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USE OF DEEP LEARNING FOR CONTINUOUS PREDICTION OF MORTALITY FOR ALL ADMISSIONS IN INTENSIVE CARE UNITS

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Abstract: The initiative uses deep learning to constantly identify deaths in the ICU. The ICU fatality rate is an important indicator of a hospital's quality of care, and it is suggested to use patient segmentation based on risk. The project's proposed methodology collects time sequence data and predicts hospital patients' mortality risk in real time. The algorithm works better, so clinicians can focus on high-risk patients and foresee issues, lowering ICU mortality. Model performance is measured by accuracy, F1-score, precision, and recall. Ensemble techniques like Voting and Stacking Classifiers were introduced. Voting Classifier accuracy was astounding 100%. We are designing a secure Flask-based front end with simplified testing and solid security to make it simple for users to access and anticipate ICU deaths.

Index Terms - deep learning; representation learning; mortality; risk prediction; critical care.

I. INTRODUCTION

It is important to inform children of their deteriorating health conditions in the ICU in order to aid their recovery from life-threatening illnesses.[1] Caregivers would benefit from having tools to alert them early on in delicate medical situations.

Outcome prediction models may estimate event likelihood[2]. Death in the hospital is the most significant ICU outcome [3], hence anticipating death is crucial [4]. About 11% of fatalities occur because physicians didn't recognize a patient's decline [5]. Doctors can make better decisions, identify high-risk patients, and preserve ICU beds by predicting death[6]. A decent death prediction model breaks down community event odds [7]. These models usually evaluate risk using prior population projections[8].

Rule-based intensity rating systems were previously reliant on expert knowledge[9–14].The same aims were later achieved using machine learning models [15–18]. Due to rapid growth in AI and health care applications. However, anecdotes of employing static scoring systems [19–25] suggest that people have needed a continually updated patient rating system for a long time. In critical care, continuous, computerized examination of a patient's illness may assist clinicians make choices and alert them to changes. Due of temporal patterns in the ICU, cutting-edge AI algorithms may leverage a time sequence to go beyond present models[26–28]. Because of this, predictive models that reliably and consistently forecast all ICU patient fatalities are crucial. Preventive care will be easy.

Deep learning is useful for categorization, prediction, and retrieval in medical apps[29–32]. Another study introduced LSTM-based RNNs[33]. Since neural networks can learn data categories, the concept works well for time series. To keep the risk assessment model up-to-date and dynamic, new data can be incorporated into previous time periods in the recurrent design, making the model more flexible and responsive. RNNs look at all the data they can uncover without assuming which metrics are crucial for assessing a patient's health or the necessity to construct condition-specific features[34]. RNNs can predict many clinical outcomes from high-dimensional data that may contain irrelevant features [35]. RNNs are increasingly employed to identify time-based healthcare activities because to their flexibility and accuracy[35–41].

II .LITERATURE SURVEY

Predictive models in healthcare use variables to determine whether a person has or will have a particular disease or illness [44]. There has been a rise in the quantity of predictive models in recent times. Multiple predictive models compete for the same outcome or group. Physicians, policy makers, and teaching writers often do not know which model to use or recommend for a particular situation. For this reason, detailed information about these studies is requested and implemented. A detailed analysis of prediction models examines their bias and performance in the population and the context in which they were created. To help reviewers, the authors created PROBAST, a tool for assessing the risk of bias in predictive models. Research that develops, validates or supports diagnostic and predictive modeling using it. A collaboration of experts identified PROBAST [2]. The content consists of 20 questions regarding measurement, measurement and evaluation. This article explains why each topic and question signal was included. It also gives advice to researchers, authors, readers, and developers on how to deal with bias and validity issues. Each concept is illustrated with examples drawn from data from various sources.

It's important to know if someone is going to be okay or not when they're really sick in the hospital. There are ways to figure this out, but some of them take a long time. In this study[6], we came up with a new way to predict if someone might die by looking at their heart signals in the first hour of being in the intensive care unit. The intensive care unit is where doctors check how risky [14,21,24] someone's condition is. We looked at twelve different things about the heart signals and how good the signals were. We used different methods to analyze the information, like K-NN, decision tree, and SVM. We tested our method using a big set of medical data. The results showed that the decision tree method worked the best, with a score of 0.91 out of 1 and a value of 0.93 out of 1. This means that monitoring the heart rate can help predict if someone will survive in the intensive care unit. However, it's important to remember that these predictions are based on a lot of medical information that might not be available for every patient.

