Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

An Automated Engineering Model to Forecast Cardiac Arrests' Need for Heart Surgery

Ravi Hosur[1], Sunanda Alur[2], Sana Mohammadi A. Mulla[2]

[1]*Associate Professor, Deptartment of Artificial Intelligence & Machine Learning, BMS Institute of Technology & Management, India, hosuravi@bmsit.in*
[2]*Assistant Professor, Deptartment of CSE(Artificial Intelligence & Machine Learning), BLDEA's V.P.Dr.P.G.Halakatti College of Engg. & Tech., India*

Cardiac surgery continues to be an essential component in the treatment of a wide range of cardiovascular illnesses. It provides essential treatments for problems such as coronary artery disease, valve disorders, and congenital heart abnormalities. This research article examines recent developments in cardiac surgery techniques, including the transition from conventional open-heart surgeries to minimally invasive and robotic-assisted approaches. Additionally, the report suggests an improvement to the methods that are now in use. The influence that these advancements have on patient outcomes, such as decreased surgical morbidity, shortened recovery periods, and increased long-term survival rates, is the primary focus of this discussion. Furthermore, it discusses the significance of using interdisciplinary techniques in the treatment of patients and the provision of postoperative care. In order to give insights into the continuous development of cardiac surgery and its consequences for clinical practice, the purpose of this study is to conduct a complete review of present trends and future directions.

Keywords: cardiac, surgery, Support Vector Machine (SVM), cancer.

1. Introduction

In addition to being an essential component in the treatment of heart conditions, cardiac surgery has the ability to improve both the function of the heart and the quality of life for patients. Having said that, it is essential to recognize that this technique is not without its connected dangers. Complications that arise after heart surgery may be difficult to manage and have an effect on the patient's recovery [1]. Not only do these problems, which include perioperative hemorrhage, cardiac dysfunction, and valve diseases, present immediate concerns, but they also have long-term implications on the health of the patient [2]. In order to give the best possible treatment and to aid in the recovery of patients, it is essential for medical professionals to have a thorough understanding of these issues. Our effort is centered on solving the problem of overfitting in predictive models in order to develop precise algorithms that are capable of predicting the possibility of problems after heart surgery. In addition, we investigate long-term consequences in order to acquire a better understanding of how patients heal over time. The purpose of our research is to increase the accuracy of prediction models by focusing on long-term outcomes and eliminating overfitting. This will eventually lead to improvements in patient care and results in the area of cardiac surgery[3].

In the setting of a statewide quality collaborative approach to the review of cardiac surgical mortalities in intensive care units (ICUs), variations in complication-related outcomes became apparent. Utilizing "failure to rescue" methodology Wide variations in mortality after major surgery are becoming increasingly apparent. The clinical mechanisms underlying these variations are largely unexplored. all Medicare beneficiaries undergoing major operations like ancreatectomy, esophagectomy, abdominal aortic aneurysm repair, coronary artery bypass grafting, aortic valve replacement, and mitral valve replacement. [4]. Use of failure-to-rescue (FTR) as an indicator of hospital quality has increased over the past decade, but recent authors have used different sets of complications and deaths to define this measure [5]. Through the use of machine learning (ML) algorithms, it may be possible to give a dependable solution that is advantageous to both patients and physicians by forecasting the possibility of future issues facing patients. Machine learning, sometimes known as ML, is a subfield of artificial intelligence that focuses on the creation of software that is capable of learning and adapting to new data sets without the need for human intervention [6].

2. Literature survey

The purpose of this study [7] is to evaluate a risk prediction model for predicting mortality in thoracic surgery. This review focuses on mortality and ignores other outcomes such as progressive lung complications and overall.This research evaluates a thoracic surgical mortality risk prediction algorithm. Death is prioritized above other outcomes like pulmonary disease and morbidity in this research. Thoracic surgery patients should undergo a thorough preoperative assessment, following guidelines. Several risk prediction models have been developed to estimate laparoscopic surgical mortality, but their usefulness and quality have not been properly studied. Methodical study and performance assessment of these models are the goals. We searched MEDLINE and Cochrane Library for 1990–2019 articles. Models for prolonged mortality following thoracic surgery were developed or confirmed. Data extraction was based on a checklist of critical systematic review and retrospective study assessments. Even if risks have been foreseen, modern thoracic surgery does not benefit from them. Validating or creating new models is needed to better estimate contemporary thoracic surgery risks.

