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PREDICTION OF MORTALITY FOR ALL ADMISSIONS IN ICU

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Abstract: The point is to use deep learning out how to recognize ICU mortality rate is a crucial gauge of its clinical quality and hazard based patient division is recommended. The methodology introduced for this exploration accumulates time succession information and makes ongoing expectations about the mortality hazard of emergency clinic patients. The superior presentation of the model permits doctors to all the more likely screen high-risk patients and expect possible issues, in this manner lessening ICU mortality. Measures like review, exactness, accuracy, and F1-score are utilized to survey the model's adequacy. Moreover, gathering methods were consolidated, including the Voting Classifier and the Stacking Classifier. Astonishingly, the Voting Classifier accomplished 100 percent precision. To simplify it for clients to utilize and to keep making expectations about who will die in the emergency unit, are fostering a solid Cup based front end with effective testing and powerful security**.**

Key Words- deep learning; representation learning; mortality; risk prediction; critical care.

I. INTRODUCTION

Intensive care unit (ICU) patients frequently have dangerous ailments or could secure one while they are there. Illuminating youngsters when their circumstances decay is important to help their recuperation from sicknesses and mishaps that may be deadly as well as to keep up with their health[1]. Guardians might profit from apparatuses that can definitively conjecture the beginning stages of fragile clinical issues.

Utilizing result expectation models is one technique for deciding the likelihood that a specific occasion will occur[2]. Foreseeing passing is a vital errand since it's the main result in the emergency unit [4]. Research demonstrates that 11% of fatalities happen because of clinical experts neglecting to perceive a patient's declining condition [5]. Specialists might settle on better choices, distinguish patients who are at risk, and hold ICU beds for the people who truly need them by utilizing passing prediction[6]. An exact passing expectation model separates the probability of an occasion happening in a general public [7]. Ordinarily, these models utilize verifiable populace expectations to evaluate risk[8].

Previously, rule-put together force evaluation frameworks depended with respect to master information [9-14]. Afterward, AI models were utilized to achieve similar objectives [15-18]. since artificial intelligence and its applications in medical services are extending rapidly. Then again, reports of utilizing static scoring frameworks [19-25] infer that people have long required a patient rating framework that is refreshed consistently. Ceaseless, robotized evaluation of a patient's condition might assist doctors with deciding and tell them of changes in basic consideration. Moreover, time groupings utilizing cutting edge man-made intelligence calculations outperform current standard models because of transient examples in the intensive care unit [26-28]. Prescient calculations that precisely and reliably guess all ICU patient passings are consequently fundamental. Care for counteraction will be straightforward.

In clinical applications, profound learning is useful for order, recovery, and prediction[29-32]. LSTM-based RNNs were introduced in another study[33]. Time series are ideal for this thought since brain networks are equipped for learning information types. In the repetitive design, new information might be added to before timesteps to keep the model's gamble gauge current. carrying life to the model as opposed to inflexibility. Without assuming which measurements are fundamental for assessing a patient's wellbeing or the need to make condition-explicit highlights, RNNs look at every one of the information they can find[34]. RNNs may precisely foresee many clinical results from high-layered information including insignificant data, as shown by research [35]. Since RNNs are precise and adaptable, they are being utilized increasingly more to distinguish time sensitive medical services activities[35-41].

II. LITERATURE SURVEY

In the clinical field, forecast models use indicators to determine whether a patient has or will procure a sickness or condition [44]. Distributions of expectation models have expanded as of late. Various expectation models compete for similar outcome or set of results. As a rule, medical services suppliers, lawmakers, and creators of rules are uncertain about which model to utilize or recommend for specific circumstances. Subsequently, thorough assessments of these investigations are being requested and completed on a more regular basis. Expectation models are completely dissected to perceive how effective and one-sided they are for the populace and circumstance they were made for. The creators created PROBAST (Forecast model Gamble Of Predisposition Appraisal Apparatus) to help commentators. Utilized in examinations create, approve, or add to prognostic and symptomatic expectation models. Specialists cooperated to decide PROBAST [2]. There are twenty flagging inquiries altogether, organized into four classes: points, markers, results, and investigation. The reasoning for the consideration of each subject and flagging inquiry is made sense of and explained in this distribution. It likewise gives direction on the most proficient method to use rules to address worries about inclination and appropriateness for perusers, scholars, specialists, and rules' designers. Each idea is represented utilizing occasions drawn from an assortment of topic writing.

For intensivists who wish to go with the best therapy decisions for basically sick patients housed in concentrated care units, early medical clinic demise determining is pivotal. Accordingly, many ways to deal with settling this issue have been created with the utilization of master information. Then again, handling a portion of the lab test discoveries takes some time. In this study [6], we propose an original way to deal with decide the penchant for patient passing by looking at qualities removed from their ECG during the primary hour of admission to the emergency unit). The pulse indications of patients in the basic consideration unit have been utilized to build numbers to appraise the gamble [14, 21, 24]. We portray each sign utilizing twelve factual and signal-based highlights. The next eight classifiers—K-NN, decision trees, SVMs, random forests, enhanced trees, Gaussian SVMs, and linear discriminants — all utilize extricated highlights. Various examinations have evaluated the proposed approach utilizing the notable clinical dataset Clinical Data Store for Concentrated Care III (Copy III). The precision, memory, F1-score, and AUC of the investigations approve the proposed approach. With a F1-score of 0.91 and an AUC of 0.93, the choice tree method performs better compared to the others regarding precision and lucidness. It demonstrates that heart record readings might be utilized to anticipate the length of endurance for emergency unit. These evaluations perform similarly to the cutting edge assesses that depend on complex information from clinical records that might have missing data and need handling.

