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ICU Patient Risk Level Monitoring System using Supervised Learning Approaches

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Abstract: Present-day intensive care units, or ICUs, offer critically ill patients who are susceptible to several problems, including death and morbidity, round-the-clock monitoring. ICU environments produce a lot of data and call for a high staff-to-patient ratio. Making decisions and interpreting data in real time is a difficult task for clinicians. In intensive care units (ICUs), machine learning (ML) tools are advancing the early detection of high-risk events. because of more powerful computers and publicly accessible databases like the Medical Information Mart for Intensive Care (MIMIC). Techniques in ICU settings uses MIMIC data. The ICU patient risk level monitoring system plays a crucial role in improving patient safety, optimizing resource allocation, and enhancing clinical decision-making in intensive care settings. By continuously monitoring and analyzing patient data, it provides valuable insights that help healthcare providers intervene promptly and prevent adverse outcomes.

Keywords: Intensive Care Unit, Critical Care, MIMIC, ML, AI, NLP.

1. Introduction

Critically sick patients with many comorbidities that impact morbidity and death are continuously monitored in modern ICUs. ICU environments produce a lot of data and call for a high staff-to-patient ratio. Making decisions and interpreting data in real time is a difficult task for clinicians. Thanks to enhanced processing and publicly available datasets like the Medical Information Mart for Intensive Care (MIMIC), machine learning approaches in the intensive care unit are progressing in the early detection of high-risk events. ICU techniques make use of MIMIC data. The ICU patient risk level monitoring system plays a crucial role in improving patient safety, optimizing resource allocation and enhancing clinical decision-making in intensive care settings.by continuously monitoring and analyzing patient data, it provides valuable insights that help healthcare providers to prevent adverse outcomes.

The term artificial intelligence (AI) refers to a wide range of technological advancements that attempt to mimic human cognitive processes and intelligent behavior. A branch of artificial intelligence called machine learning (ML) focuses on methods that let computers create complicated correlations or patterns from empirical data without needing to be explicitly programmed. With the growing availability of healthcare data, machine learning (ML) is being applied to a wide range of clinical tasks, from outcome prediction to diagnosis. The more examples that are available for learning, the more predictive potential machine learning has. Depending on the kind of learning rule used, machine learning algorithms can be either supervised or unsupervised.

Well-labeled data is used to train an algorithm in supervised learning. Once the system has acquired information from the training data, it uses that knowledge to predict on unseen data. Decision tree methods, Random Forest (RF), and Support Vector Machines (SVM) are the most often used supervised machine learning models. Ground truth labeling is not necessary for unsupervised learning. Rather, the machine gains knowledge from the unlabeled data's intrinsic structure. In both cases, machine learning is an iterative process where the algorithm searches for the best possible combination of model variables and variable weights in order to minimize the error in the anticipated result. Predictions where the outputs are unknown can be made using the technique if it operates with a fairly low error rate.

Underfitting and overfitting are the outcomes of improper bias and variance selection. To prevent both underfitting and overfitting, it is essential to identify the "sweet spot" between bias and variation. By taking inspiration from

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biological neural networks, deep learning (DL), a subcategory of machine learning, achieves great power and flexibility compared to conventional ML models. DL can solve a wide range of complex tasks, such as natural language processing (NLP) and the classification of medical imaging. The most popular deep learning models are Multi-Layer Perceptron's (MLP) and Artificial Neural Networks (ANN). ML models are typically data-driven and depend on a thorough comprehension of the system to create predictions, enabling users to make wise decisions.

In order to enhance the quality of patient care and promote translational research, The intensive care unit (ICU) needs a high staff-to-patient ratio and produces a massive amount of data. Early detection and intervention in patients at risk of complications is essential to prevent adverse outcomes and lengthy stays in the intensive care unit. Due to these reasons, there has been a rise in the utilization of ICU patient data in the ML literature for clinical event prediction and secondary usage, including sepsis and septic shock.

Because of greater processing power and publicly available datasets like the Medical Information Mart for Intensive Care (MIMIC), machine learning (ML) approaches in intensive care units (ICUs) are making progress in the early detection of high-risk events. The MIMIC database contains both unstructured data, such as free-text interpretations of imaging studies from the radiology department, and highly organized data from time-stamped, nurse-verified physiological measurements made at the bedside.