Clinical practice requires strong data administration, generalizability, and quality assessment [8]. Problems include sample size, implementation, latency-opening, and details. Daily treatment increasingly requires integrated risk prediction and short- and long-term planning. The surgical community emphasizes risk prediction models, risk communication, collaborative decision making, and informed consent before treatments and screening[9]. Surgical prediction models focus on post-surgery cancer risk indicators. Many patient care prognostic models employ regression to be dependable and interpretable. Traditional statistical modeling uses expert knowledge to anticipate sickness traits and create equations like logistic hazard or Cox proportional hazards models to measure predicted risk. Adaptive machine learning (ML) techniques may be better than model-based ones[10]. As computational power and storage capacity expand, intelligence-based research increases, and interest in applying these techniques to all parts of contemporary medicine rises, so will publications and prediction models. Surgeons contemplating AI-based risk assessment should know their benefits and pitfalls. Many studies suggest that the ML algorithm is predictive, although a direct comparison with conventional regression models has not proven significant predictive value, provided correct procedures are used. The ML technique may need massive data sets to produce good predictions. Many studies must examine efficacy with a sufficient sample size since obesity may not be totally treated. Clinicians' ML-based prediction model performance and knowledge are crucial. Standard statistical methods cannot analyze enormous amounts of complex, varied, and unstructured data like ML algorithms[9]. This gain may increase complexity, resulting in bizarre forms doctors cannot understand.

Prediction of the risk of death after heart surgery [11] is based on a small number of variables, such as age, sex, ventricular ejection fraction (LVEF), and preoperative cardiac risk factors. However, the current risk score does not differ in classification, especially for high-risk patients. The introduction of new clinical risk scores, such as EuroSCORE II, leads to the use of different variables, resulting in different data due to the large number of missing values in the new-variable score. Little is known about using hybrid learning to combine behavior statistics from heterogeneous data. In our study, we tested the hypothesis that the combination of convective machine learning (ML) improves the dynamic model (DMA) when combining historical data from EuroSCORE I and EuroSCORE II to estimate cardiac surgery risk. We used data from the National Adult Cardiac Surgery Registry, based on two-variable models, EuroSCORE I (LogES) or EuroScore II (ES II), and trained 12 primary learning models with limited organized. . These learning models are built using nine different combinations of six ML algorithms to create the same or different combinations, whose performance is evaluated using validation metrics.

The benefit of surgery has been carefully evaluated through published data on immediate and long-term outcomes [12] and the calculation and analysis of surgical margins. Calculating operational risk is not enough for effective joint decision-making. An important aspect of the risk/benefit analysis is the evaluation of the potential benefits of the intervention. This consensus statement, prepared based on the 2019 National Recommendation, ERAS and the development policy for postoperative recovery guidelines (ERAS Standards), describes the process of establishing an expert group to develop guidelines, review the literature, evaluate the evidence, and produce. statement. and preparing the manuscript. The development team consisted of a diverse panel of cardiac surgeons, anesthesiologists, primary care physicians, and allied health professionals selected for their based on previous guidelines, examples from other areas and expert opinions, divided into different surgical care processes. This effort was aligned with the Society of Surgeons (STS) evidence-based surgical practice guidelines and was thoroughly reviewed by STS staff prior to admission morbidity. The guidelines recommend a thorough preoperative evaluation for patients undergoing thoracic surgery. There has been a lack of rigorous evaluation of the quality and efficacy of the many risk prediction models that have been created to estimate the risk of mortality after laparoscopic surgery. Our goal is to take a systematic look at these models and evaluate their performance.

Additionally, publications published between 1990 and 2019 were searched using MEDLINE and the Cochrane Library. Studies with the overarching goal of developing or validating models to anticipate chronic mortality after thoracic surgery were also included. Critical evaluations of retrospective research and systematic reviews formed the basis of the data extraction checklist. Although several risks have been predicted, these are not considered favorable for modern thoracic surgery. Validation of existing models or the development of new models is necessary to better evaluate the surgical risks of current thoracic surgery.