Mortality forecast models are utilized in the emergency unit to order patients as per risk and work with examinations. To guarantee that the suitable estimate models are used for these exercises, the best-performing models should be recognized. At first, we set off on a mission to completely look at each model that endeavors to conjecture a patient's mortality while they are in horrible shape. [7] Four sources were looked through involving the accompanying boundaries to find mortality forecast models: these sources were made with grown-up ICU patients in big league salary nations as a main priority [21], with death as the essential or optional result. The qualities and usefulness of the models were summarized. Proportions of location, alignment, and in general execution gave in the first distribution were utilized to exhibit execution. Eventually, 43 passing forecast models were utilized in the examination. Different mortality expectation models utilize various methods, and there are contrasts in each model's approval potential and level of progress. The shortfall of outer approval from the first specialists requires quick straight on examinations to distinguish the best demise forecast models that can coordinate clinical consideration and exploration across different populaces and conditions.

to analyze the latest alterations to the equations used to decide the likelihood of medical clinic demise for grown-up emergency unit patients. Contrasting framework parts and potential utilization is the fundamental objective. Information sources: A couple of distributed articles examined the procedures. For ICU patients, the essential seriousness techniques are MPP II, SAPS II, and APACHE III [14, 21, 24]. [8] Openly accessible articles were utilized to analyze information with respect to the factors that the frameworks accumulated, the data sets that the models were gotten from, and the models' implied viability. APACHE III and SAPS II give a number and an opportunity of emergency clinic passing in view of the most horrendously terrible readings of different variables during the initial 24 hours in the ICU. One sort of the MPM II framework is accessible at the ICU's entry. It has an alternate model for 24, 48, and 72 hours into the stay. The SAPS II and MPM II strategies might be utilized to information that has recently been disclosed. The APACHE III score might be determined utilizing openly open information, however the loads that are utilized to switch the worth over completely to a likelihood are classified. They were all in arrangement that the beneficiary working trademark bend's districts under each bend were phenomenal. For the SAPS II and MPM II models, the fit was phenomenal; nonetheless, the APACHE III variants didn't fit well. After broad exploration, the models were all evolved, and it was accounted for that they performed well. These may be in every way used to survey a patient's forecast, assess their presentation in the emergency unit, dole out them to clinical review gatherings. Direct examination on a typical gathering is required.

The structure and test consequences of APACHE II, a device for evaluating the seriousness of a condition, are displayed in an examination [12]. APACHE II conveys a point score in view of 12 basic body gauges, the individual's age, and their verifiable wellbeing status to give a surmised gauge of how horrible their sickness is. A larger number (from 0 to 71) was considerably associated with a more serious gamble of mortality in the clinic for 5815 people confessed to basic consideration from 13 emergency clinics. This relationship was likewise recognized for various common afflictions. At the point when APACHE II information are connected with a legitimate depiction of the condition, they might help specialists figure the guess of fundamentally debilitated patients and survey the viability of new or elective types of treatment. This scoring framework might be utilized to take a gander at how successfully clinic assets are being used and to look at how well concentrated care functions in different clinics or over the long haul.

Intense consideration represents an enormous piece of the medical services consumption. While proceeding to give basically sick patients the most obvious opportunity with regards to endurance, this therapy has become more practical throughout the course of recent years because of better asset use. This is where the SAPS-I and other basic sickness seriousness evaluation appraisals prove to be useful [15]. They assist specialists with choosing which patient determinations and medicines to give and how to spend assets. These numbers additionally show how the passing paces of ICU patients are impacted by drugs, medical services practices, medical procedure, and different mediations. To assess medical clinic fatalities, we exhort utilize the Covered up Markov model and strategic relapse. This model would utilize test results, important bodily functions, and observing of ICU liquids. Two new arrangements of 4000 ICU patients were utilized to assess the framework after it had been prepared on 4000 ICU patient information [14, 21]. The 2012 PhysionNet/CinC Challenge, which energized ICU passing estimates, is where these information were gathered. The procedure was assessed utilizing two measurements: Event1, the base of responsiveness and positive prescient worth, and Event2, an integrity of fit measure (range-standardized Hosmer-Lemeshow (H) measurement). In all approval datasets, it performed better compared to SAPS-I, with Occasion 1 scores of 0.50, 0.50 and Occasion 2 scores of 15.18, 78.9. Considering that the recommended technique coordinates constant essential signs and research facility results, it could possibly be utilized as an ongoing mortality risk marker.

III. METHODOLOGY

1. Proposed Work:

The proposed approach computes the constant gamble of mortality in the emergency unit utilizing profound learning, all the more unequivocally RNNs. By recognizing fleeting examples, delivering expectations continuously, and beating standard AI models, it avoids the current issues. This method diminishes the casualty rate in the emergency unit), (assists doctors and attendants with focusing on high-risk patients, and expects issues. Moreover, group approaches like the Democratic Classifier and the Stacking Classifier — which accomplished a dumbfounding 100 percent exactness in casting a ballot — are highlighted. We are utilizing the Cup structure to make an easy to use front end that will increment client openness to the framework and work with the most common way of foreseeing the demise of every ICU passage progressively. As well as simplifying testing for clients, this point of interaction will give vigorous client security to forestall unapproved access.