2. Literature Survey

Machine learning algorithms for dynamic mortality prediction in acute cardiovascular situations. The link and its component parts are developed. The identification of the model structure incorporates the patient's state, treatment phases, and treatment dynamics. It offers an improved model structure prediction for the next stages and makes a request for the data needed to improve the forecast and enable better-informed decision-making. Analysis was done on dynamic data that was taken straight out of the medical information system, which is extremely similar to the actual procedure. Early mortality risk prediction is feasible with machine learning techniques.

Mortality Prediction in ICU Patients Using Machine Learning Models

Medical professionals face a difficult challenge in trying to save precious human lives when it comes to the effective use of limited intensive care unit (ICU) allocations. Patients who are waiting for ICU accommodations may suffer potentially fatal consequences from the extended ICU stays of reasonably stable patients and patients with poor prognoses. This is where machine learning-based methods for early mortality prediction come in handy. This study uses linear discriminant analysis and the support vector machine (SVM) to provide two mortality prediction models. The suggested algorithms predict death early by utilizing clinical data from ICU patients. During pre-processing, distribution filtering is carried out using the chi-square distribution. The suggested method is evaluated using a subset of the Medical Information Mart for Intensive Care (MIMIC-III v1.4) dataset, which is made available to the public.

Length-of-stay and mortality prediction for a major hospital through interpretable machine learning.

Comprehending the hospital discharge procedure is essential for enhancing effectiveness and treatment quality. Examine the ways in which machine learning can be used to predict a range of factors related to patient discharges, including as length of stay, discharge destination, and hospital mortality.

Identifying Predictors of COVID-19 Mortality Using Machine Learning.

Context The respiratory sickness coronavirus disease 2019 (COVID-19) is a prevalent and quickly spreading illness. The variables determining COVID-19 mortality are still unknown, though. There are no adequate mortality predictions and uncertainty around the pathophysiology of COVID-19. The purpose of this study was to look into COVID-19 mortality in patients who already had health issues and to see whether there was any correlation between COVID-19 mortality and other morbidities.

Mortality Prediction in the ICU

Patients who are admitted to the intensive care unit (ICU) have serious illnesses or injuries and a high mortality rate. Depending on the underlying illness process, intensive care unit mortality rates can vary significantly. For patients in after elective surgery, the rate of death can be as low as 1 in 20, whereas for patients with respiratory disorders, it can reach up to 1 in 4. Assessing the degree of a patient's sickness based on significant physiologic, clinical, and demographic factors can help estimate the probability of mortality. In clinical practice, estimates of mortality risk can be helpful in deciding on appropriate levels of treatment, triaging patients, allocating resources, and even having conversations about predicted outcomes with patients and their families. Estimates of mortality risk, however, are derived from the analysis of combined data.

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3. Theory / Calculation

Accuracy Calculation

Accuracy = (TP + TN) / (TP + TN + FP + FN)

The easiest performance metric to understand is accuracy, which is just the ratio of properly predicted observations to total observations. If our accuracy is high, one might assume that our model is the best. Indeed, accuracy is an excellent statistic, but only in cases when the datasets are symmetric, meaning that the false positive and false negative values are almost equal.

Precision Calculation

Precision: the percentage of optimistic forecasts that come true.

Precision = TP / (TP + FP)

The ratio of accurately anticipated positive observations to all predicted positive observations is known as precision. Of all the passengers labeled as surviving, the question this metric answer is: How many actually survived? Good accuracy is associated with a low false positive rate. Our precision is 0.788, which is quite good.

4. Design

ICU patient risk level monitoring system utilizing supervised learning techniques. This system would assist healthcare professionals in assessing and monitoring the risk levels of patients in intensive care units (ICUs) in real-time. Gather a comprehensive dataset consisting of patient demographics, vital signs, laboratory results, medical history, medication records, and other relevant variables for ICU patients. This dataset will serve as the input for training and validating the supervised learning models. Split the collected data into training and validation sets. Use the training set to train the supervised learning models, tuning their hyper parameters and optimizing their performance.

Real-Time Risk Level Monitoring: Implement a system that continuously collects real-time patient data from the ICU, applies the trained models, and provides risk level predictions for individual patients. This system can generate alerts or it’s important to note that the specific implementation details and choice of supervised learning algorithms may vary depending on the available data, healthcare institution, and desired performance objectives.

