Journal of Communicable Diseases
Volume 56, Issue 2 - 2024, Pg. No. 6-14
Peer Reviewed & Open Access Journal

Research Article

Artificial Intelligence (AI) Model to Predict the Risk of COVID-19 ICU Severity: A Pandemic Success Story

Sara Alshaya[1], Maryam Sayed Jaffar[2], Aji Gopakumar[3], Sheik Abdullah Jamal Mohideen[4], Vibhor Mathur[5], Sudheer Kurakula[6], Badshah Mukherjee[7]

[1,2,3,4,5,6]Data and Statistics Department (DSD), Emirates Health Services (EHS), Dubai, United Arab, Emirates.
[7]SAS Middle East FZ, Dubai, United Arab Emirates.
DOI: https://doi.org/10.24321/0019.5138.202426

I N F O

Corresponding Author:
Aji Gopakumar, Department (DSD), Emirates Health Services (EHS), Dubai, United Arab, Emirates.
E-mail Id:
aji.gopakumar@ehs.gov.ae
Orcid Id:
https://orcid.org/0000-0002-7485-8662
How to cite this article:
Alshaya S, Jaffar M S, Gopakumar A, Mohideen S A J, Mathur V, Kurakula S, Mukherjee B. Artificial Intelligence (AI) Model to Predict the Risk of COVID-19 ICU Severity: A Pandemic Success Story. J Commun Dis. 2024;56(2):6-14.
Date of Submission: 2024-03-17
Date of Acceptance: 2024-05-23

A B S T R A C T

Background: WHO considers a crucial indicator of infectious disease severity to be its mortality rate. With multiple COVID-19 waves, variant emergence, and case surges, timely prediction of severity risks for fatal outcomes in the UAE was essential. Amid pandemic challenges, prioritising critical care for high-risk patients was vital. This research on critical care severity risks adds significant value to current knowledge.

Objective: The plan was for the development of an AI model with high accuracy and estimation of patients at risk of severity across various characteristics.

Method: A retrospective cohort study design was used to conduct the research. Correlation and causation analytics were conducted using exploratory data analysis. A statistical risk scoring mechanism was built and combined with the other data attributes to build the AI model, then determined all the key factors determining the fatal outcome.

Results: Retrospective data spanning five months, including 71 variables from an EHS facility in Sharjah, was analysed. Among 783 positive PCR cases, less than one-fourth were found severe in the ICU admissions. The optimal model, using the Gradient Boosting Algorithm, demonstrated high accuracy (90%), with training and validation accuracies of 94% and 91%, respectively. The key severity risk factors identified included elevated ferritin levels, ventilator usage, high MCHC, and hypotension.

Conclusion: A highly interpretable machine learning model predicts severity risk in emergency care, and can contribute to the revision of EHS's procedural manual and enable resource mobilisation, and effective care strategy.

Keywords: COVID-19 Severity, Prediction Model, ICU Mortality Risk, United Arab Emirates

Introduction

Countries witnessed a series of COVID-19 waves, and the emergence of different variants and surges in cases, resulted in constraints on the availability of ICU resources. It was essential to identify the patients at the most risk of severity to prioritise the needs for critical care. According to WHO[1], an important measure of the severity of an infectious disease is its ability to cause death. The pandemic continued to add pressure on hospitals around the world with huge threats to supplies, hospital operations, and surgeries. Like any other healthcare system, Emirates Health Services (EHS) also faced difficulties in resource mobilisation in the ICU during the COVID-19 pandemic, as it consists of several hospitals, primary healthcare centres, public health centres, preventive measure centres, specialised dental centres, rehabilitation centres, and several COVID-19 field hospitals. In this context, it was essential to estimate the severity rate in different patient categories and by the availability of critical care facilities. The lack of technological advancement in handling huge hospital data and early prediction of risk factors needs substantial improvement in the internal mechanism through research and innovations. To achieve the objective of finding the severity of risk in the ICU, a technical project was conceived as a comprehensive AI-driven COVID-19 Response Program that developed an AI model including potential risk factors that support care providers to give targeted personalised care. The organisation carries high responsibility for supporting the national objective of reducing COVID-19 severity. Hence it was the prime duty of EHS to build a COVID-19 registry during the severe crisis and it was essential to have a tool that was developed through a deep-learning-based AI algorithm to predict the COVID-related severity risk of critical care for best health outcomes. Due to surges in cases and ICU deaths, there was a need for timely prediction of COVID-19 severity risks in the UAE population. Having constraints on the availability of ICU resources, it was imperative to identify the patients at most risk of severity and prioritise the needs for critical care. As severity risk remains substantially high in patients under critical care, a study on critical care severity risk will add more value to the current knowledge.