Clinical practice requires strong data administration, generalizability, and quality assessment [3]. Problems include sample size, implementation, latency-opening, and details. Daily treatment increasingly requires integrated risk prediction and short- and long-term planning. The surgical community emphasizes risk prediction models, risk communication, collaborative decision making, and informed consent before treatments and screening. Surgical prediction models focus on post-surgery cancer risk indicators. Many patient care prognostic models employ regression to be dependable and interpretable. Traditional statistical modeling uses expert knowledge to anticipate sickness traits and create equations like logistic hazard or Cox proportional hazards models to measure predicted risk. Adaptive machine learning (ML) techniques may be better than model-based ones. As computational power and storage capacity expand, intelligence-based research increases, and interest in applying these techniques to all parts of contemporary medicine rises, so will publications and prediction models.

Surgeons contemplating AI-based risk assessment should know their benefits and pitfalls. Many studies suggest that the ML algorithm is predictive, although a direct comparison with conventional regression models has not proven significant predictive value, provided correct procedures are used. ML can also accurately forecast large data sets, not just little observations[9]. Many studies must examine efficacy with a sufficient sample size since obesity may not be totally treated. Clinicians' ML-based prediction model performance and knowledge are crucial. Standard statistical methods cannot analyze enormous amounts of complex, varied, and unstructured data like ML algorithms. This gain may increase complexity, resulting in bizarre forms doctors cannot understand.

A few variables, such as age, sex, LVEF, and preoperative cardiac risk factors, predict heart surgery mortality [8]. The current risk score does not vary in categorization, particularly for high-risk individuals. New clinical risk scores, such EuroSCORE II, incorporate various factors and provide different results owing to the high amount of missing values. Blending heterogeneous data behavior statistics with hybrid learning is unknown. We investigated whether convective machine learning (ML) enhances the dynamic model (DMA) when merging EuroSCORE I and II historical data to forecast cardiac surgery risk. Based on two-variable models EuroSCORE I (LogES) or EuroScore II (ES II), we trained 12 main learning models with minimal organization using data from the National Adult Cardiac Surgery Registry. These learning models use nine combinations of six ML algorithms to build the same or different combinations, and validation measures assess their success.

Deep learning and autoencoders are used to diagnose human cardiac arrest [14]. This work's auto-encoders detect cardiac problems. They proved its efficacy by reviewing SAE recipients' cardiac arrest data. The dataset includes sudden cardiac arrest deaths. The method described appears to detect cardiac arrest victims.ANN and statistical analysis engines estimated results utilizing learned records. Framingham, Massachusetts cardiovascular research volunteers provided this dataset. Try Kaggle Framingham instead of Cleveland, Hungarian, or Long Beach. Because the Kaggle Framingham heart dataset (4238) has more observations than the other three. This dataset estimates coronary heart disease risk. DAE is compared against ANN, BPNN, SVM, DT, XG Boost, RF, DNN, and SAE. Compared to state-of-the-art models, the suggested technique improves f-measure, accuracy, precision, and recall. Optimizing PSO alone yields slow, low-quality results, and no classifier can enhance CHD prediction. The prediction system should use an ensemble classifier and meta-heuristic optimization methods like HSO, EHO, and TSOA to overcome these difficulties.

As [15] shows, several modern technologies, paired with deep learning and machine learning, can monitor patients and their medical records 24/7, which could greatly minimize sudden cardiac arrest mortality. The analysis found that most studies have employed ECG signals from the MIT-BH or CSV files with complete history data from the OHCA. Random Forest has a 99% success rate, higher than other categorization models. The NN+AMSA algorithm uses deep learning to achieve 94% accuracy on the 24-hour interval ECG dataset. This article supports other writers' work on heart disorders such heart attacks and sudden cardiac arrest. This article says artificial intelligence helps forecast sudden cardiac arrest. However, AI can only forecast abrupt cardiac arrest for a limited time. To quickly save a cardiac arrest patient, the prediction time interval must be extended.