2. System Architecture:

This examination checked patients over the course of time utilizing MIMIC-III databases[43]. Significant tertiary consideration offices' ICU patient information is arranged into one monstrous data set in one area. This study analyzed all ICU confirmations, except for those that met four severe necessities: (1) no lab estimations all through the stay; (2) no ICU experience; (3) no data on endurance; and (4) research center estimations without any trace of numbers. The first wellspring of these markers was demise declarations. In conclusion, 334 722 associations with 46 467 people were considered. Information handling is displayed in

Fig. 1.

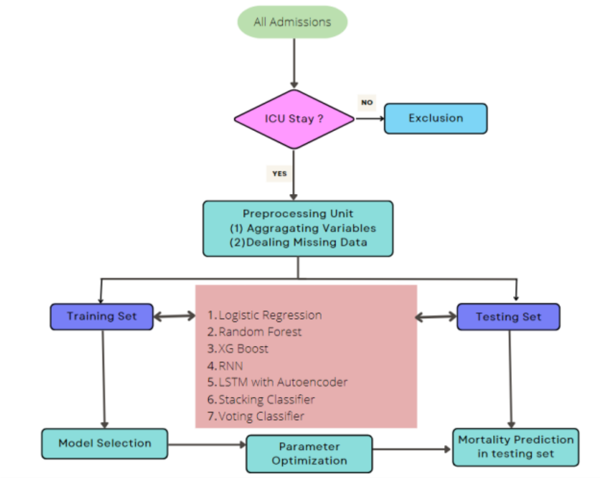

Fig 1 Proposed architecture

3. Dataset collection:

The death pace of ICU patients is anticipated utilizing this dataset [14]. The clinical history, drugs, power appraisals, medical procedures, term of stay, and results (passing or life) of the patient are undeniably included.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
1	group	ID	outcome	age	gendera	BMI	hypertensi	atrialfibrill	CHD with r	diabetes	deficiency	depressior	Hyperlipen	Renal failu	COPD	heart rate	Systolic blc	Diastolic b	Respirator	temperatu	SP O2	Urine outp	hematocr
2	1	125047	0	72	1	37.58818	0	0	0	1	1	0	1	1	0	68.83784	155.8667	68.33333	16.62162	36.71429	98.39474	2155	26.27273
3	1	139812	0	75	2	NA	0	0	0	0	1	0	0	0	1	101.3704	140	65	20.85185	36.68254	96.92308	1425	30.78
4	1	109787	0	83	2	26.57263	0	0	0	0	1	0	0	1	0	72.31818	135.3333	61.375	23.64	36.4537	95.29167	2425	27.7
5	1	130587	0	43	2	83.26463	0	0	0	0	0	0	0	0	0	94.5	126.4	73.2	21.85714	36.28704	93.84615	8760	36.6375
6	1	138290	0	75	2	31.82484	1	0	0	0	1	0	0	1	1	67.92	156.56	58.12	21.36	36.7619	99.28	4455	29.93333
7	1	154653	0	76	1	24.26229	1	1	0	0	1	0	1	1	1	74.18182	118.1	52.95	20.54545	35.26667	96.81818	1840	27.33333
8	1	194420	0	72	1	39.66743	1	0	0	0	0	0	1	1	1	69.63636	106.5652	47.82609	19.14815	35.60317	95.63636	2450	28.9375
9	1	153461	0	83	2	22.31111	1	1	0	1	1	0	0	0	0	84.66667	141.1304	46.91304	18.4	36.67361	97.875	3039	28.8
10	1	113076	0	61	2	19.99224	1	1	0	1	0	0	0	1	0	91.91667	98.43478	52.65217	18.58333	37.10317	98.04167	1625	31.24118
11	1	147252	0	67	1	45.03203	1	0	0	1	0	0	0	0	0	75.08333	122	56.75	18.125	36.86111	94.45833	6107	30.3
12	1	104216	0	70	2	50.46121	1	0	0	1	0	0	1	0	0	95.62963	149.0357	48.78571	17.48148	37.55556	95.25	1305	27.48182
13	1	135608	0	83	2	25.3919	1	0	0	1	1	0	1	0	0	65.16	103.2609	50.47826	17.4	36.47778	96.08	2360	33.275
14	1	178662	0	77	2	22.69896	1	0	0	0	0	0	0	0	1	78.83333	126.9032	61.6129	15.83333	36.41667	95.75	1130	32.54444
15	1	178671	0	83	1	33.89106	1	1	0	1	0	0	1	1	0	65.86957	112.1429	44.14286	25.43478	36.15741	94.66667	2220	31.6125
16	1	127360	0	69	2	20	1	0	0	0	0	0	0	0	0	98.54412	107.36	54.24	34.69343	36.50926	89.11029	2300	44.16
17	1	103753	0	87	2	35.19894	1	0	0	1	0	0	1	1	0	73.48	159.6957	59.08696	20.69231	36.93333	97.44	3700	28.56
18	1	191838	1	83	2	NA	1	0	0	0	1	0	0	1	0	83.69231	157.2895	58.23684	15.65217	36.92222	99.81579	1495	23.65455
19	1	141668	0	56	2	27.85162	1	0	0	1	1	1	0	1	0	64.6	113.28	61.56	16.07143	36.69444	99.76	332	25.05385
20	1	114085	0	45	2	91.17665	1	0	0	0	1	0	0	0	0	82	162.24	86.72	28.15385	36.85185	93.80769	5710	26.21667
21	1	185887	0	89	2	NA	0	0	0	0	1	0	0	1	0	70.08333	112.4167	50.91667	25.58333	36.00794	95.54167	2415	27.66
22	1	129574	0	62	1	28.09917	0	0	0	0	0	0	0	0	0	93.17391	105.6087	64	20.04348	36.85714	96.52174	2475	22.94545
23	1	182755	1	78	2	37.85143	1	0	0	1	0	0	0	0	0	76.38462	95.44444	60.25926	21.75	36.12037	94.38462	1766	34.1625
24	1	104305	0	86	2	NA	1	0	0	1	1	0	0	0	1	72.75862	117.0263	51.57895	18.8	36.06944	98.10345	1112	29.34286