The proposed system provides a high-level overview of the key components involved in developing an ICU patient risk level monitoring system using supervised learning techniques. Notifications to healthcare professionals when a patient's risk level exceeds a predefined threshold, enabling early intervention and timely medical attention.

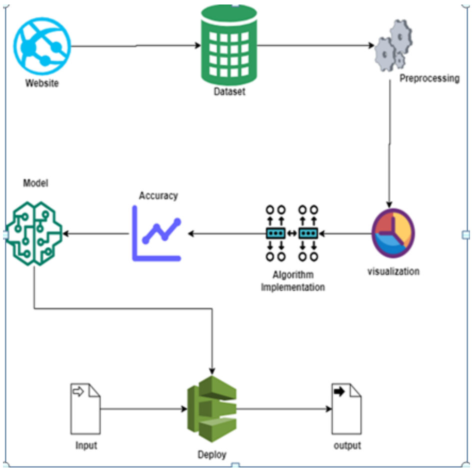

Figure.1 Architecture of Proposed System

5. Results and Discussion

This is the data flow diagram which can be easily analyzed the flow of process involved in this work.

Creating a dataflow diagram for an ICU patient risk level monitoring system using supervised learning involves depicting how data moves through the system, from data collection to the output of risk predictions. This system typically processes a large amount of data coming from various sensors and medical records to predict the risk levels of patients, aiding in timely medical interventions.

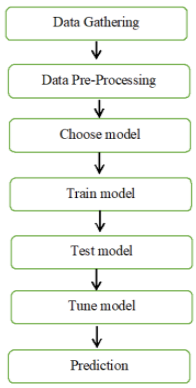

Figure.2 Data Flow Diagram

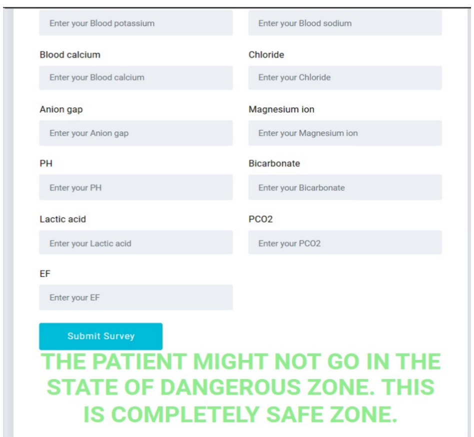

Figure. 3 Output screen which displayed after given the data to the model

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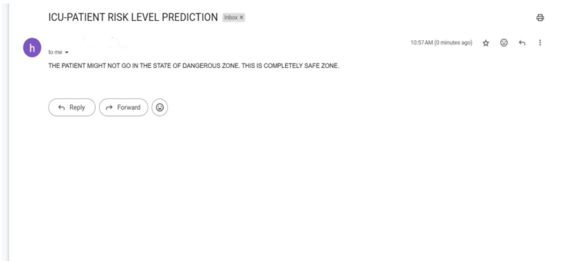

Figure. 4 Mail notification send to healthcare professionals when the patient risk is high.

6. Conclusion and Future Scope

This study outlined the analytical procedure, which started with data preparation, cleaning, and missing value identification. Next, exploratory analysis was conducted to ascertain the distribution and correlation of the data, and lastly, a model was constructed by training on the training set and assessing its accuracy and precision. The best accuracy on the patient data set will be determined. This application can assist in the prediction of patients who are at danger. Prediction methods to connect with cloud model. To optimize the work there may be implemented in IOT System and integrating with wearable devices.

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Declaration

We R Harshitha, A Keerthana, K Haripriya, N Manisha here by declare that the Project work entitled "ICU Patient Risk Level Monitoring System Using Supervised Learning Approaches" is a bonafide work done by us under the guidance of M. Veeresh Babu, MTech,(Ph.D.) submitted in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science & Engineering, Aditya College of Engineering, Madanapalle affiliated to Jawaharlal Nehru Technological University Anantapur, Anantapuramu, during the academic year 2023-24. The results embodied in this work have not been submitted to any other University or Institute for the award of any degree or diploma.

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