The whole EHS system and its facilities carry the responsibility of supporting the national objective of reducing COVID-19 severity and promoting precautionary measures among the UAE population. The current technical project has been conceived as a comprehensive AI-driven COVID-19 Response Program to identify the severity risk factors in ICU that support care providers to give targeted personalised care. The study also aimed at building a COVID-19 registry and the tool developed through a deep-learning-based AI algorithm may help in predicting the severity risk of critical care in COVID-19 patients. There are many studies available in the literature that revealed several risk factors associated with death in critical care units due to COVID-19 attacks. Research by Chen et al. aimed at finding risk factors for COVID-related severity in intensive care units and concluded that the AI model that combined IL-6 and D-dimer was valuable for predicting the severity of patients with COVID-19 with excellent performance.[2] The findings published in the research paper that reported the severity rate was higher in older patients with comorbidities such as hypertension and CVD and therefore the research recommended early recognition of high-risk patients to improve care and reduce severity.[3] In another study that developed an RF model which was applied among 66 parameters and found 15 factors with the highest predictive values. The predictors identified were gender, age, blood urea nitrogen (BUN), creatinine, international normalised ratio (INR), albumin, mean corpuscular volume (MCV), white blood cell count, segmented neutrophil count, lymphocyte count, red cell distribution width (RDW), and mean cell haemoglobin (MCH) along with a history of neurological, cardiovascular, and respiratory disorders.[4] In a study where the DL model and explainable artificial intelligence (EAI) were combined to identify the impact of certain attributes on the prediction of severity in COVID-19 patients. The optimisation of the DL model was performed using the Adam optimiser. Patient's demographic information, laboratory investigations, and chest X-ray (CXR) findings were the potential predictors used in the model.[5] In the proposed study, the researchers hypothesised that patients' characteristics, clinical parameters, and comorbidities have a significant impact on COVID-19-related ICU severity. Accordingly, a highly interpretable machine learning model was planned to develop for the prediction of the severity of risk in emergency care. This may add value to the process and procedures of each healthcare facility during the pandemic season, ultimately benefiting policies and the strategic direction of EHS.

A technical solution such as the AI model is expected to empower EHS processes and to plan on the necessary resource mobilisation, lab test planning, and care strategy for improved health outcomes in emergencies. The technical innovation will immensely help all the EHS facilities in its critical care settings and has wider adaptability with ease of implementation, and avoidance of adverse outcomes by providing special care. This will result in an overall workload reduction in the precious critical care units of EHS facilities. Investigators expected that EHS's AI model will ensure care excellence through its healthcare settings, while the world is fighting a relatively unknown pandemic.

Methodology

The research was conducted by the Data & Statistics Department (DSD) of Emirates Health Services (EHS) in collaboration with one of the EHS facilities in the Emirate of Sharjah. The research was initiated upon the receipt of ethics committee approval from the Ministry of Health and Prevention (MoHAP) and administrative approval from the research section of EHS. The team of investigators includes data scientists, experienced research staff, and statisticians of the DSD and EHS. The study participants were COVID-19 patients reported in the ICU of a hospital in Sharjah, UAE. There was no direct interaction between the investigators and the patients and therefore consent form intake was exempted. All investigators were engaged in planning, research designing, and adopting appropriate research methods. The team collaboratively worked to choose a suitable analytical model, deriving valid conclusions, and meaningful reporting. The research problem was well defined to all the collaborators focusing on its relevance and impact in the healthcare sector of UAE.

After obtaining ethical approval from the MoHAP, hospital authorities were informed regarding the details of the study and the required information was shared with the concerned department for using their data for model building. An important measure of the severity of an infectious disease is its ability to cause death. During the series of COVID-19 waves, intensive critical care units were expected to remain a key element in ensuring the best chances of survival. Therefore, an accurate prediction of COVID-19 severity across various patient factors and ICU features was essential to find the severity of the scenario. Having constraints on the availability of ICU resources, it was imperative to identify the patients at most risk of severity and prioritise the needs for critical care. As it was an observational study, there were no investigator-led interventions proposed as in experimental research but adopted an AI-augmented technological innovation.

The study followed a retrospective cohort design, where patient details were retrospectively collected/ extracted from the Wareed online platform. Clinicians and administrative staff of ICU were approached to elaborate on the problem and the data scientists investigated its impact on the delivery of healthcare services and patient care. After the brainstorming sessions with healthcare providers and a thorough literature review, the research staff and statisticians of DSD supported in identifying the potential risk factors of COVID-19 severity for fatal outcomes.