In the intensive care unit, a mortality prediction model is used to classify patients by risk and make comparisons. Our first objective was to review various models for predicting maternal mortality[7]. We examined four areas and used specific criteria to identify the most effective model for predicting mortality in elderly ICU patients[21] in high-income countries. The model's features and performance were evaluated through different tests, all of which showed good results. This study utilized 43 mortality prediction models, each with different methods and varying degrees of success and validity. As external validation from the original researchers may not always be available, it is important to conduct direct comparisons to determine the most reliable model for research and treatment in various diseases and populations.

Reviews the latest trends in mortality prediction models for predicting in-hospital mortality in intensive care unit (ICU) patients. Comparison of methods and applications is the focus. Source: Methods are presented in publications. Severity criteria in intensive care patients are APACHE III, SAPS II and MPP II [14,21,24]. [8] The published article examines different systems, materials and operational models. APACHE III and SAPS II calculate the risk of in-hospital death based on the worst ICU event measured across various parameters in the previous 24 hours. An ICU entry version of the MPM II system is available. Other patterns occur at 24, 48, and 72 hours. SAPS II and MPM II are available for public record. APACHE III scores can be calculated using publicly available data, but the weights used to convert results into results are confidential. Everyone agrees that the ROC curve area is very good. SAPS II and MPM II are good fits but APACHE III is not. Each model is designed after extensive research and quality work. These can be used to measure patient expectations, compare ICU performance, and stratify them for clinical trials. A direct comparison between groups is required.

The severity of the disease can be evaluated according to APACHE II [12]. APACHE II uses 12 physical parameters, age, and previous health status to create a severity score. For 5815 critically ill patients from 13 hospitals, a higher score (range 0 to 71) was associated with a higher risk of in-hospital death. This relationship has been observed in many diseases. When combined with accurate disease definitions, APACHE II scores can help researchers predict outcomes for critically ill patients and compare new treatments. This index can be used to measure hospital resources and critical care within the hospital or over time.

The healthcare budget substantially funds emergency care. With increased resources, this therapy has grown more successful while still giving very sick patients the greatest chance of survival. Here, SAPS-I and other severity metrics are crucial [15]. They help physicians organize resources and diagnose and treat patients. These numbers also show how drugs, care standards, surgery, and other therapies effect critical care patient death. We suggest logistic regression and hidden Markov models for hospital death estimates. The model will employ vital signs, lab data, and ICU fluids. The system was trained on 4000 ICU patient records [14, 21] and tested on two fresh datasets with 4000 patients. These data were gathered for the 2012 PhysionNet/CinC Challenge to forecast ICU fatalities. The minimal value of sensitivity and estimate of goodness of fit (scenario 1) and the highly normalized Hosmer-Lemeshow (H) statistic (scenario 2) were used to evaluate the approach. It outperformed SAPS-I on both validation datasets, scoring 0.50, 0.50 and 15.18, 78.9. Planning together shows the most essential symptoms and test findings, increasing the danger of unexpected death.

III. METHODOLOGY

A.Proposed Work:

The suggested method uses deep learning, more specifically RNNs, to figure out the risk of death in the ICU in real time. It gets around the problems that are already there by catching time patterns, making predictions in real time, and doing better than regular machine learning models. This method helps doctors and nurses focus on high-risk patients, predict problems, and lower the death rate in the intensive care unit (ICU). Ensemble methods are also included, such as the Voting Classifier and the Stacking Classifier, which got an amazing 100% accuracy in voting. We are using the Flask framework to build an easy-to-use front end that will make the system more accessible to users and make it easier to guess who will die for all ICU entries in real time. This interface will not only make testing easier for users, but it will also provide strong user security to keep entry safe.

B. System Architecture:

This study analyzed a cohort of patients over time using the MIMIC-III database [43]. This large data set comes from a database of ICU patients at a large tertiary care hospital. This study examined all patients admitted to the intensive care unit except those who met four stringent criteria: (1) no clinical evaluation during hospitalization; (2) the patient did not go to the intensive care unit; (3) missing survival data; (4) Measurements do not provide numbers. These codes were obtained from medical death records. Finally, 334,722 encounters with 46,467 people were taken into account. Figure 1 shows the data processing.