Fig 2 Mortality Dataset

4. Data Processing:

The demonstration of changing over unstructured information into data that associations can use is known as information handling. Information researchers frequently oversee information, which involves gathering, coordinating, cleaning, checking, breaking down, and changing data into lucid arrangements like papers or charts. Information might be taken care of in three distinct ways: physically, precisely, or electronically. The objective is to expand the utility of information and work with direction. Organizations might work all the more proficiently and settle on techniques quicker on the grounds that to this. PC programs and other mechanized information dealing with advances assume a significant part in getting this going. Huge information and different types of information might be changed into data that is useful for decision-making and quality assurance.

5. Feature selection:

The method involved with picking the most trustworthy, pragmatic, and non-repetitive characteristics to incorporate into a model is known as element determination. It is pivotal to painstakingly limit the spans of records as both their amount and assortment rise. Further developing an expectation model's presentation while utilizing less handling assets is one of component choice's essential goals.

The demonstration of choosing the most significant highlights to include into AI calculations is known as element determination, and it is one of the most urgent parts of component designing. Highlight determination procedures dispense with superfluous or immaterial data, leaving just those that are basic to the AI model. Accordingly, there are less information factors. Here are the primary benefits of choosing the most significant elements ahead of time instead of depending on the AI model.

6. Algorithms:

Logistic Regression:

- A typical essential model for twofold grouping issues is calculated relapse.
- It could be utilized in this venture to recreate the probability of ICU demise as per patient qualities.
- It offers intelligible coefficients that might be utilized to pinpoint critical attributes connected to the gamble of death.

Random Forest:

- Random Forest is a decision tree-based troupe learning procedure.
- It is fitting for clinical datasets with different information types as it can deal with both mathematical and straight out data.
- Random Forest is a proficient technique for dealing with high-layered information and may catch unpredictable relationships among's ascribes and results.
- Upgrading speculation capacities and forecast accuracy is most likely utilized.

XGBoost:

- The better angle helping strategy XGBoost is notable for its adequacy and effectiveness while working with huge datasets.
- It further develops expectation execution by building trees consecutively to fix botches in prior models.
- Due of its extraordinary speed and accuracy, it is much of the time utilized in both serious and genuine settings.
- XGBoost may be utilized to further develop the mortality prediction model's presentation considerably further.

RNN (Recurrent Neural Network):

- Brain networks utilizing RNNs are particularly appropriate to arrangement information, where the result of the organization depends on the data sources that preceded it.

- RNNs may be used in this review to reenact transient patterns in understanding information that was assembled in the ICU over the long run.
- They can distinguish examples and connections in time series information, for example, drug use or important bodily functions, which might be fundamental for guaging passing in concentrated care units.

LSTM with Autoencoder:

- A RNN type called a LSTM (Long Short-Term Memory) network was made to address the evaporating slope issue and distinguishlong-term relationships.
- Neural networks called autoencoders are utilized to recuperate input information by means of unsupervised learning.
- LSTM with autoencoder might be utilized in this venture to diminish the dimensionality and concentrate highlights from high-dimensional ICU information.
- The model might learn significant portrayals that contain relevant data for mortality expectation by packing and modifying the information.

Voting Classifier:

- The class with the best votes (the middle) is anticipated by the Voting Classifier, which consolidates numerous fundamental classifiers.
- By consolidating the forecasts of numerous classifiers, it might upgrade expectation execution.
- It got an astonishing 100 percent exactness in this venture, showing great understanding among the fundamental classifiers.

Stacking Classifier:

- The method involved with preparing a meta-model to incorporate the forecasts of many base models is known as stacking, or layered speculation.
- It looks to give more dependable figures by utilizing the benefits of each unmistakable model.
- The gathering's forecast ability might be additionally expanded by utilizing the Stacking Classifier, which figures out how to blend the aftereffects of numerous calculations ideally.

IV. **EXPERIMENTAL RESULTS**

Precision: How much accurately identified occasions or tests in the hits is the accuracy. Subsequently, the accompanying strategy might be utilized to guarantee that it is precise:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

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

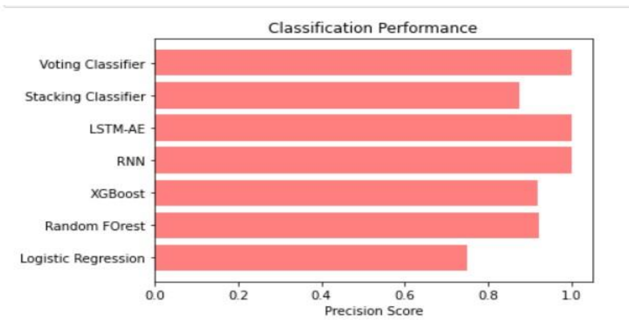

Fig 3 Precision comparison graph

Recall: A machine learning variable called recall shows how well a model can find all the important examples of a certain class. When you expect to feel good, what percentage of those feelings actually happen? This shows how well a model can catch instances of a certain type.