The study population included COVID-19 patients in a hospital in Sharjah, UAE, specifically among the patients who were COVID-19 positive and reported in the selected study setting, both gender and nationality. Patients diagnosed as COVID-19 negative, and patients with ages less than 18 years were excluded from the study. Patients whose information was missing were removed in the stage of data cleaning and analysis. In order to achieve the study objective of determining the incidence of patients at risk of COVID-19 severity in critical care, the research adopted a retrospective cohort design. Theoretically, the size of the participants has to be determined according to the design of the study and the statistical method used for analysis. As it aimed at developing an AI model incorporating all probable factors of COVID-related severity in ICU and finding the incidence rate of severity risk in the different patient categories, the sample size included entire patients of selected 5 months and it was also as per the availability of critical care facilities. Because the research primarily focused on estimation rather than using inferential techniques, a population-based study was proposed to get a highly précised incidence rate. The COVID-19 cases were classified according to various patient characteristics and ICU features. Then the severity of fatal outcomes was observed in the selected different categories. Data from confirmed cases was gathered from January 2021 to May 2021 to encompass the midpoint of the pandemic, facilitating rapid implementation aligned with existing criteria. It was expected to have approximately 800 COVID-19-infected cases in the selected study settings. This population-based data consisted of more than 70 features including probable predictors of COVID-19 severity in critical care. Since it was a population-based retrospective study, the researchers proposed to include all the COVID-19-positive cases reported in the Wareed platform (electronic medical record system) of EHS during the 5 months (Figure 1).

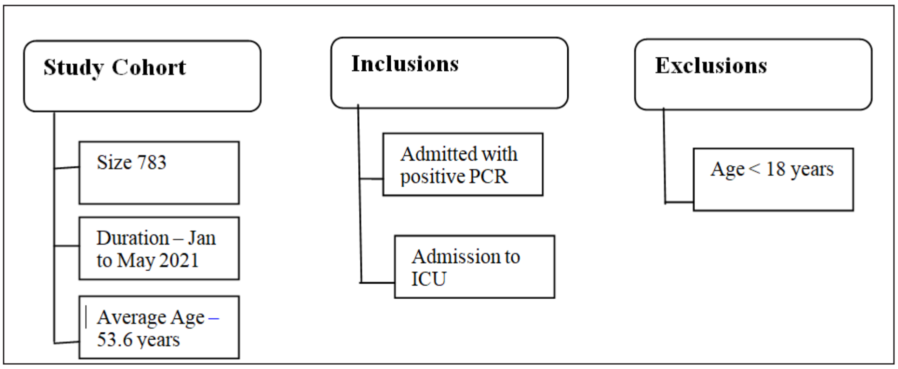

Figure 1.Data Collection Strategy

ISSN: 0019-5138
DOI: https://doi.org/10.24321/0019.5138.202426

The study included the main outcome variable as binary, with categories “patients survived/ not” in ICU due to COVID-19 infection. The model considered more than 70 characteristics as explanatory variables (Figure 2). These independent variables include categorical and quantitative types such as patient demographic characteristics, ventilator use, severity status, vaccination status, other clinical parameters and so on. From the literature, important and potential factors were identified and included in the AI model. Other variables were selected as per the nature of ICU facilities and patient experience in the care units of EHS facilities.

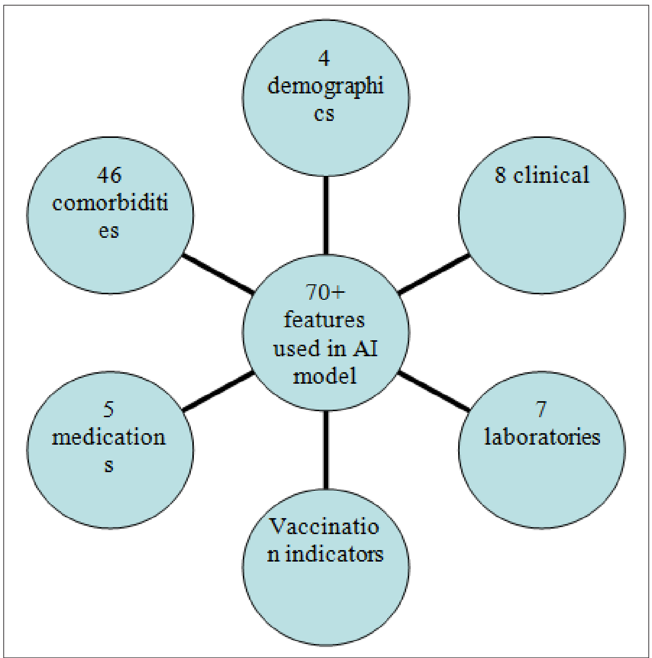

Figure 2.Study Variables Included in the AI-Model

The data quality checks showed a minimal discrepancy in patient demographics, comorbidities, medications, laboratories, and clinical attributes, including using a defined and reviewed feature set. The reason was that the data had been gathered from Electronic Medical Record Systems. The missing values for the labs and clinical variables were imputed. Correlation and causation analytics were conducted using the exploratory data analysis and visual insights were built to understand patterns with respect to the patient group that had fatal outcomes against those patients who survived. The admit mode and entry type of the patients were encoded using SAS one hot encoding methods. Correlation and causation analytics were conducted using the exploratory data analysis; Various machine learning algorithms were compared, and a suitable model was chosen based on the level of accuracy. A statistical risk scoring mechanism (Tables 1 and 2) was built and combined with the other data attributes to build the AI model; then all the key factors determining the fatal outcome were analysed.