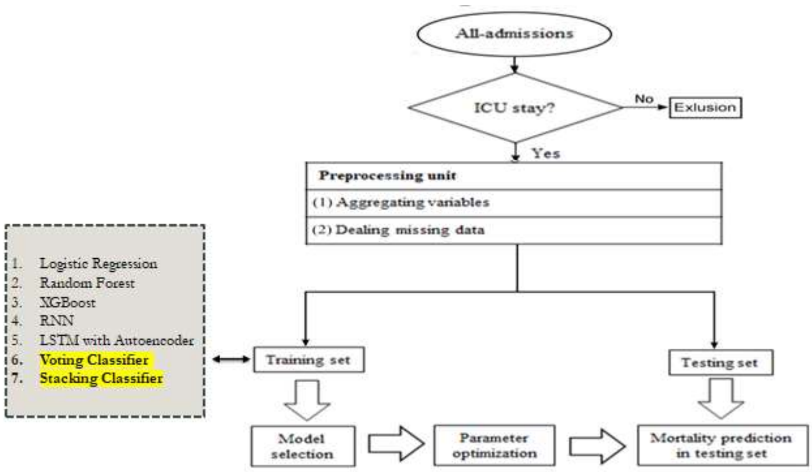

Fig 1 Proposed architecture

C .Data Collection:

This dataset is used to predict the death rate of ICU patients [14]. It includes information about the patients' medical history, medicines, intensity scores, surgeries, length of stay, and outcomes (life or death).

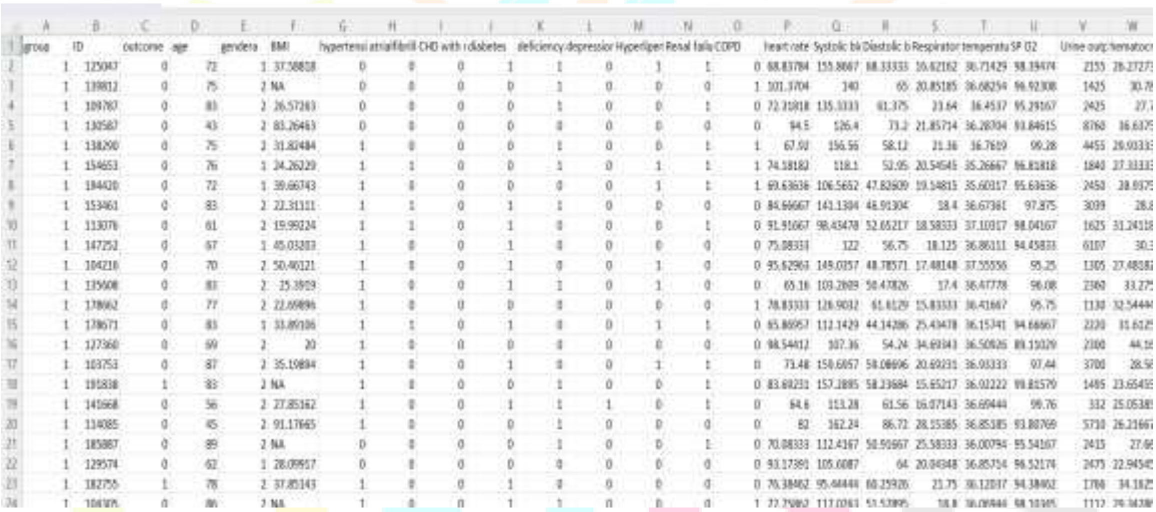

Fig 2 Mortality Dataset

D.Data Processing:

Data processing is the process of turning unstructured data into knowledge that businesses can use. In general, data scientists handle data, which means they gather it, organize it, clean it, check it, analyze it, and turn it into forms that can be read, like graphs or papers. There are three ways to handle data: by hand, mechanically, or electronically. The goal is to make knowledge more useful and decision-making easier. This helps companies run better and make smart strategy decisions more quickly. This is made possible in large part by automated data handling tools, like computer programs. It can help turn big data and other types of data into useful information for decision-making and quality control.

