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RESEARCH

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Prediction of postoperative intensive care unit admission with artificial intelligence models in non-small cell lung carcinoma

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Abstract

Background There is no standard practice for intensive care admission after non-small cell lung cancer surgery. In this study, we aimed to determine the need for intensive care admission after non-small cell lung cancer surgery with deep learning models.

Methods The data of 953 patients who were operated for non-small cell lung cancer between January 2001 and 2023 was analyzed. Clinical, laboratory, respiratory, tumor's radiological and surgical features were included as input data in the study. The outcome data was intensive care unit admission. Deep learning was performed with the Fully Connected Neural Network algorithm and k-fold cross validation method.

Results The training accuracy value was 92.0%, the training F1 1 score of the algorithm was 86.7%, the training F1 0 value was 94.2%, and the training F1 average score was 90.5%. The test sensitivity value of the algorithm was 67.7%, the test positive predictive value was 84.0%, and the test accuracy value was 85.3%. Test F1 1 score was 75.0%, test F1 0 score was 89.5%, and test F1 average score was 82.3%. The AUC in the ROC curve created for the success analysis of the algorithm's test data was 0.83.

Conclusions Using our method deep learning models predicted the need for intensive care unit admission with high success and confidence values. The use of artificial intelligence algorithms for the necessity of intensive care hospitalization will ensure that postoperative processes are carried out safely using objective decision mechanisms.

Keywords Artificial Intelligence, Intensive care unit, Non-small cell lung cancer

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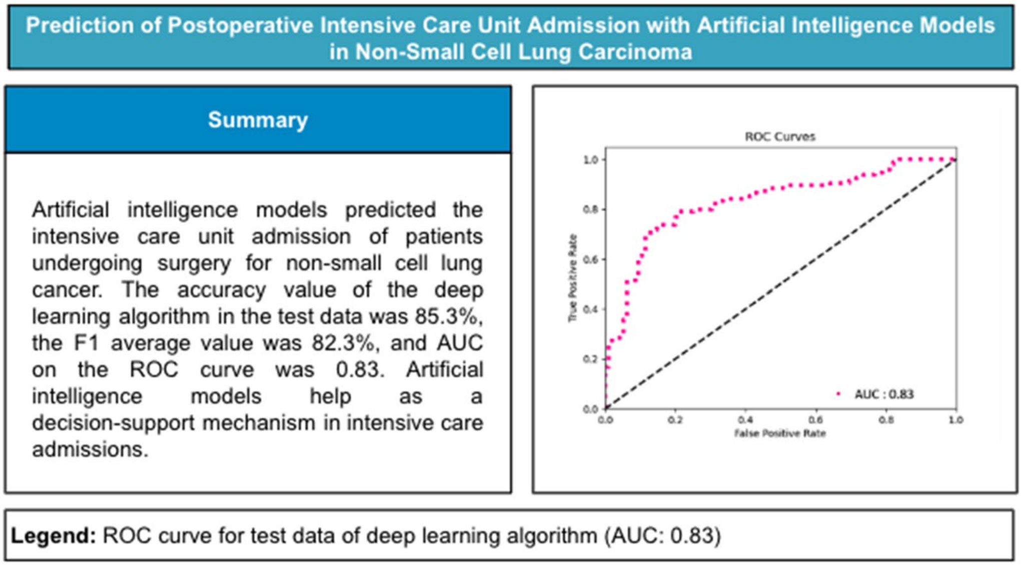
Graphical Abstract



Background

Lung cancer is one of the most frequently diagnosed and leading causes of cancer-related deaths worldwide. [1, 2] Non-small cell lung cancer (NSCLC) accounts for approximately 85% of lung cancer diagnoses, while small cell lung carcinoma accounts for approximately 15% [3]. Risk factors for lung cancer include smoking, exposure to asbestos, family history of lung cancer, history of chronic lung disease, exposure to radiation, toxic substances, such as polycystic aromatic hydrocarbons, heavy metals, and radon gas [4–6]. Electronic cigarette use has been identified as a factor in the development of lung adenocarcinoma in animal studies. [4, 7]