Table 1.Risk Scoring Mechanism for Demographics

Patient Demographics	Variables	Score
Age (years)	> 60	5
	> 50–60	4
	> 40–50	3
	≤ 40	2
Gender	Male	3
	Female	2
Disease Symptoms	Body temperature > 38 °C	2

Table 2.Risk Scoring Mechanism for Clinical Parameters

Score	1	2	3	4	5
C-reactive protein (RT-PCR) (mg/L)	< 5	5-50	50-80	80-100	> 100
Score	1	2	3	4	5
LDH (U/L)	< 140	140-225	226-280	281-300	> 300
Score	1	2	3	4	5
D-dimers (ng/mL)	< 225	225-400	400-450	450-600	> 600
Score	1	2	3	4	5
Procalcitonin (ng/mL)	< 0.04	0.49-0.6	0.61-0.8	0.81-0.99	> 1
Score	1	2	3	4	5
Lymphocyte count (%)	2.0-4.0	4.0-4.5	4.5-5.0	5.0-5.5	> 5.5
Score	1	2	3	4	5

Patient data from Wareed was integrated with the EHS intelligence (PaCE) platform (internal system) to develop the dashboard. This platform was augmented with SAS analytical features and consists of data marts for different types of clinical/ administrative/ operational data linked with various sources such as Wareed, Patient Surveys, HR E-Gate, Disease Registries, Customer Feedback/ CRM etc. The platform’s SAS features facilitated extensive data cleaning, statistical analysis and visual representation of results. Prediction models were worked on and trend analysis was performed using machine learning techniques. In addition, the research data was stored in an Excel spreadsheet with the appropriate code system for all qualitative variables. Access to anonymised data was given only to investigators and statisticians of DSD in the EHS office. Participant details were kept confidential. Anonymity was maintained by not including participants' names or personal identification. Participant ID was replaced with dummy codes. The data was analysed in groups and the results were presented in aggregate. No results with individual details were open for other members. Patient details were kept private and used only for current research purposes. The research data in the Excel spreadsheet was securely stored in the Data and Statistics Department of EHS in alignment with the institutional research policies. All investigators were trained and proficient in data extraction, scheduling and preparing reports. Their skills were enhanced and updated through the Arqamee workshop; which is a powerful insight Instructor-Led Training Sessions conducted by DSD of EHS. In essence, researchers were acquainted with data collection from the Wareed platform, data management, data management or integration policies, and analysis using AI techniques.

Results

Study results were generated through the EHS (PaCE) intelligence platform to share the aggregated results with leaders for timely decisions and actions (Figures 3 and 4).

AI model was built on 783 positive PCR cases by adopting the above-mentioned statistical risk scoring mechanism. The optimal model built using the Gradient Boosting Algorithm had a high degree of accuracy (90%) and the major severity risk factors were identified as increased ferritin levels, ventilator usage, high MCHC, and hypotension. The new AI model empowered EHS to plan the necessary resource mobilisation for improved health outcomes, leading to the avoidance of adverse outcomes in the critical care units of EHS facilities. The model indicated a higher likelihood of risk of fatal outcomes at various precision levels. The best AI model that was developed by comparing various algorithms, reflected the predictive factors of ICU severity and its statistical/ clinical significance for future events. The best model was identified based on the ROC curve and AUC value (Figure 5). The incidence rate of severity was calculated by identifying the total number of new severe cases for fatal outcomes and it is divided by the count of patients who have reported ICU with PCR positive during the specified study period.