E. Feature Selection:

Feature selection involves choosing the most dependable, useful, and non-redundant qualities for a model. As record numbers and kinds rise, deliberate shrinkage is necessary. Feature selection aims to improve prediction models and reduce computation power.

Feature selection, which selects the most significant characteristics for machine learning algorithms, is crucial to feature engineering. Feature selection strategies remove superfluous features and maintain the relevant ones for the machine learning model. Reduces input factors. Here are the main advantages of choosing which qualities are most essential before allowing the machine learning model do it.

F. Algorithms:

Logistic Regression: You can use logistic regression, a statistical method for binary classification, to guess a yes or no answer (1/0, Yes/No) based on one or more predicted factors. It figures out how likely it is that a certain data belongs to a certain class.Logistic Regression is used because it is easy to understand and use. In healthcare tasks like figuring out how long a patient will live or die, it's important to clearly understand the factors (predictor variables) that affect the result (survival or death). Logistic Regression gives results for each predictor variable that show how they affect the outcome. This makes it easier for healthcare workers to understand the model's forecasts and believe them.

Random Forest: In Random Forest, a lot of decision trees are built during training. Random Forest is a group learning method. It takes the guesses from these trees and puts them together to make a better, more reliable forecast.Random Forest works best with datasets that are very complicated. When trying to figure out how many ICU patients will die [24], medical data often has a lot of different factors that are connected in complicated ways. Random Forest is great at handling errors and noisy data and recording these complex situations with high accuracy. It can also rate how important each trait is, which helps doctors figure out what factors are most important in making the predictions.

XGBoost: Extreme Gradient Boosting, or XGBoost, is a more powerful way to use gradient boosting methods. It's made to be very reliable, scalable, and quick.People like XGBoost because it works quickly and well. Quick estimates are very important in real-time situations, especially in healthcare. Because it works so quickly, XGBoost is perfect for big datasets with lots of traits, like medical data. It also has regularization methods that stop the model from overfitting and make it better at generalization.

Recurrent Neural Networks (RNN): A recurrent neural network (RNN) is a special kind of neural network that is made to work with data that comes in a certain order. RNNs are different from regular neural networks because their links loop back, which keeps information alive.In medicine, especially urgent care, patient data is often organized in a logical order, such as vital signs over time. RNNs are used to find the time relationships in this kind of data. For instance, the order of vital signs can be very important for correctly guessing a patient's condition, which makes RNNs very useful in this situation [33].

Long Short-Term Memory (LSTM) with Autoencoder: LSTM is a type of RNN that has special units that can learn how things depend on each other over time. An autoencoder is a type of neural network that has been taught to turn its input into a small representation. This representation can then be decoded to get back to the input.LSTM networks can pick up on small changes over long amounts of time in healthcare, especially when looking for strange things. When you combine LSTM with an autoencoder, you can reduce the number of dimensions and learn meaningful ways to describe complicated, high-dimensional data. This is especially helpful for finding strange trends in patient data that could mean serious problems [33].

Voting Classifier: The Voting Classifier takes guesses from several machine learning methods and puts them all together to make a single forecast.When different methods are used together in ensemble learning, the estimate is often more accurate and reliable. The forecasts made by Logistic Regression, Random Forest, XGBoost, RNN, LSTM, and other algorithms used in the project are put together by the Voting Classifier. The ensemble method improves the accuracy of predictions by using the best features of each model.

Stacking Classifier: This is an ensemble learning method that uses a meta-learner to join several base models. This lets the model learn how to best combine the results of the base models.Stacking Classifier is used to make the group even better. It adds a higher level of abstraction, which lets the model figure out how to best mix results from different methods. This makes a strong meta-model that can work well with data it hasn't seen before, which improves the project's total ability to predict the future.