The 8th TNM staging is used in the staging of non-small-cell lung carcinoma [8]. Size and characteristics of the tumor (tx, T0, T1a(mi), T1, T2, T3, T4), characteristics of the lymph node (Nx, N0, N1, N2, N3), and distant metastasis status (M0, M1a, M1b, and M1c) are examined under the heading of staging [8]. In early stage NSCLC, the gold standard treatment is surgery if there are no contraindications in terms of pulmonary functions [9]. Multidisciplinary treatment options come to the fore in the locally advanced-stage patient group [10]. Surgical treatment options come to the fore following direct surgery or neoadjuvant chemotherapy, immunotherapy, and/or radiotherapy modalities. [11, 12]

The need for an intensive care stay after surgery is one of the reasons why lung cancer surgery is among the special surgeries [13, 14]. In our clinical practice, the need for intensive care admission is decided by evaluating the patient's current clinical condition and planned surgery. Intensive care admission after NSCLC surgery is required in patients who require close monitoring and are at risk of major complications [15]. Patients who require surgery due to NSCLC are generally a high-risk patient group accompanied by various comorbid conditions, such as heavy smokers, a history of coronary artery disease, and a history of COPD [16]. The need for intensive care admission increases with the presence of accompanying comorbid conditions, and ASA classification (American Society of Anesthesiologists), CCI risk index (Charlson Comorbidity Index), cardiac risk index, and pulmonary risk indexes are used in evaluation (Supplementary Tables S1, S2, S3, S4) [16–21]. In clinical practice, factors such as the patient's additional comorbid conditions, respiratory function data, need for mechanical ventilation, and postoperative hemodynamic instability are evaluated as factors related to the patient in determining the need for postoperative intensive care unit admission [22, 23]. For surgical procedure risk factors, intraoperative complications and the risk posed by surgery are also taken into account [22, 23]. In addition, the surgeon, anesthesia team, and hospital experience are also important for the patient's ward or intensive care unit follow-up [22, 23]. While the need for postoperative intensive care unit admission after NSCLC surgery is important in terms of cost management, length of hospital stay, and nosocomial infection management, there is no objective evaluation standardization [23, 24]. Routine postoperative intensive care unit admission to every patient who undergoes surgical resection for NSCLC will result in inefficient use of qualified infrastructure. [23, 24]

With the increasing use of artificial intelligence and machine learning algorithms in the field of healthcare, cost, time management, patient comfort, and ease of teaching and learning have been achieved [25]. Machine learning is a subgroup of artificial intelligence methods that tries to minimize the error between the ideal action and the current action based on existing data [26–28]. The error minimization process is carried out with the feedback mechanism of machine learning, and performance improvement is achieved [26]. Algorithms are rules consisting of statistical techniques defined to learn data and map all the decisions the model can make, while models are mathematical equations that are the result of the algorithm [26]. Training data is used to train machine learning models, while testing data is used to test machine learning models after the training procedure. [26]

Deep learning is a subgroup of machine learning that is effective in solving problems involving complex, unstructured data with multilayer neural networks [26, 29]. In deep learning, the dimensionality problem, which is the main limitation of machine learning, can be solved [26, 30]. In deep learning, there is an input layer that receives data input from multiple sources and an output layer that produces outputs. There are many hidden layers between the input and output layers [26]. The number of intermediate layers and the number of sensors in the intermediate layers vary depending on the nature of the problem [26]. There are one or more intermediate layers in the multilayer artificial neural network; the weights of the data are variable and kept up-to-date; this variability is adjusted by the back propagation method according to the error rate obtained in the previous iteration, thus reducing error rates and increasing the reliability of the model. [26, 31]

FCNN (Fully Connected Neural Network) is an algorithm consisting of many connected layers, where every neuron in one layer is connected to every neuron in the other layer, and its basic principle is backpropagation (Fig. 1) [32, 33]. There is an input layer and an output layer; the intermediate layers are hidden layers, and although there is a connection between the layers, there is no connection between the neurons in the same layer. The aim is to have fast learning and a low error rate. [34–36]

This study aimed to detect the need for postoperative intensive care hospitalization in patients who underwent thoracic surgery due to lung cancer with high accuracy and success using artificial intelligence and machine learning algorithms.