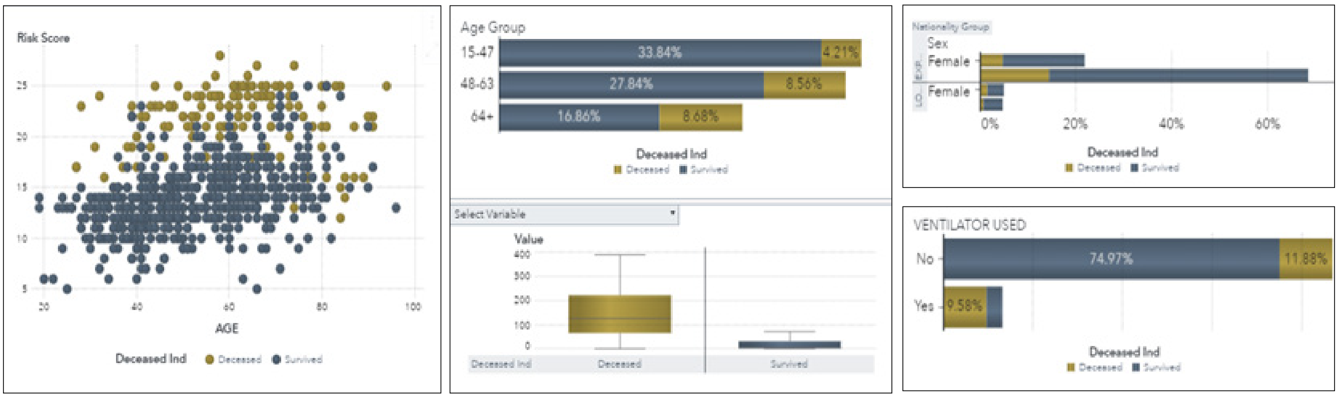

Figure 3.ICU-Related Severity Outcomes by Patient Characteristics

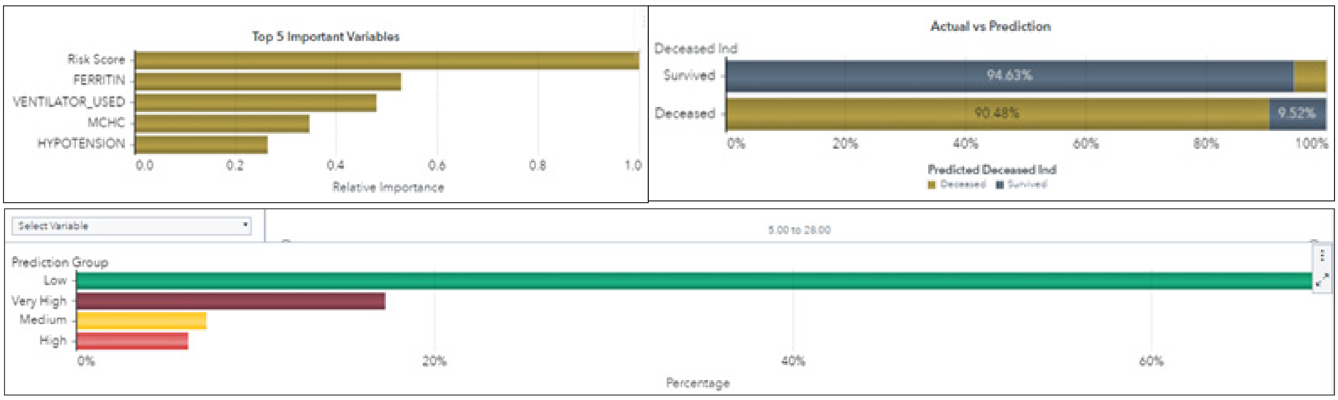

Figure 4.Predictive Results: Dashboard Overview

ISSN: 0019-5138
DOI: https://doi.org/10.24321/0019.5138.202426

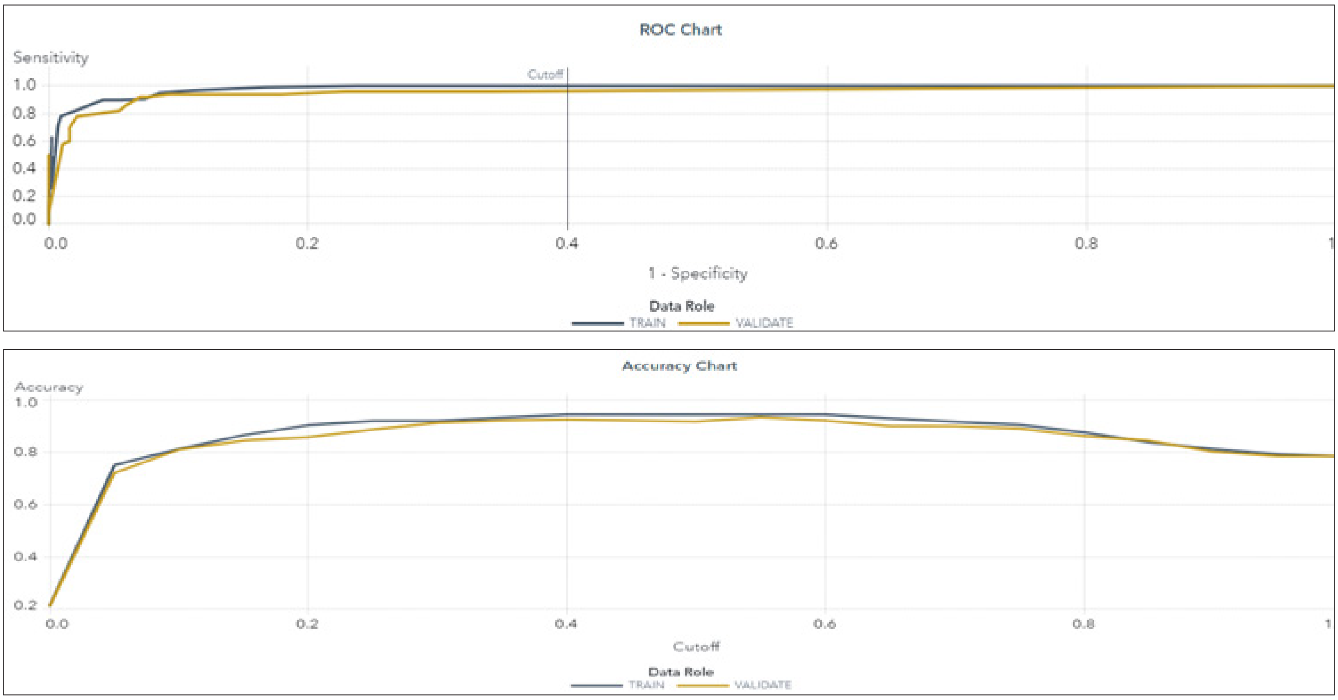

Figure 5.Model Accuracy

The machine learning models used for prediction evaluated several algorithms, including Gradient Boosting, Random Forest, Ensemble, Decision Tree, Neural Network, and Logistic Regression. Among these, the Gradient Boosting model emerged as the champion, based on its superior performance across various metrics.

The model achieved a Root Mean Squared Error (RMSE) of 0.126, indicating high prediction accuracy. It also recorded an Area Under the ROC Curve (AUC) of 0.966, demonstrating excellent capability in distinguishing between different severity levels. The accuracy was 0.981, showing that 98.1% of the predictions were correct. The F1 Score was 0.881, reflecting a strong balance between precision and recall. Additionally, the Gini coefficient was 0.931, and the Lift was 6.704, indicating significant predictive power and improvement over random guessing. The False Positive Rate (FPR) was notably low at 0.008, and the Misclassification Rate was just 0.019, meaning only 1.9% of predictions were incorrect. Furthermore, the model's Gain was 8.178, and the KS statistic (Youden's Index) was 0.893, both underscoring the model's efficacy in accurately predicting ICU severity for COVID-19 patients (Table 3).

Table 3.Model Comparison Results

Model Applied	Root Average Squared Error (RMSE)	Area Under ROC – (AUC)	Accuracy	F1 Score	Gini Coe-fficient	Lift	False Positive Rate	Mis-classi-fication Rate	Gain	KS (Youden)