This research found [16]. Due to their low sensitivity and positive predictive abilities, standard early warning systems generally sound the alarm without warning. A time-series analysis predicted cardiac arrest using biosignal and laboratory data. Data variables affecting cardiac arrest likelihood were connected with biosignal and laboratory data. They assessed the system's effectiveness based on biosignal data length, laboratory data, and patient data range to improve early cardiac arrest prediction. Their deep learning and machine learning tools include the LSTM-GRU hybrid model, logistic regression, decision trees, and LSTM. Several cardiac arrest prediction methods were examined.An LSTM model with 89.70% sensitivity and 85.92% PPV was suggested. They proposed machine learning-based cardiac arrest prediction models at Soonchunhyang University Cheonan Hospital. Adjusting input parameters (maximum SBP, minimum SBP; ignore: sex, DBP, AST) improved output. They performed better after 64 hours of patient data. Decision trees (k set 10), random forests (k set 10), logistic regressions (k set 4), LSTMs, GRUs, and LSTM-GRU hybrids performed better after hyperparameter adjustments. Only cardiac arrest can be detected with these approaches. They want to develop a risk assessment tool for doctors and an explainable artificial intelligence (XAI) model for cardiac arrest prediction. They wanted a one-, two-, four-, eight-, twelve-, or sixteen-hour cardiac arrest forecast. Our machine learning approaches will be tested at Seoul, Soonchunhyang University Gumi, Bucheon, and Cheonan hospitals.

The work [17] is evident in their efforts to Cardiovascular illness rising, offered unique and effective disease-fighting solutions with wearable technology. When doctors identify quickly, heart attack compatibility increases and meditation is prescribed. Despite the sensitive topic, a wearable smart gadget that could identify heart attack symptoms used decentralized computational phenomena and hybrid computing architecture. Some people react faster and detect heart attacks earlier. Track and initiate cardiac status with implanted cardiac diagnostic parametric sensors and an Android app. This research creates three classification models using SVM, AdaBoost, and Random Forest. We analyze the proposed system utilizing accuracy, error rate, and reaction time. They found that non-invasive remote cardiac health monitoring could reduce heart attack risk and avoid sudden heart failure. We created an advanced wearable cardiac arrest monitoring system. We employ IoT and hybrid computing. Early medical help and cardiac arrest monitoring save lives. Their smart cardiac arrest monitoring technology detects and predicts heartbeat anomalies via IoT. They made sensors, Android apps, and low-power IoT connection. Smartphone users can remotely track their heart rates with this discovery. The classification algorithm's ability to recognize normal and abnormal heart rhythms was tested using hospital vital signs. To confirm efficacy, they tried it on others. SEHAD-HC gives 97% accuracy, confirming our technique works.

In reference [18], the author investigated the potential benefits of big data in enhancing the treatment of congenital heart disease in both children and adults. When it comes to diagnosing, predicting, and treating congenital cardiac disease, artificial intelligence is still underutilized. This research examines the relationship between AI and congenital cardiac disease and serves as a rallying cry. In this domain, it examined issues, investigated potential solutions, and uncovered key areas for implementing AI.
One of the most impressive things about AI models is their capacity to learn from new data. More powerful computers, an explosion in data volume and complexity, and the advent of AI all point to promising new directions for the study and treatment of coronary heart disease. Both patients and doctors stand to gain from clinical decision-support systems that dynamically adjust diagnoses, prognoses, and treatments based on data from real-time health indicators. Despite the challenges, AI in CHD enables researchers to probe several facets of the illness. Deep learning algorithms powered by artificial intelligence, digital twins, and federated learning can sift through mountains of data. The development of prediction models and pharmaceutical treatments for coronary heart disease (CHD) can be advanced by the study of CHD across the lifespan, which presents potential for collaborative research.