Methods

Ethics committee approval was received for this study from the local ethics committee of our institution (Ethics committee number: 83045809-604.01.01-415691). After receiving ethics committee approval, we compiled the data retrospectively. All data were obtained from clinical patient files and the hospital database. During data collection and the study, we did not perform any additional procedures on the patients and did not request additional examinations or imaging.

The study included patients who underwent lung resection and systematic lymph node dissection due to NSCLC in our clinic between 2001 and 2023. The study excluded patients with inaccessible data or missing information. There were 953 patients who met these criteria.

We recorded the patients' demographic data, including their age and gender. Clinical data include the presence of comorbidities, history of chronic obstructive pulmonary disease (COPD), history of hypertension, history of diabetes, history of tuberculosis, presence of additional malignancy, history of hemoptysis, presence of excessive secretions, history of neoadjuvant treatment, history of smoking (pack x year), cardiac risk index score, pulmonary risk index score, Charlson comorbidity risk index score, and body mass index.

Among the respiratory parameters, FVC, %FVC, FEV1, %FEV1, FEV1/FVC, DLCO, %DLCO, DLCO/VA, PO2, and PCO2 were noted. Laboratory data revealed values for hemoglobin, albumin, C-reactive protein, lactate dehydrogenase, leukocyte, lymphocyte, monocyte, and neutrophil. In PET/CT, maximum FDG uptake of the lymph node and tumor (lymph node SUVmax and tumor SUVmax values) was recorded.

We recorded information on the tumor's location, the side of the lesion, the type of surgical resection (lobectomy, bilobectomy, pneumonectomy, wedge, segmentectomy), and the type of surgical incision (open surgery–thoracotomy; closed surgery–VATS, RATS).

Tumor diagnosis, tumor diameter, N lymph node status (N0, N1, N2), and TNM stage were recorded from the pathology data. We recorded current parameters for each patient, which formed the input data. In this study, patients with missing data were excluded, and no imputation method was applied to fill in the missing data.The majority of patients (88.2%) were not included as input data, because they belonged to the ASA 2–3 group and did not contribute to the model's training. In addition, data such as surgery duration and blood loss, which are key indicators of postoperative complications, were