Gradient Boosting	0.126	0.966	0.981	0.881	0.931	6.704	0.008	0.019	8.178	0.893
Forest	0.154	0.975	0.971	0.806	0.950	6.156	0.006	0.029	7.883	0.875
Ensemble	0.168	0.977	0.964	0.748	0.953	6.198	0.006	0.036	7.637	0.873
Decision Tree	0.189	0.902	0.956	0.726	0.805	5.305	0.019	0.044	6.795	0.772

ISSN: 0019-5138
DOI: https://doi.org/10.24321/0019.5138.202426

Neural Network	0.206	0.921	0.944	0.605	0.843	4.765	0.017	0.056	5.929	0.749
Forward Logistic Regression	0.226	0.897	0.931	0.465	0.794	4.245	0.016	0.069	5.030	0.682
Stepwise Logistic Regression	0.226	0.897	0.931	0.460	0.794	4.259	0.017	0.069	5.051	0.675

Overall, from 783 positive PCR cases, less than one-fourth of patients were found under severe categories. The model identified the top severity risk factors as increased ferritin levels, ventilator usage, high MCHC and hypotension. The training and validation accuracy were 94% and 91% respectively. The finding obtained from the model was an informative dashboard that facilitated knowledge sharing among all the stakeholders and easy decision-making for the leadership team.

Discussion and Future Work

The Emirates Health Services (EHS) through its advanced health care system (a total of 134 facilities) consisting of 17 hospitals, more than 100 centers including several COVID-19 field hospitals carried the responsibility of supporting the national objective of reducing COVID-19 severity. Accordingly, a highly accurate AI model was developed. This new AI model identified increased ferritin levels, ventilator usage, high MCHC and hypotension as the major predictors of COVID severity in the ICU.