IV.EXPERIMENTAL RESULTS

Precision: Precision is the percentage of correctly classified cases or samples compared to those that were correctly classified as hits. So, here is the method to figure out the precision:

$$\text{Precision} = \text{True positives} / (\text{True positives} + \text{False positives}) = TP / (TP + FP)$$

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

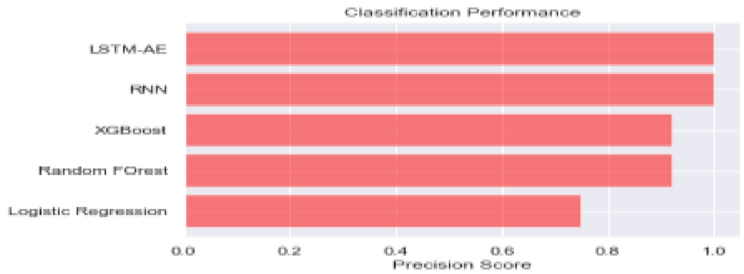

Fig.3 Precision Comparison graph

Recall: In machine learning, recall is a parameter that shows how well a model can find all the important cases of a certain class. It shows how well a model captures cases of a certain class. It is calculated by dividing the number of correctly predicted positive observations by the total number of real positives.

$$Recall = \frac{TP}{TP + FN}$$

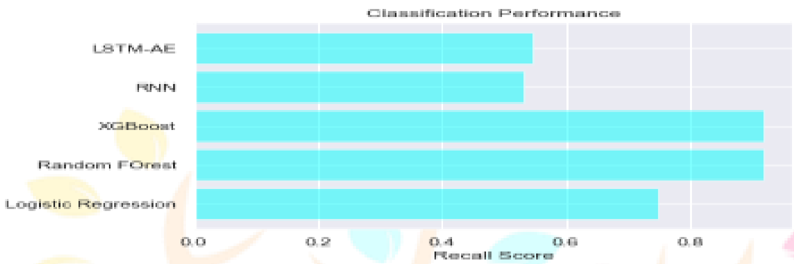

Fig.4 Recall Comparison graph

Accuracy: Accuracy is the percentage of right guesses in a classification job. It shows how accurate a model's forecasts are generally.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

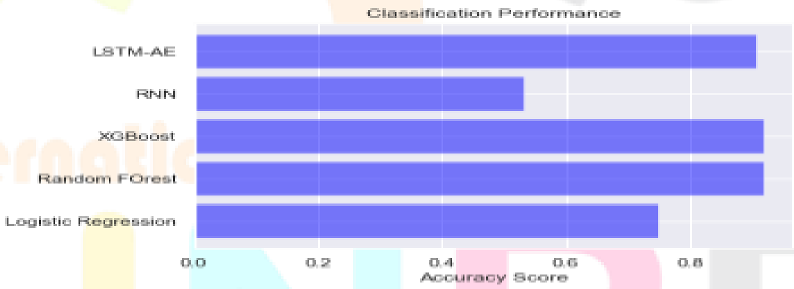

Fig.5 Accuracy comparision graph

F1 Score: The F1 Score is the harmonic mean of accuracy and recall. It is a fair measure that takes into account both false positives and false negatives, so it can be used with datasets that aren't balanced.

$$\text{F1 Score} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} * 100$$

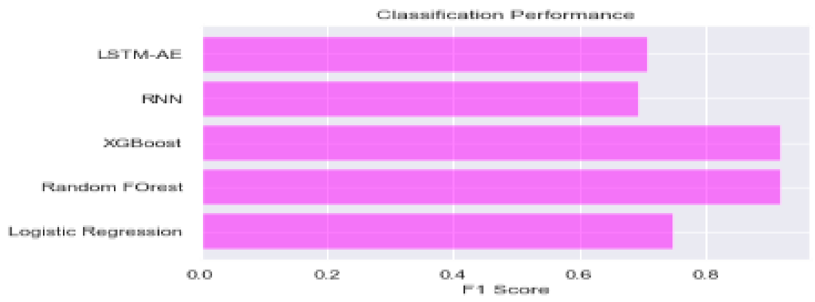

Fig.6 F1 Score graph

ML Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.749	0.749	0.749	0.749
Random Forest	0.920	0.921	0.920	0.920
XG Boost	0.920	0.920	0.920	0.920
RNN	0.533	1.000	0.533	0.695
LSTM – AE	0.906	1.000	0.546	0.707
Stacking Classifier	0.875	0.875	0.875	0.875
Voting Classifier	1.000	1.000	1.000	1.000