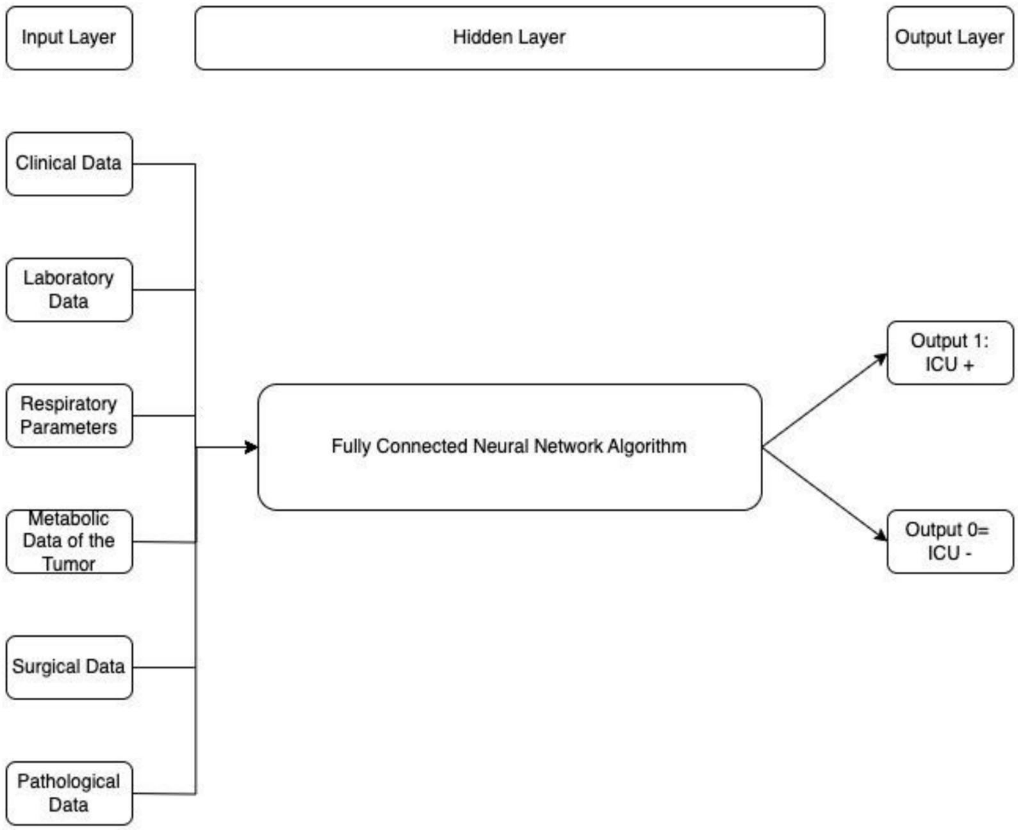


Fig. 1 Schematic drawing of the fully connected neural network algorithm Input data includes clinical data, laboratory data, respiratory parameters, and tumor characteristics for each patient. Forward and feedback feeds establish connections between the intermediate layers. As a result, learning success increases. The last layer contains the output data. The number of intermediate layers and neurons varies depending on the characteristics of the problem and the data

excluded to prevent overfitting and bias in the model. Intensive care unit admission was the outcome data.

As statistical methods, mean values, standard deviations, and ratios were calculated. The SPSS® 27.00 (IBM, Armonk, NY, United States) program was used in statistical analyses. For deep learning algorithms, the success of the algorithm was evaluated by calculating specificity, sensitivity (recall), negative predictive value, positive predictive value (precision), accuracy, and F1 score. The F1 score is the harmonic average of precision (positive predictive value) and recall (sensitivity) values, which is an indicator of success in artificial intelligence studies. The model's success value for predicting postoperative intensive care unit presence was shown as F1 1 (Output: ICU+). The model's success value for predicting postoperative intensive care unit absence was shown as F1 0 (Output: ICU−). The F1 average value was the average of the F1 1 and F1 0 values. It showed the presence or absence of intensive care hospitalizations with the highest optimization. The success of deep learning algorithms was evaluated using the area under the curve on the ROC curve. The Python implementation was used for artificial intelligence applications (Python 3.8.2, Van Rossum G, Drake Jr FL, Amsterdam, Holland). The FCNN (Fully Connected Neural Network) algorithm was used in the Python application, and k-fold cross validation was used to reduce randomness. 90% of the data was used for training and 10% for testing.

Results

Between 2001 and 2023, the average age of 953 patients who operated on our clinic due to NSCLC was 61.3 ± 9.8 years. 80.5% of the patients were male (767 patients), and 19.5% were female (186 patients). 32.7% (312 patients) were admitted to postoperative intensive care units.