Scientific literature shows several findings regarding the factors associated with ICU severity or mortality. One of the studies aimed to identify and describe COVID-19 patient features in an ICU of a multispecialty hospital in Riyadh, Saudi Arabia found (n-333) that 76% of patients were male, with an average BMI of 22.07 and an average age of around 49 years. Diabetes was present in 39.34% of patients, followed by hypertension in 31.53%. Among the 333 patients, 63 required intubations upon admission, and 22 patients died during therapy. Patients with both diabetes and hypertension had a 7.85-fold higher risk of death, while those with only diabetes or hypertension had a 5.43-fold and 4.21-fold higher risk, respectively. Out of the 63 intubated patients, 13 died. Despite a high incidence of intubation, the fatality rate was lower than in other countries due to enhanced healthcare management in the ICU.[6] Another study exploring the impact of various right ventricular (RV) involvement phenotypes on mortality in COVID-19 patients with acute respiratory distress syndrome (ARDS) admitted to the ICU, it was found that RV involvement was common among ventilated patients. The study revealed that different RV involvement phenotypes were linked to varying ICU mortality rates, with acute cor pulmonale (ACP) associated with the highest risk of mortality, as demonstrated by a hazard ratio of 3.25 (2.38–4.45, $p < 0.001$).[7] From 783 positive PCR cases, our current study observed less than one-fourth of patients severely affected (deceased) after being admitted to ICU. However, our project was mainly focused on developing an AI model to predict the factors significantly associated with ICU severity. In the context of this, a study was found in the literature that employed dynamic modelling and clustering analysis to identify homogeneous groups of COVID-19 patients, aiming to develop robust classifiers for ICU admission and mortality prediction. The classifiers achieved a sensitivity of 0.83 and specificity of 0.83 for ICU admission, and a sensitivity of 0.74 and specificity of 0.76 for mortality prediction, resulting in a 4% increase in sensitivity and specificity for mortality prediction. Risk factor analysis highlighted various factors such as lymphocyte count, $SatO_2$, PO_2/ FiO_2, and oxygen supply type for ICU admission, and neutrophil and lymphocyte percentages, PO_2/ FiO_2, LDH, and ALP for mortality prediction.[8] One of the study developed AI-based methods to predict COVID-19 severity in 475 COVID-19-positive patients, using 46 variables. The AI-Score predicted severity on a dataset of 95 patients with 98.59% accuracy, 98.97% specificity, and 97.93% sensitivity. The CXR-Score module achieved 99.08% accuracy in grading chest X-ray severity and concluded that integrating clinical, biological, and chest X-ray data accurately predicted severity upon hospital admission.[9] In another study involving 642 participants, deep learning models were developed to predict in-hospital mortality of COVID-19 patients in the ICU. Deceased patients exhibited elevated white blood cell count, decreased absolute lymphocyte count, elevated creatine concentration, and higher incidence of cardiovascular and chronic kidney disease. A model based on all longitudinal chest X-rays (both pre-ICU and ICU) achieved an AUC of 0.702 and an accuracy of 0.694. Meanwhile, a model relying solely on clinical data attained an AUC of 0.653 and an accuracy of 0.657. Combining longitudinal imaging with clinical data in a unified model significantly enhanced performance, yielding

ISSN: 0019-5138
DOI: https://doi.org/10.24321/0019.5138.202426

an AUC of 0.727 (p = 0.039) and an accuracy of 0.732.[10] In the current study, the top severity risk factors identified by the model were elevated ferritin levels, ventilator usage, high MCHC, and hypotension. The training and validation accuracies stood at more than 90%.

Considering those determinants of ICU severity, the process, and procedures in ICUs of EHS facilities are revised to give the best clinical solution for care excellence in ICU settings and it balanced the allocation of resources and services in supplies, hospital operations and surgeries. Severity rates and their trends/ patterns, utilisation of ICU resources, and other operational Key Performance Indicators (KPIs) are regularly monitored using an advanced data analytics SAS-based platform. System-generated dashboards with purpose-built visualisations are used for the comparison of actual values and benchmarks for continuous improvement in the patient care unit. Ultimately the study results lead to process improvement, adoption of new strategies, and their implementation in the ICU. It has also been decided to collect the staff/ physician/ patient experience in the care unit, using an online feedback system and accordingly model will be improved/ revised for another cycle of ICU performance upgrade. The current study points out the importance of adopting innovative and customised technology-driven solutions that can support in collection and analysis of real-life big data and derive patient-centered results and it brings timely delivery of health care services. The AI-driven models and platforms ensure highly précised clinical solutions and its implementation in EHS through the dashboard is the best evidence of research-oriented practice in the healthcare sector of UAE.

As an extension of this research, new AI models were developed including more patient characteristics. There are a few other relevant ICU features that were not included in the current AI model, those variables were added to the existing machine-learning models to identify the higher likelihood of COVID-19-related severity. In future, new AI models shall be developed expanding the data including other ICU services to leverage advanced technology in providing essential additional services in the EHS. According to its impact, individualised departmental strategies shall be improved and related policies/ procedures can be revised. The processed data shall be further utilised to make COVID-19 registries and used as input to the Manara platform to build multiple models. In such a scenario, the model comparison component of the platform will be used to determine the optimal model with a high degree of accuracy.

Conclusion

During the pandemic period, countries witnessed a series of COVID-19 waves, emergence of different variants and surges in cases. The research developed an AI model with high accuracy and estimation of patients at risk of severity across various characteristics. A COVID-19 registry including EHS patients was built, and the tool was developed through a deep-learning-based AI algorithm with the aim of predicting the severity risk of critical care in COVID-19 patients. This is the success story of a comprehensive AI-driven COVID-19 Response Program of EHS that supported care providers to give targeted personalised care. The new AI model empowered EHS to plan on the necessary resource mobilisation, lab test planning, and care strategy for improved outcomes. The technical innovation has immensely benefited EHS in its critical care settings and those were, wider adaptability with ease of implementation, avoidance of adverse outcomes by providing special care, and overall workload reduction in the precious critical care units of EHS facilities.