In [19], the author suggests a solution to cardiovascular disease (CVD) and death. This issue is crucial to us. This illness's early diagnosis determines a patient's survival. This chapter discusses two cardiac diagnostic methods. Both use pattern recognition, but one uses machine learning and the other linguistics. First, the syntactic pattern recognition approach breaks down ECG waves from different leads into primitive patterns. Diagnostic criteria are used to discover patterns. These primitives are endpoints in the proposed syntax. Grammar is updated with pattern primitives. It concludes whether the patient is healthy or unwell.Five aberrant disorders are covered here. Machine learning (ML) can help healthcare systems identify cardiovascular disease patients. These let us understand and apply big dataset patterns. It uncovers latent dataset linkages in data analysis. It's learning time. These technologies provide complete pattern analysis of unknown patterns. Deep Learning (DL) can quickly examine data due to its flexible structure. Deep learning is a good neural network example. DL-based prediction programs examine heart disease patients.A hybrid technique using Convolutional Layers and Gated-Recurrent Units diagnoses cardiac disease. Healthcare helps explain international health challenges. We'll examine cardiovascular disease detection in humans from two angles in this chapter. Both methods investigate electrocardiogram (ECG) syntactical patterns and develop prediction models using deep learning. Pattern discovery is interesting but difficult to implement because it requires formal language construction. Deep neural networks underpin predictive modeling. The second method uses multiple neural networks. Since neural networks work like the brain, it's important to highlight their uses. This research encourages the development of a sophisticated computer algorithm to simplify CVD categorization. Separating them would help the medical unit focus on CVD patients. Our work illuminates critical questions to help clinicians make better judgments.

Data on immediate and long-term results [4] and surgical margin computation and analysis have rigorously assessed surgery's benefits. Joint decision-making requires more than operational risk calculation. The intervention's possible advantages are crucial to the risk/benefit analysis. Based on the 2019 National Recommendation, ERAS, and the development policy for postoperative recovery guidelines (ERAS Standards), this consensus statement describes how to form an expert group to develop guidelines, review the literature, evaluate the evidence, and write the manuscript. A varied panel of cardiac surgeons, anesthesiologists, primary care doctors, and allied health workers with ERAS experience formed the development team. In 2021, a panel of professionals convened for the first time to examine surgical treatment alternatives based on past recommendations, examples from other fields, and expert views. Staff from the Society of Surgeons (STS) examined this work before admission to ensure it followed evidence-based surgical practice standards.

3. Methodology

The primary objective of this technique, which is also known as statistical learning or predictive analytics, is to identify patterns and insights hidden within data. Supervised machine learning techniques, such as the Random Forest classifier, are evaluated in this research using a dataset that is freely available to the public. The model that was developed is evaluated using a dataset for the prediction of cardiac complications. This dataset consists of twelve features, each of which represents a distinct characteristic of each individual patient. Using data obtained from Kaggle.com, this research was able to build the dataset that was used for the prediction of cardiac complications. The characteristics that are included in the dataset are following: age, diabetes, hypertension, renal disease, pulmonary disease, ejection fraction, complications four years after surgery, gender, type of coronary artery bypass grafting (CABG) surgery, type of congenital surgery, type of transplant surgery, and type of heart valve surgery.

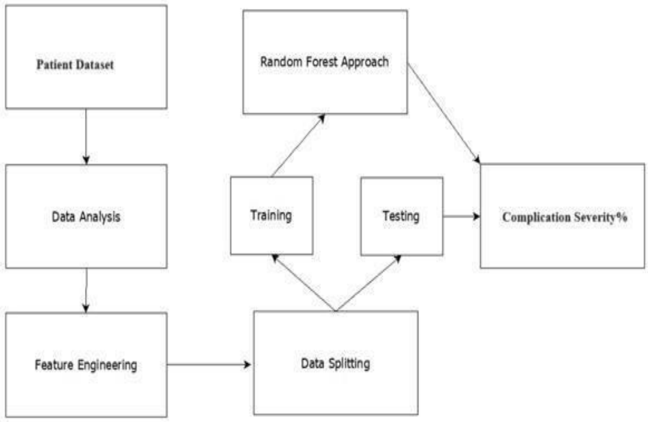

Fig 3.1: Random Forest used for Predicting Complications following Cardiac Surgery

1. Preprocessing

- The initial phase consists of preparing and converting the unprocessed data to ensure compatibility with machine learning algorithms.
- This process encompasses activities like addressing null values, encoding categorical data, and standardizing attributes..

2. Data Resources

- The data employed in the machine-learning process is sourced from a variety of places, including structured data from databases, CSV files, APIs, or any other data source..