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

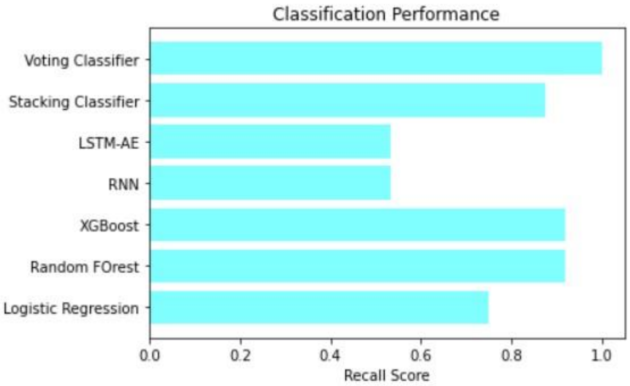

Fig 4 Recall comparison graph

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

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

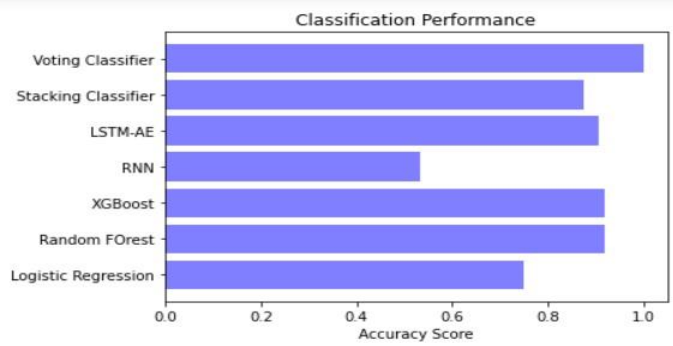

Fig 5 Accuracy graph

F1 Score: There is a tool for judging machine learning models called the F1 score that tells you how accurate they are. It adds up a model's review and accuracy scores. With the accuracy measurement, you can see how often, across the whole set, a model got what would happen right.