The data of the deep learning model created using the FCNN algorithm and the k-fold cross validation method for postoperative intensive care unit admission prediction in patients operated on for NSCLC are given in Table 1. For the point where the algorithm was most successful, the repetition step in which the F1

Table 1 Data analysis results of the FCNN algorithm-created model for postoperative intensive care admission prediction. The algorithm's most successful point is the 1700th step, which determines the maximum test F1 average value. The data corresponds to step 1700 of the algorithm

	Train (%(	Test
Specificity	97.7	93.8
Sensitivity (recall)	80.1	67.7
Negative predictive value	91.0	85.7
Positive predictive value (precision)	94.5	84.0
Accuracy	92.0	85.3
F1 1 Score	86.7	75.0
F1 0 Score	94.2	89.5
F1 Average Score	90.5	82.3

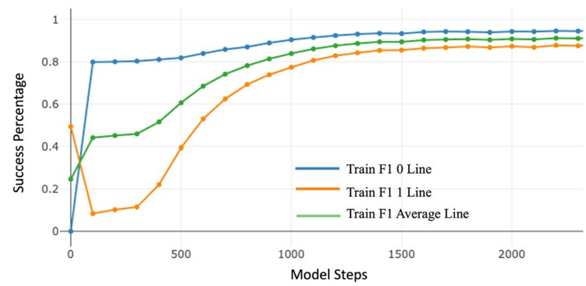


Fig. 3 Graphical representation of F1 1, F1 0, and F1 average values for the training data of the model created for postoperative ıntensive care unit admission requirement estimation with the FCNN algorithm and k-fold cross validation. (Values for the 1700th step, where the maximum value for the Test F1 average score was determined, are given: training F1 1 value: 86.7%, training F1 0 value: 94.2%, training F1 average value: 90.5%)

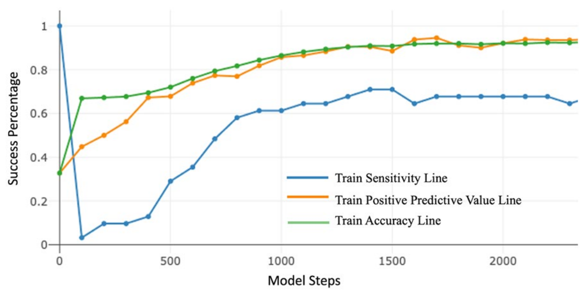


Fig. 2 Graphical representation of accuracy, positive predictive value, and sensitivity values for the training data of the model created for postoperative intensive care unit admission prediction with the FCNN algorithm and k-fold cross validation. (Values for the 1700th step, where the maximum value for the test F1 average score was determined, are given: training accuracy value: 92.0%, training positive predictive value: 94.5%, training sensitivity value: 80.1%.)

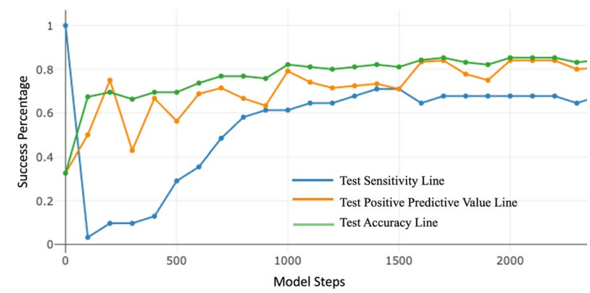


Fig. 4 Graphical representation of the accuracy, positive predictive value, and sensitivity values for the test data of the model created for postoperative intensive care unit admission Requirement estimation with the FCNN algorithm and k-fold cross validation. (Belonging to the 1700th step, where the maximum value for the test F1 Average Score was detected, values are given: test accuracy value: 85.3%, test positive predictive value: 84.0%, test sensitivity value: 67.7%.)

average value of the test data was the maximum was taken. We determined the maximum test F1 average value at step 1700 (Table 1).

The algorithm's sensitivity value for the training data was 80.1%; the positive predictive value was 94.5%; and the accuracy value was 92.0% (Fig. 2). The algorithm's F1 1 score for the training data was 86.7%, the F1 0 value was 94.2%, and the F1 average score was 90.5% (Fig. 3).