3. Training Model:

- Train the SVM model using the selected features and corresponding outcomes.
- Utilize the SVM algorithm to learn the decision boundary that best separates patients with and without postoperative complications.

4. Prediction for New Data:

- Use the trained SVM model to predict postoperative complications for new patient data.
- Input the relevant features of a new patient into the model and obtain a prediction of the likelihood of complications.

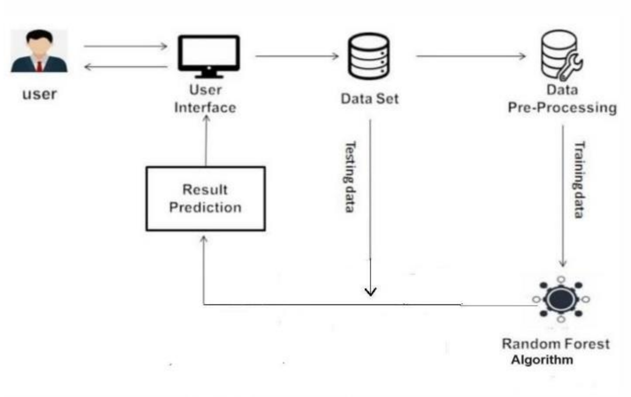

Fig 3.2: System Architecture of Complications following cardiac surgery

4. Results

Fig 4.1: User Interface of an application

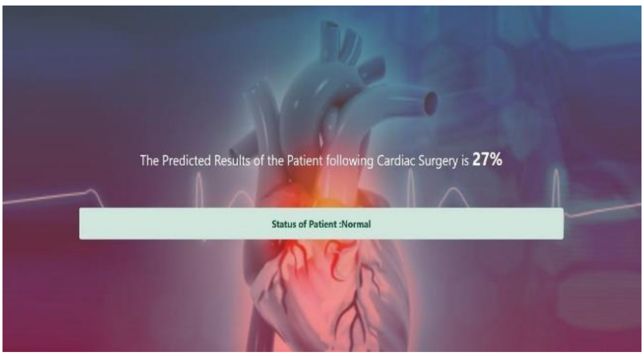

Fig 4.2: Patient Report Interface of an application

5. Conclusion

The extensive overview of cardiac surgery problems emphasizes the importance of understanding the obstacles and hazards of this crucial treatment. Our approach solved

Fig 4.3: Predicted Result of Complication

overfitting in predictive models, improving our post-surgery complications projections. Expanding our analysis to include these problems' long-term implications has revealed important insights into how heart surgery affects patient health and recovery. Clinical practitioners may better anticipate and treat problems using these data, improving heart surgery patient outcomes and care. Future study and prediction model enhancement will help us identify and treat post-surgical problems to improve patient safety and surgical effectiveness. Cutting-edge imaging, AI-driven diagnostics, and continuous remote monitoring will help spot heart surgical issues faster. Genetic profiling and biomarker analysis will personalize risk evaluations. Real-time monitoring will be possible with improved EHRs and telehealth technologies. This collaborative strategy improves early intervention and patient outcomes.

References

1. Horwitz LI, Cuny JF, Cerese J, Krumholz HM. Failure to rescue: validation of an algorithm using administrative data. Med Care 2007;45:283–7.
2. Reddy HG, Shih T, Englesbe MJ, et al. Analyzing “failure to rescue”: is this an opportunity for outcome improvement in cardiac surgery? Ann Thorac Surg 2013;95:1976–81; discus sion 1781.
3. “Predicting Hospital Mortality and Analysis of Long-Term Survival After Major Noncardiac Complications in Cardiac Surgery Patients” by Parwis B. Rahmanian, MD, David H. Adams, MD, Javier G. Castillo, MD, Alain Carpentier, MD, PhD, and Farzan Filsoufi,,pp. Ann Thorac Surg 2010;90:1221–9.
4. Ghaferi AA, Birkmeyer JD, Dimick JB. Complications, failure to rescue, and mortality with major inpatient surgery in medicare patients. Ann Surg 2009;250:1029–34.
5. Silber JH, Romano PS, Rosen AK, Wang Y, Even-Shoshan O, Volpp KG. Failure-to-rescue: comparing definitions to measure quality of care. Med Care 2007;45:918–25.
6. “Using machine learning for predicting severe postoperative complications after cardiac surgery” , Article in Journal of Cardiothoracic and Vascular Anesthesia · August 2018
7. After Cardiac Operations: All Are Not Created Equal" by Todd C. Crawford, MD, and colleagues from the Annals of Thoracic Surgery journal ,pp.Ann Thorac Surg 2017;103:32–40
8. "Cardiac Complications Following Cardiac Surgery Procedures" by Jakub Udzik et al. in the

Journal of Clinical Medicine, Volume 9, Issue 10, 2020.