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

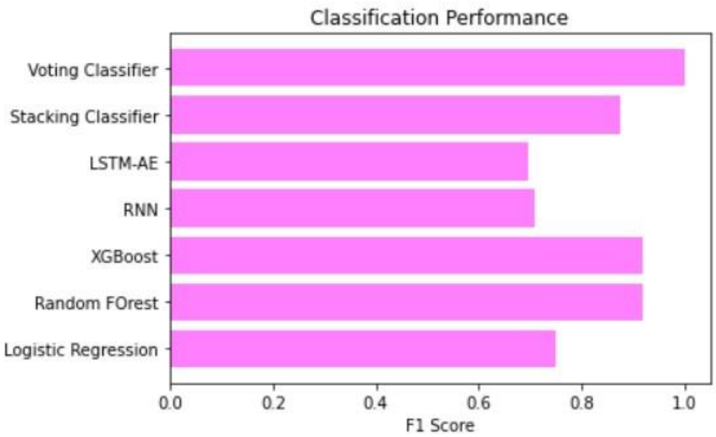

Fig 6 F1Score

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

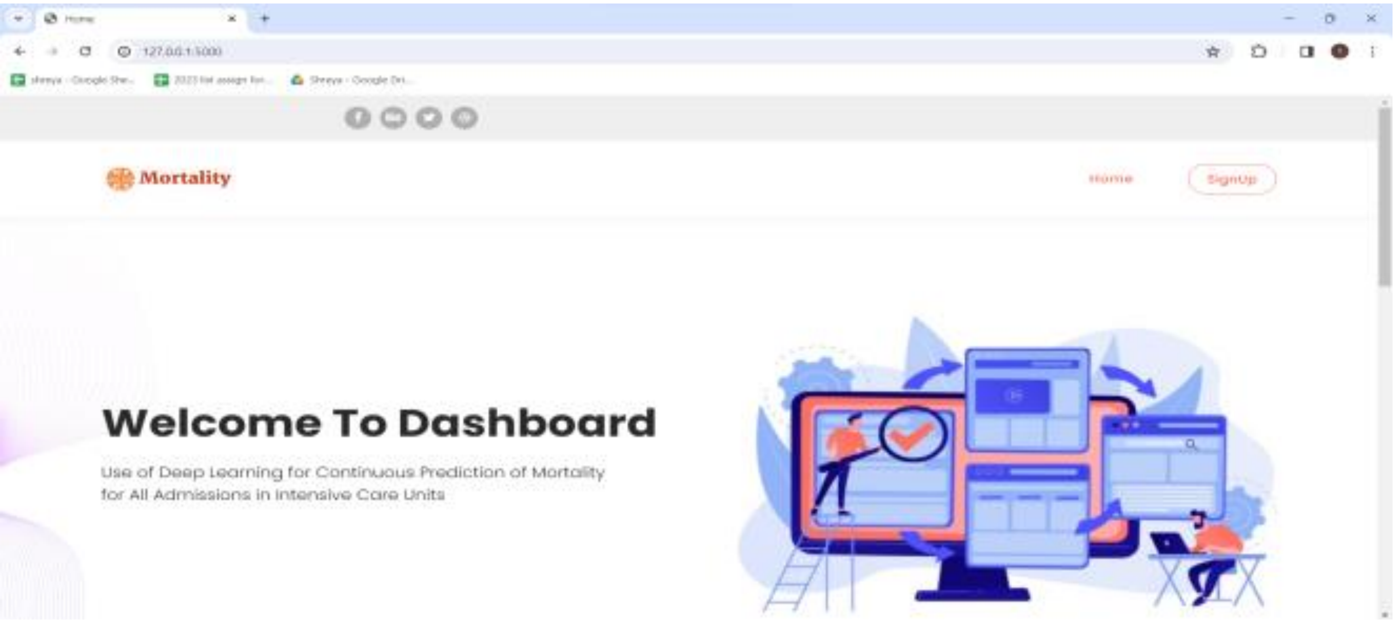

Fig 8 Home page

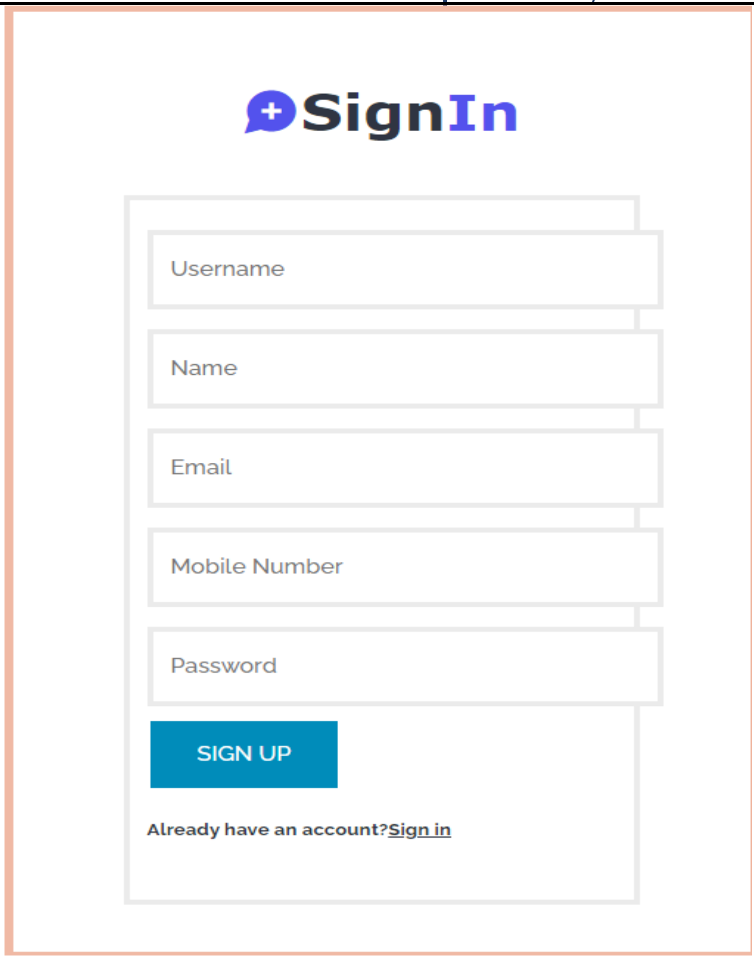

Fig 9 Signin page

Fig 10 Login page

Fig 11 User input

Fig 12 Predict result for given input

V. CONCLUSION

A successful model for guaging death rates in the emergency unit was created and utilized by the task [2, 3]. Constant gamble expectation utilizing this calculation may enormously work on persistent treatment and results. For this review, an extensive variety of AI strategies were inspected, including profound learning models like RNN and LSTM, calculated relapse, irregular woods, and XGBoost [33]. There is a complete way to deal with mortality forecast due to the scope of models. The class bungle issue was settled with the utilization of Destroyed testing, fortifying and working on the model's capacity to deal with information with shifting death rates. The calculation's noteworthy outcomes, especially the Voting Classifier's 100 percent precision, demonstrate that it can possibly be a significant and powerful device. With this advancement, the precision of mortality expectation has essentially improved, giving doctors and medical attendants an amazing device to pursue informed choices in crisis care situations. The Flagon system makes the undertaking's UI easy to utilize and fathom. This works with the section of patient information and furnishes doctors and medical attendants with exceptional appraisals of their mortality risk. The result of the review engages clinical experts to make brief, proof put together decisions with respect to the therapy of patients in the emergency unit, 5, 6]. This might bring about early intercessions, more proficient utilization of assets, and better persistent results, all of which would improve long haul medical care administrations.

VI. FUTURE SCOPE

To ceaselessly guess which ICU patients would die, the examination could do further to upgrade and augment the capability of the proposed deep learning model. More noteworthy and more different datasets may be utilized to confirm and approve the model's viability in dealing with a wide range of people and medical services situations. To additional help doctors in deciding and evaluating gambles continuously, the model might be coordinated with the electronic wellbeing record frameworks presently utilized in escalated care units. Further exploration could analyze how including other clinical qualities or pointers into the model could work on its capacity to gauge future occasions and sort people into risk-based classes. The proposed model may likewise be utilized to anticipate other wellbeing results or issues that ICU patients might have [14, 21, 24], for example, the length of emergency clinic stay, the prerequisite for helped breathing, or the probability of sepsis.

VII. References

[1] G. Rouleau, M. P. Gagnon, and J. Cot ˆ e, Impacts of ´ information and communication technologies on nursing care: An overview of systematic reviews (protocol), Syst. Rev., vol. 4, no. 1, p. 75, 2015.

[2] K. G. M. Moons, R. F. Wolff, R. D. Riley, P. F. Whiting, M. Westwood, G. S. Collins, J. B. Reitsma, J. Kleijnen, and S. Mallett, PROBAST: A tool to assess risk of bias and applicability of prediction model studies: Explanation and elaboration, Ann. Intern. Med., vol. 170, no.1, pp. W1–W33, 2019.

[3] R. Lilford and P. Pronovost, Using hospital mortality rates to judge hospital performance: A bad idea that just won't go away, BMJ, vol. 340, p. c2016, 2010.