The algorithm had a sensitivity value of 67.7% for the test data, a positive predictive value of 84.0%, and an accuracy value of 85.3% (Fig. 4). The algorithm's F1 1 score was 75.0% for the test data, F1 0 score was 89.5%, and F1 average score was 82.3% (Fig. 5). The algorithm's test data success analysis produced a ROC curve with an area under the curve of 0.83 (AUC: 0.83) (Fig. 6).

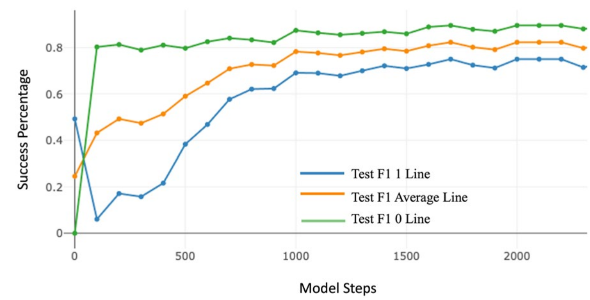


Fig. 5 Graphic representation of F1 1, F1 0, and F1 mean values for the test data of the model created for postoperative intensive care unit admission requirement estimation with the FCNN algorithm and k-fold cross validation. (Values for the 1700th step, where the maximum value was determined for the test F1 Average Score, are given: test F1 1 value: 75.0%, test F1 0 value: 89.5%, test F1 average value: 82.3%)

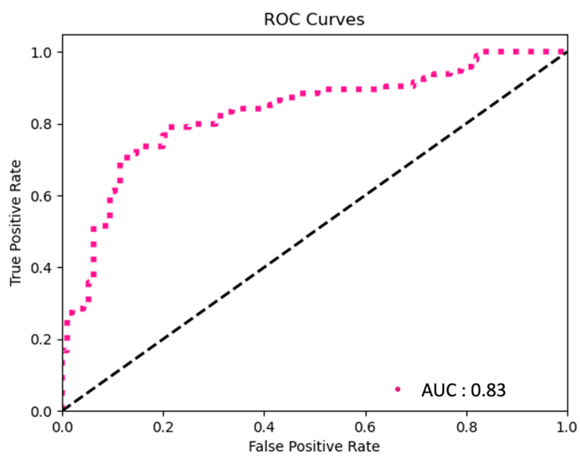


Fig. 6 Evaluation of the success of the model created for postoperative intensive care unit admission prediction with the FCNN algorithm and k-fold cross validation with the ROC curve (AUC:0.83)

Discussion

Close patient follow-up is required after thoracic surgery, and postoperative intensive care unit admission varies depending on the patient's additional comorbidities, the surgery performed, and the physician's decision [16–23]. For this reason, an objective evaluation of the need for postoperative intensive care unit admission in the preoperative period is important in terms of cost, social, and medical aspects [23, 24]. In this study, the accuracy value of the deep learning algorithms developed for the prediction of postoperative intensive care unit admission requirements in the test data is 85.3%, the F1 average value is 82.3%, and the area under the curve in the ROC curve is 83%, indicating that the algorithm makes predictions with high accuracy and high success values. What we intended to convey as high accuracy and success in this study is that the test F1 mean value of the model is 82.3%, and the area under the ROC curve (AUC) is 83%. This value represents the combined evaluation of patients requiring and not requiring ICU admission and is considered highly accurate and successful due to its potential clinical contribution. We believe that this model can serve as a starting point for ICU admission prediction and AI-based decision-making.