9. "Explainable machine-learning predictions for complications after pediatric congenital heart surgery " by Xian Zeng, Yaoqin Hu, Liqi Shu, Jianhua Li, Huilong Duan2, Qiang Shu & Haomin Li ,pp. (2021) 11:17244.
10. "Determinants of Long-Term Survival After Major Surgery and the Adverse Effect of Postoperative Complications" by Shukri F. Khuri, MD, William G. Henderson, PhD,Ralph G. DePalma, MD, Cecilia Mosca, MSPH,§ Nancy A. Healey, pp. Ann Surg 2005;242: 326–343.
11. "Impact of postoperative complications after cardiac surgery on long-term survival(2021)" by Siddharth Pahwa MBBS, Annalisa Bernabei MD, Hartzell Schaff MD, John Stulak MD, Kevin Greason MD, Alberto Pochettino MD, Richard Daly MD, Joseph Dearani MD ,pp. May 2020 DOI: 10.22541/au.158977808.89830126
12. "The Impact of Major Postoperative Complications on Long-Term Survival After Cardiac Surgery(2020)" by Laura Seese, MD, Ibrahim Sultan, MD, Thomas G. Gleason, MD, Forozan Navid, MD, Yisi Wang, MPH, Floyd Thoma , pp. Ann Thorac Surg 2020;110:128- 35.
13. Silber JH, Williams SV, Krakauer H, Schwartz JS. Hospital and patient characteristics associated with death after surgery. A study of adverse occurrence and failure to rescue. Med Care 1992;30:615–29.
14. Sakthivel M, SivaSubramanian S, Priyanka Brahmaiah V, Hosanna Princye P, Prasad GNR, Thangamani M, "Automated detection of cardiac arrest in human beings using auto encoders", Volume 27, 2023,100792,ISSN 2665-9174, https://doi.org/10.1016/j.measen.2023.100792.
15. Suman Raj, Shahzad Alam, Tanvir Ahmad, "Prediction of Cardiac Arrest using Artificial Intelligence - A Systematic Review", 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), pp. 1-6, 2022
16. Chae, Minsu, Hyo-Wook Gil, Nam-Jun Cho, and Hwamin Lee. 2022. "Machine Learning-Based Cardiac Arrest Prediction for Early Warning System" Mathematics 10, no. 12: 2049. https://doi.org/10.3390/math10122049
17. Abdul Hannan, Sehrish Munawar Cheema, Ivan Miguel Pires, "Machine learning-based smart wearable system for cardiac arrest monitoring using hybrid computing", Biomedical Signal Processing and Control, Volume 87, Part B, 2024,105519, ISSN 1746-8094, https://doi.org/10.1016/j.bspc.2023.105519
18. Pei-Ni Jone, Addison Gearhart, Howard Lei, Fuyong Xing, Jai Nahar, Francisco Lopez-Jimenez, Gerhard-Paul Diller, Ariane Marelli, Laura Wilson, Arwa Saidi, David Cho, Anthony C. Chang, "Artificial Intelligence in Congenital Heart Disease", Current State and Prospects, JACC: Advances, Volume 1, Issue 5, 2022, 100153, ISSN 2772-963X, https://doi.org/10.1016/j.jacadv.2022.100153
19. Shawni Dutta, Payal Bose, Vishal Goyal and Samir Kumar Bandyopadhyay, "Machine Learning Techniques and Syntactic Pattern Recognition based Heart Disease Prediction for Smart Health", International Journal of Medical Research & Health Sciences, 2021, 10(7): 43-59, ISSN No: 2319-5886