Fig.7 Performance Evaluation

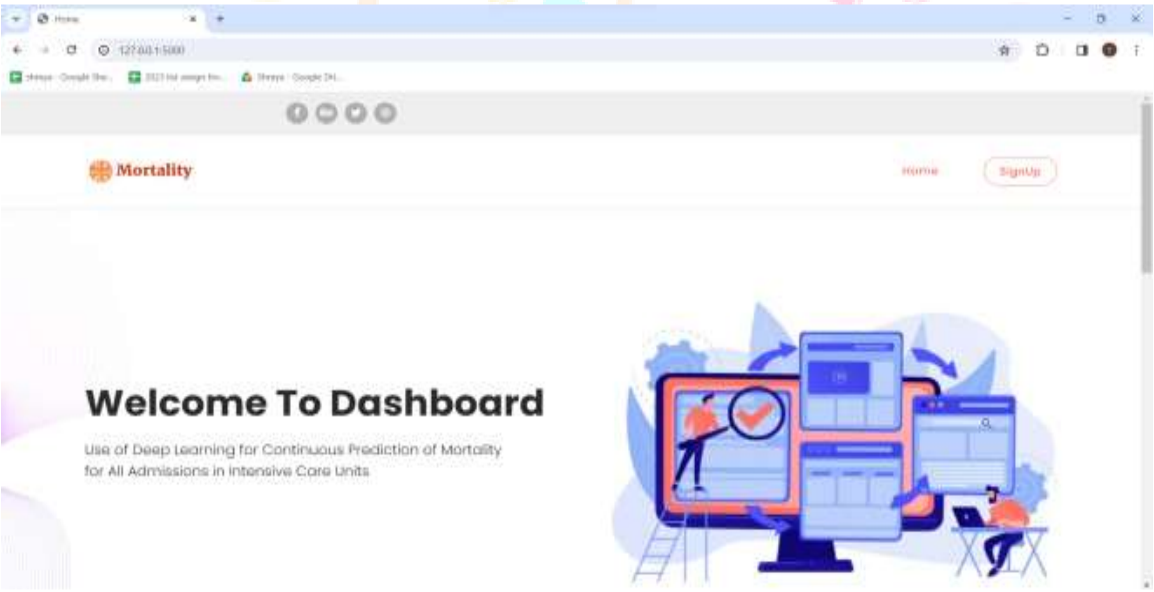

Fig.8 Home Page

Fig.9 Signin Form

Fig.10 Login Page

Fig.11 User Input

Fig.12 Predict result for given input

V. CONCLUSION

The project successfully created and put into use a model for predicting death rates in the intensive care unit (ICU) [2, 3]. This model predicts risks in real time, which can make care for patients and their results much better. A lot of different machine learning methods were looked at for this project, such as logistic regression, random forest, XGBoost, and deep learning models like RNN and LSTM [33]. The variety of models allows for a complete method for predicting death. Using SMOTE sampling helped fix the problem of class mismatch, which made the model stronger and better able to handle data with different death rates. The algorithm's great performance, especially the Voting Classifier's 100% accuracy, shows that it could be a useful and powerful tool. This addition shows a huge improvement in the accuracy of predicting death, giving doctors and nurses in urgent care situations a great tool for making smart choices. The project's user interface is easy to understand and use thanks to the Flask framework. This makes it easy for doctors and nurses to enter information about their patients and get real-time estimates of their death risk. The project's result gives doctors and nurses the power to make quick, data-driven decisions about how to care for patients in the ICU [4, 5, 6]. This could lead to earlier treatments, better use of resources, and better results for patients, all of which would improve healthcare services in the long run.

VI. FUTURE SCOPE

The study could continue in the future to improve and make the most of the suggested deep learning model for constantly predicting who will die in ICU patients. Larger and more varied datasets could be used to test and confirm the model's usefulness and ability to work with a wide range of patients and healthcare situations. In addition, the model could be added to ICUs' current electronic health record tools to help doctors make decisions and measure risks in real time. More study could look into how adding more clinical factors or signs to the model could make it better at predicting the future and dividing people into groups based on their risk. The suggested model could also be used to guess other health effects or problems that might happen to ICU patients [14, 21, 24], like how long they will stay in the hospital, whether they will need assisted breathing, or whether they will get sepsis.

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