It provides contributions such as estimating the need for intensive care unit admission in the preoperative period with objective criteria, making intensive care unit preparations, and preparing patients and their relatives for intensive care. We use the ASA classification (American Society of Anesthesiologists), CCI risk index (Charlson Comorbidity Index), cardiac risk index, and pulmonary risk index for an objective evaluation of the need for intensive care unit admission [16–21]. Admission to the intensive care unit after thoracic surgery has changed over the years. For example, while in the 1990s, all patients were followed in advanced intensive care units after thoracic surgeries, today they are referred to as intermediate-level intensive care units (PACU, Post Anesthesia Care Unit) It is considered appropriate to follow up during maintenance [16, 22]. The increasing application of ERAS (Enhanced Recovery After Surgery) protocols in thoracic surgery has led to a general consensus that hospitalizing patients who do not require intensive care units for intensive care units is unnecessary and may lead to additional complications [37, 38]. However, we must remember that neglecting this service for patients requiring intensive care unit admission leads to a rise in morbidity and mortality [16, 22]. Given these reasons, it is critical to correctly identify patients who require intensive care unit admission and those who do not.

In this study, using deep learning algorithms to detect patients who require and do not require intensive care unit admission with high accuracy and success will help physicians in clinical practice. Our study's deep learning algorithm will objectively aid physicians in assessing the necessity of an intensive care unit admission during the preoperative period. By making comparisons simultaneously with physicians' decisions, the algorithm will be able to improve itself further, and with the development of the algorithm, it will provide more support to physicians in clinical practices with higher predictive power, higher success, and higher confidence data.

When evaluating the clinical necessity of our model, we observed that although the vast majority of our patients (88.2%) were preoperatively classified as ASA 2–3, 32.7% required ICU hospitalization. High ASA scores were not directly correlated with ICU admission, nor were low ASA scores directly linked to ward hospitalization. The test evaluation of our model demonstrates its ability to distinguish between patients who require ICU care and those who do not. We believe that our model can contribute to existing clinical scoring systems.

Artificial intelligence models can prevent unnecessary intensive care unit admissions, prevent possible complications, and optimize the use of existing resources in patients identified as low risk for intensive care unit admission. During the preoperative period, patients at high risk for intensive care unit admission receive an objective understanding of potential risks. Artificial intelligence models can support physicians as decision-support mechanisms for intensive care unit admission. Our goal is to achieve clinical integration by utilizing the current model as an application in the future, allowing for preoperative evaluation of each patient. The combination of artificial intelligence assessment and clinical scores will assist physicians in making informed clinical decisions moving forward.

The main limitation of artificial intelligence studies is that the algorithm does not have enough data to provide sufficient learning. In this study, modeling was performed with the data of 953 patients, and it was sufficient for training, but the success of the model will increase with the increase in data diversity and amount of data. Another reason why artificial intelligence applications are used less in clinical decision mechanisms is the presence of multiple and complex input data. In this study, this problem was eliminated by optimizing the weights and bias values of the data. Incorporating data from different clinical practices to better predict real-life data is also an important issue. Considering the temporality of the data, it reflects 20 years of clinical experience. In fact, it is a positive situation that it shows wide clinical application. On the other hand, developing technology and innovations in patient care cause heterogeneity. In the future, with the simultaneous evaluation of artificial intelligence models and physician decisions, the success of the models will come closer to real-life data. In this study, although the specificity and sensitivity values were closer in the training model, the specificity was higher (93.8%) and the sensitivity was lower (67.7%) in the test model. This performance discrepancy represents a limitation of this study.

Conclusion

In this study, intensive care unit admission predictions were made with high accuracy and confidence using artificial intelligence models. The artificial intelligence model will assist clinicians in the decision-support mechanism for assessing the need for intensive care unit admission and will contribute to objective evaluation.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40001-025-02553-z.

Supplementary Material 1.

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Author contributions

G.Ö.I did Conceptualization, Data curation, Methodology, Analysis, Writing-Original Draft, and Writing-Review and Editing. B.K., E.E.,and M.K.K., reviewed the manuscript. O.S.Ö and T.Y. contributed to the analysis and methodology part. A.T. and H.V.K did Conceptualization, Methodology, Writing-Review and Editing.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

Ethics committee approval was received for this study from the local ethics committee of our institution (Ethics committee number: 83045809-604.01.01-415691).

Competing interests

The authors declare no competing interests.

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