Acknowledgements

Investigators would like to acknowledge Emirates Health Services (EHS) for encouragement in the success of this research project. We thank all the healthcare workers involved in the diagnosis and treatment of ICU patients in the EHS healthcare system and the medical staff for their efforts in collecting their medical records.

Source of Funding: None

Conflict of Interest: None

References

1. World Health Organization [Internet]. Global excess deaths associated with COVID-19, January 2020 - December 2021; 2022 [cited 2024 Feb 24]. Available from: https://www.who.int/data/stories/global-excess-deaths-associated-with-covid-19-january-2020-december-2021
2. Chen Y, Liu Z, Li X, Zhao X, Zhao J, Wu D, Xiao M, Zhang D, Gao P, Tian R, Xie J, Fan S, Li B, Xu Y, Li Y, Zhang S. Risk factors for severity due to COVID-19 in intensive care units: a single-center study. Ann Transl Med. 2021;9(4):276. [PubMed] [Google Scholar]
3. Al Saleh M, Alotaibi N, Schrapp K, Alsaber A, Pan J, Almutairi F, Abdullah M, Aboelhassan W, AlNasrallah N, Al-Bader B, Malhas H, Ramadhan M, Hamza M, Abdelnaby H, Alroomi M. Risk factors for mortality in patients with COVID-19: the Kuwait experience. Med Princ Pract. 2022;31(2):180-6. [PubMed] [Google Scholar]
4. Jamshidi E, Asgary A, Tavakoli N, Zali A, Setareh S, Esmaily H, Jamaldini SH, Daaee A, Babajani A, Kashi MA, Jamshidi M, Rahi SJ, Mansouri N. Using machine learning to predict mortality for COVID-19 patients on day 0 in the ICU. Front Digit Health. 2022;3:681608. [PubMed] [Google Scholar]
5. Aslam N. Explainable artificial intelligence approach for

the early prediction of ventilator support and mortality in COVID-19 patients. Computation [Internet]. 2022 [cited 2024 Feb 22];10(3):36. Available from: https://doi.org/10.3390/computation10030036 [Google Scholar]
6. Almuqbil M, Almoteer AI, Suwayyid AM, Bakarman AH, Alrashed RF, Alrobish M, Alasalb F, Alhusaynan AA, Alnefaie MH, Altayar AS, Alobid SE, Almadani ME, Alshehri A, Alghamdi A, Asdaq SM. Characteristics of COVID-19 patients admitted to intensive care unit in multispecialty hospital of Riyadh, Saudi Arabia: a retrospective study. Healthcare (Basel). 2023;11(18):2500. [PubMed] [Google Scholar]
7. Huang S, Vieillard-Baron A, Evrard B, Prat G, Chew MS, Balik M, Clau-Terre F, Backer DD, Dessap AM, Orde S, Morelli A, Sanfilippo F, Charron C, Vignon P; ECHO-COVID Study Group. Echocardiography phenotypes of right ventricular involvement in COVID-19 ARDS patients and ICU mortality: post-hoc (exploratory) analysis of repeated data from the ECHO-COVID study. Intensive Care Med. 2023;49(8):946-56. [PubMed] [Google Scholar]
8. Pezoulas VC, Kourou KD, Mylona E, Papaloukas C, Liontos A, Biros D, Milionis OI, Kyriakopoulos C, Kostikas K, Milionis H, Fotiadis DI. ICU admission and mortality classifiers for COVID-19 patients based on subgroups of dynamically associated profiles across multiple timepoints. Comput Biol Med. 2022;141:105176. [PubMed] [Google Scholar]
9. Udriștoiu AL, Ghenea AE, Udriștoiu Ș, Neaga M, Zlatian OM, Vasile CM, Popescu M, Tieranu EN, Salan AI, Turcu AA, Nicolosu D, Calina D, Cioboata R. COVID-19 and artificial intelligence: an approach to forecast the severity of diagnosis. Life (Basel). 2021;11(11):1281. [PubMed] [Google Scholar]
10. Cheng J, Sollee J, Hsieh C, Yue H, Vandal N, Shanahan J, Choi JW, Tran TM, Halsey K, Iheanacho F, Warren J, Ahmed A, Eickhoff C, Feldman M, Barbosa Jr EM, Kamel I, Lin CT, Yi T, Healey T, Zhang P, Wu J, Atalay M, Bai HX, Jiao Z, Wang J. COVID-19 mortality prediction in the intensive care unit with deep learning based on longitudinal chest X-rays and clinical data. Eur Radiol. 2022;32(7):4446-56. [PubMed] [Google Scholar]

ISSN: 0019-5138
DOI: https://doi.org/10.24321/0019.5138.202426