[4] K. M. D. M. Karunarathna, Predicting ICU death with summarized patient data, presented at the 2018 IEEE 8th Annu. Computing and Communication Workshop and Conf. (CCWC), Las Vegas, NV, USA, 2018, pp. 238–247.

[5] R. T. Thomson, D. Leuttel, F. Healey, and S. Scobie, Safer Care for the Acutely Ill Patient: Learning from Serious Incidents. London, UK: National Patient Safety Agency, 2007.

[6] R. Sadeghi, T. Banerjee, and W. Romine, Early hospital mortality prediction using vital signals, Smart Health, vols. 9–10, pp. 265–274, 2018.

[7] B. E. Keuning, T. Kaufmann, R. Wiersema, A. Granholm, V. Pettila, M. H. Møller, C. F. Christiansen, J. C. Forte, H. ¨ Snieder, F. Keus, et al., Mortality prediction models in the adult critically ill: A scoping review, Acta Anaesthesiol. Scand., vol. 64, no. 4, pp. 424–442, 2020.

[8] S. Lemeshow and J. R. Le Gall, Modeling the severity of illness of ICU patients: A systems update, JAMA, vol. 272, no. 13, pp. 1049–1055, 1994.

[9] J. I. F. Salluh and M. Soares, ICU severity of illness scores: APACHE, SAPS and MPM, Curr. Opin. Crit. Care, vol. 20, no. 5, pp. 557–565, 2014.

[10] J. L. Vincent, R. Moreno, J. Takala, S. Willatts, A. De Mendonc¸a, H. Bruining, C. K. Reinhart, P. M. Suter, and L. G. Thijs, The SOFA (Sepsis-related Organ Failure Assessment) score to describe organ dysfunction/failure, Intensive Care Med., vol. 22, no. 7, pp. 707–710, 1996.

[11] J. E. Zimmerman, A. A. Kramer, D. S. Mcnair, and F. M. Malila, Acute Physiology and Chronic Health Evaluation (APACHE) IV: Hospital mortality assessment for today's critically ill patients, Crit. Care Med., vol. 34, no. 5, pp. 1297–1310, 2006.

[12] W. A. Knaus, E. A. Draper, D. P. Wagner, and J. E. Zimmerman, APACHE II: A severity of disease classification system, Crit. Care Med., vol. 13, no. 10, pp. 818–829, 1985.

[13] T. L. Higgins, D. Teres, W. Copes, B. Nathanson, M. Stark, and A. Kramer, Updated mortality probability model (MPM-III), Chest, vol. 128, no. 4, p. 348S, 2005.

[14] K. Strand and H. Flaatten, Severity scoring in the ICU: A review, Acta Anaesthesiol. Scand., vol. 52, no. 4, pp. 467–478, 2008.

[15] S. Vairavan, L. Eshelman, S. Haider, A. Flower, and A. Seiver, Prediction of mortality in an intensive care unit using logistic regression and a hidden Markov model, presented at the 2012 Computing in Cardiology, Krakow, Poland, 2012, pp. 393–396.

[16] S. Barnes, E. Hamrock, M. Toerper, S. Siddiqui, and S. Levin, Real-time prediction of inpatient length of stay for discharge prioritization, J. Am. Med. Inform. Assoc., vol. 23, no. e1, pp. e2–e10, 2016.

[17] N. El-Rashidy, S. El-Sappagh, T. Abuhmed, S. Abdelrazek, and H. M. El-Bakry, Intensive care unit mortality prediction: An improved patient-specific stacking ensemble model, IEEE Access, vol. 8, pp. 133541–133564, 2020.

[18] G. Gutierrez, Artificial intelligence in the intensive care unit, Crit. Care, vol. 24, no. 1, p. 101, 2020.

[19] S. Leteurtre, A. Duhamel, B. Grandbastien, F. Proulx, J. Cotting, R. Gottesman, A. Joffe, B. Wagner, P. Hubert, A. Martinot, et al., Daily estimation of the severity of multiple organ dysfunction syndrome in critically ill children, CMAJ, vol. 182, no. 11, pp. 1181–1187, 2010.

[20] S. Leteurtre, A. Duhamel, V. Deken, J. Lacroix, F. Leclerc, and Groupe Francophone de Reanimation et Urgences ´ Pediatriques, Daily estimation of the severity of organ ´ dysfunctions in critically ill children by using the PELOD-2 score, Crit. Care, vol. 19, no. 1, p. 324, 2015.

[21] O. Badawi, X. G. Liu, E. Hassan, P. J. Amelung, and S. Swami, Evaluation of ICU risk models adapted for use as continuous markers of severity of illness throughout the ICU stay, Crit. Care Med., vol. 46, no. 3, pp. 361–367, 2018.

[22] M. J. Rothman, S. I. Rothman, and J. Beals IV, Development and validation of a continuous measure of patient condition using the electronic medical record, J. Biomed. Inform., vol. 46, no. 5, pp. 837–848, 2013.

[23] M. J. Rothman, .J. J. Tepas, A. J. Nowalk, J. E. Levin, J. M. Rimar, A. Marchetti, and A. L. Hsiao, Development and validation of a continuously age-adjusted measure of patient condition for hospitalized children using the electronic medical record, J. Biomed. Inform., vol. 66, pp. 180–193, 2017.

[24] C. W. Hug and P. Szolovits, ICU acuity: Real-time models versus daily models, presented at the AMIA 2009 Symp. Proc., American Medical Informatics Association, San Francisco, CA, USA, 2009, pp. 260–264.

