photos. As a result, the Random Forest classifier is given this dataset. The dataset is subdivided and distributed to each decision tree. During the training phase, each decision tree gives a prediction result, and when a new data point occurs, the Random Forest classifier predicts the final choice based on the majority of outcomes. Consider the following image: L. Breiman (2001).

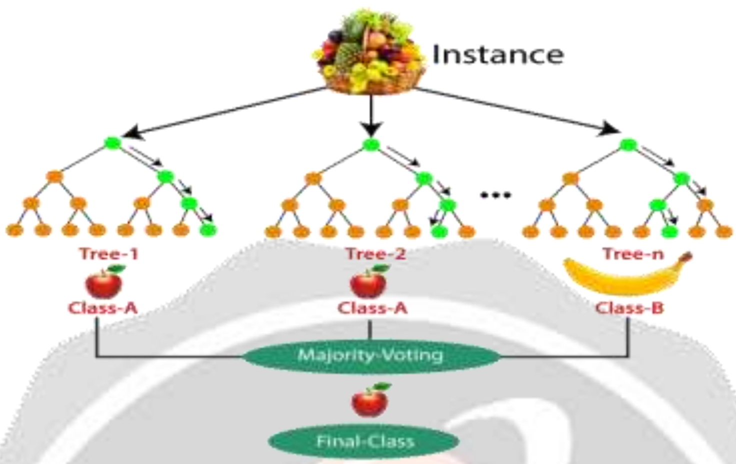

Fig -4: Example of Random Forest Operation (L. Breiman 2001).

3.8 Application of random Forest in Health care

Random forest (RF) is a widely used machine learning technique that integrates multiple decision trees to create an ensemble model, enhancing accuracy and resilience. (Breiman, 2001). In healthcare operations, RF is used for patient flow optimization, resource allocation, and predictive modeling, especially in emergency rooms for anticipating patient disposition and optimizing flow. Rangaraju et al. (2021) used RF to forecast patient acuity levels, improving staffing and scheduling accuracy. Shi et al. (2021) found it reduced wait times and improved ED efficiency.

Kim et al. (2020) used RF to estimate patient discharges and optimize bed allocation in a hospital context, which resulted in shorter wait times and better resource allocation.

Zhang et al. (2021) utilized RF to optimize healthcare resource allocation, finding it outperformed other models. RF is a powerful tool for predictive modeling and resource allocation, improving patient outcomes and reducing costs. However, rigorous validation is needed for its reliability.

4. CONCLUSIONS

Finally, the study on several machine learning algorithms for patient flow management in the emergency department provides light on the ability of these sophisticated approaches to considerably improve operational efficiency and patient outcomes. Machine learning has potential in solving the complex difficulties related with patient flow, resource allocation, and decision-making in emergency rooms, as shown by the development of several algorithms. As healthcare systems strive to improve patient care and resource utilization, the findings of this survey highlight the importance of additional research, implementation, and customization of machine learning solutions tailored to the unique dynamics of each healthcare facility. By adopting these advances, emergency departments may get closer to simplified operations, shorter wait times, and, ultimately, better treatment for patients in critical and time-sensitive circumstances.

5. REFERENCES

[1]. Alenany, E., & Cadi, A. A. E. (2020). Modeling patient flow in the emergency department using machine learning and simulation. arXiv preprint arXiv:2012.01192.

[2]. Elalouf, A., & Wachtel, G. (2021, December). Queueing problems in emergency departments: a review of practical approaches and research methodologies. In *Operations Research Forum* (Vol. 3, No. 1, p. 2). Cham: Springer International Publishing.

[3]. Finkelstein, S. M., Wong, E., Lin, H., & Li, Y. (2021). Reducing Patient Waiting Time in Emergency Departments Using Reinforcement Learning and Queueing Theory. INFORMS Journal on Applied Analytics, 51(3), 162–179. https://doi.org/10.1287/inte.2020.1064

[4 Haripriya, G., Abinaya, K., Aarthi, N., & Kumar, P. P. (2021). Random Forest Algorithms in Health Care Sectors: A Review of Applications.

[5]. Jarvis, P. R. E. (2016). Improving emergency department patient flow. *Clinical and experimental emergency medicine*, *3*(2), 63.

[6]. Khalilnejad Tabari, M., Aghajari, S., & Salahshour, S. (2022). Reinforcement Learning for Scheduling in Emergency Departments. In 2022 IEEE International Conference on Healthcare Informatics (ICHI) (pp. 10-16). IEEE.

[7]. Lee, H., Lee, J., Lee, H., Lee, J., Lee, Y., & Kim, Y. (2021). Reducing Patient Waiting Time in Emergency Departments Using Reinforcement Learning and Multi-Agent Systems. Applied Sciences, 11(8), 3429. https://doi.org/10.3390/app11083429

[8]. Li, J., Cao, W., Yang, Y., Hu, S., & Wei, S. (2021). Data-driven optimization of emergency department operations using machine learning algorithms. Health Care Management Science, 24(1), 32-46.

[9]. Liu, J., Xie, J., Cheng, X., Zhang, Z., Li, X., & Li, Z. (2022). A Novel Reinforcement Learning Algorithm for Emergency Department Patient Flow Optimization. Journal of Healthcare Engineering, 2022, 1-11.

[10]. Liu, Y., Liu, X., Li, Q., Zhu, Y., Ma, J., & Wang, Y. (2021). An intelligent triage system for an emergency department based on machine learning and queuing theory. Journal of Medical Systems, 45(9), 1-10.

[11]. Mahesh, B. (2020). Machine learning algorithms-a review. *International Journal of Science and Research (IJSR). [Internet]*, *9*, 381-386.

[12]. Oh, S. H., Park, J., Lee, S. J., Kang, S., & Mo, J. (2022). Reinforcement learning-based expanded personalized diabetes treatment recommendation using South Korean electronic health records. *Expert Systems with Applications*, *206*, 117932.

[13]. Razavi, S., de la Hoz, E., & Akhavan-Tabatabaei, R. (2021). Optimizing Patient Flow in Emergency Departments Using Discrete Event Simulation and Deep Reinforcement Learning. International Journal of Environmental Research and Public Health, 18(9), 4722. https://doi.org/10.3390/ijerph18094722