[25] B. Shickel, T. J. Loftus, L. Adhikari, T. Ozrazgat-Baslanti, A. Bihorac, and P. Rashidi, DeepSOFA: A continuous acuity score for critically ill patients using clinically interpretable deep learning, Sci. Rep., vol. 9, no. 1, p. 1879, 2019.

[26] G. Clermont, D. C. Angus, S. M. Dirusso, M. Griffin, and W. T. Linde-Zwirble, Predicting hospital mortality for patients in the intensive care unit: A comparison of artificial neural networks with logistic regression models, Crit. Care Med., vol. 29, no. 2, pp. 291–296, 2001.

[27] G. Meyfroidt, F. Guiza, J. Ramon, and M. Bruynooghe, ¨ Machine learning techniques to examine large patient databases, Best Pract. Res. Clin. Anaesthesiol., vol. 23, no. 1, pp. 127–143, 2009.

[28] S. Kim, W. Kim, and R. W. Park, A comparison of intensive care unit mortality prediction models through the use ofdata mining techniques, Healthc. Inform. Res., vol. 17, no. 4, pp. 232–243, 2011.

[29] M. Babaie, S. Kalra, A. Sriram, C. Mitcheltree, S. J. Zhu, A. Khatami, S. Rahnamayan, and H. R. Tizhoosh, Classification and retrieval of digital pathology scans: A new dataset, presented at the 2017 IEEE Conf. Computer Vision and Pattern Recognition Workshops, Honolulu, HI, USA, 2017, pp. 760–768.

[30] A. Khatami, M. Babaie, A. Khosravi, H. R. Tizhoosh, S. M. Salaken, and S. Nahavandi, A deep-structural medical image classification for a Radon-based image retrieval, presented at the 2017 IEEE 30th Canadian Conf. Electrical and Computer Engineering (CCECE), Windsor, Canada, 2017, pp. 1–4.

[31] A. Khatami, A. Khosravi, C. P. Lim, and S. Nahavandi, A wavelet deep belief network-based classifier for medical images, in Proc. 23rd Int. Conf. Neural Information Processing, Kyoto, Japan, 2016, pp. 467–474.

[32] A. Khatami, A. Khosravi, T. Nguyen, C. P. Lim, and S. Nahavandi, Medical image analysis using wavelet transform and deep belief networks, Expert Syst. Appl., vol. 86, pp. 190–198, 2017.

[33] S. Hochreiter and J. Schmidhuber, Long short-term memory, Neural Comput., vol. 9, no. 8, pp. 1735–1780, 1997.

[34] Y. LeCun, Y. Bengio, and G. Hinton, Deep learning, Nature, vol. 521, no. 7553, pp. 436–444, 2015.

[35] E. Laksana, M. Aczon, L. Ho, C. Carlin, D. Ledbetter, and R. Wetzel, The impact of extraneous features on the performance of recurrent neural network models in clinical tasks, J. Biomed. Inform., vol. 102, p. 103351, 2020.

[36] C. S. Carlin, L. V. Ho, D. R. Ledbetter, M. D. Aczon, and R. C. Wetzel, Predicting individual physiologically acceptable states at discharge from a pediatric intensive care unit, J. Am. Med. Inform. Assoc., vol. 25, no. 12, pp. 1600–1607, 2018.

[37] M. C. Winter, T. E. Day, D. R. Ledbetter, M. D. Aczon, C. J. L. Newth, R. C. Wetzel, and P. A. Ross, Machine learning to predict cardiac death within 1 hour after terminal extubation, Pediatr. Crit. Care Med., vol. 22, no. 2, pp. 161–171, 2021.

[38] E. Choi, A. Schuetz, W. F. Stewart, and J. M. Sun, Using recurrent neural network models for early detection of heart failure onset, J. Am. Med. Inform. Assoc., vol. 24, no. 2, pp. 361–370, 2017.

[39] A. Rajkomar, E. Oren, K. Chen, A. M. Dai, N. Hajaj, M. Hardt, P. J. Liu, X. B. Liu, J. Marcus, M. M. Sun, et al., Scalable and accurate deep learning with electronic health records, NPJ Digit. Med., vol. 1, p. 18, 2018.

[40] M. Saqib, Y. Sha, and M. D. Wang, Early prediction of sepsis in EMR records using traditional ML techniques and deep learning LSTM networks, presented at the 2018 40th Annu. Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA, 2018, pp. 4038–4041.

[41] S. Kannan, G. Yengera, D. Mutter, J. Marescaux, and N. Padoy, Future-state predicting LSTM for early surgery type recognition, IEEE Trans. Med. Imaging, vol. 39, no. 3, pp. 556–566, 2020.

[42] N. Tomasev, N. Harris, S. Baur, A. Mottram, X. Glorot, J. W. ˇ Rae, M. Zielinski, H. Askham, A. Saraiva, V. Magliulo, et al., Use of deep learning to develop continuous-risk models for adverse event prediction from electronic health records, Nat. Protoc., vol. 16, no. 6, pp. 2765–2787, 2021.

[43] A. E. W. Johnson, T. J. Pollard, L. Shen, L. W. H. Lehman, M. L. Feng, M. Ghassemi, B. Moody, P. Szolovits, L. A. Celi, and R. G. Mark, MIMIC-III, a freely accessible critical care database, Sci. Data, vol. 3, p. 160035, 2016.

[44] A. J. Vickers, A. M. Cronin, E. B. Elkin, and M. Gonen, Extensions to decision curve analysis, a novel method for evaluating diagnostic tests, prediction models and molecular markers, BMC Med. Inform. Decis. Mak., vol. 8, no. 1, p. 53, 2008.