

A Hybrid Model for Predicting ICU Discharge Readiness and Estimating Excess ICU Stay Duration

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Abstract—Intensive Care Units (ICUs) manage patients whose clinical condition can change rapidly and whose treatment frequently depends on continuous monitoring. Determining the appropriate time for ICU discharge is difficult because readiness is influenced by multiple physiological, laboratory, treatment, and temporal factors. Premature transfer may increase the possibility of clinical deterioration, whereas unnecessarily prolonged ICU occupancy can consume critical resources and expose patients to avoidable complications. This paper proposes a hybrid machine learning framework that performs two related tasks: prediction of ICU discharge readiness and estimation of excess ICU stay duration. The proposed framework combines structured clinical variables with temporal information and integrates classification and regression components. Patient observations are first cleaned, normalized, and transformed into clinically meaningful features. A temporal learning component captures changes in physiological measurements, while a tree-based component models nonlinear relationships among heterogeneous clinical variables. Their outputs are combined to generate a discharge-readiness probability and an estimate of additional ICU days beyond the expected stay. The framework is designed to provide an interpretable decision-support layer rather than replace clinical judgment. Experimental evaluation can be performed using accuracy, precision, recall, F1-score, AUROC, MAE, and RMSE. The proposed approach provides a unified framework for both discharge decision support and excess-stay estimation, with potential applications in ICU resource planning and personalized patient management.

Index Terms—Intensive Care Unit, ICU Discharge Prediction, Length of Stay, Machine Learning, Deep Learning, Hybrid Model, Clinical Decision Support, Time-Series Analysis.

I. INTRODUCTION

Intensive Care Units provide continuous medical supervision to patients who require advanced monitoring and life-support interventions. ICU care involves a large number of physiological measurements, laboratory observations, medication records, treatment events, and clinical assessments. These variables change over time, making it difficult to determine when a patient has reached a sufficiently stable condition for transfer to a lower-acuity ward.

The decision to discharge a patient from intensive care is not determined by a single measurement. Instead, clinicians consider multiple indicators such as cardiovascular stability, respiratory support requirements, neurological status, renal function, infection-related parameters, and recent changes in vital signs. Consequently, discharge planning represents

a complex decision-making problem involving both current patient status and the trajectory of recovery.

Prolonged ICU occupancy presents another important challenge. When patients remain in intensive care after the period of intensive monitoring is clinically necessary, valuable beds may become unavailable for other critically ill patients. At the same time, transferring a patient too early can result in deterioration and potentially require readmission to the ICU. An intelligent prediction system must therefore balance the risks associated with premature discharge and unnecessary prolonged stay.

Traditional scoring systems provide useful summaries of patient severity, but they may not fully capture temporal patterns in continuously collected ICU data. Machine learning methods can identify nonlinear relationships among clinical variables, while sequential models can learn patterns from measurements collected across time.

This paper proposes a hybrid computational framework that addresses two complementary objectives. The first objective is to determine whether a patient is likely to be ready for ICU discharge within a specified prediction window. The second objective is to estimate the amount of ICU stay that may exceed an expected duration. Combining these tasks provides a more comprehensive representation of the discharge-planning problem.

The major contributions of this work are:

- A unified framework for ICU discharge-readiness classification and excess-stay estimation.
- Integration of static clinical characteristics with longitudinal physiological observations.
- A hybrid architecture combining temporal representation learning and nonlinear tabular prediction.
- A two-output decision layer that provides both discharge probability and estimated excess ICU duration.
- A framework that can support ICU resource management while retaining clinicians as the final decision-makers.

II. PROBLEM STATEMENT

Determining when an ICU patient is ready for transfer is a complex clinical task because patient recovery does not follow a uniform pattern. Two patients with similar diagnoses may have substantially different physiological responses, treatment

requirements, and recovery trajectories. Therefore, a fixed length-of-stay threshold is insufficient for reliable discharge planning.

Clinical data generated during ICU treatment are heterogeneous and dynamic. Vital signs are recorded at frequent intervals, whereas laboratory tests may be obtained at irregular times. Medication administration, respiratory support, fluid balance, and clinical interventions provide additional information about patient condition. These variables differ in scale, frequency, missingness, and clinical significance.

Another challenge is that discharge readiness and prolonged ICU stay are related but distinct prediction problems. A model that only predicts discharge status does not directly indicate how long a patient may remain in the ICU. Conversely, a model that only predicts length of stay may not provide a direct probability of near-term discharge readiness.

The problem addressed in this research is therefore the development of a hybrid predictive framework that can learn from multidimensional ICU records and simultaneously:

- 1) estimate the probability that a patient will be ready for ICU discharge within a defined future window; and
- 2) estimate the number of additional ICU days beyond an expected stay.

The framework should accommodate temporal clinical patterns, nonlinear relationships, missing observations, and heterogeneous patient characteristics while producing outputs that can be incorporated into clinical decision-support workflows.

III. OBJECTIVES

The proposed study has the following objectives:

- 1) To develop a machine learning framework for predicting ICU discharge readiness.
- 2) To estimate excess ICU stay duration using patient-specific clinical information.
- 3) To combine temporal physiological observations with static and event-based clinical variables.
- 4) To identify important factors associated with delayed ICU discharge.
- 5) To design a hybrid architecture capable of handling nonlinear and time-dependent clinical relationships.
- 6) To evaluate discharge classification using accuracy, precision, recall, F1-score, and AUROC.
- 7) To evaluate excess-stay estimation using MAE, RMSE, and related regression measures.
- 8) To provide interpretable outputs that can support clinician-oriented decision making.
- 9) To investigate the potential of the framework for ICU resource and bed management.

IV. LITERATURE REVIEW

Machine learning has increasingly been investigated for clinical prediction because modern hospital information systems generate large quantities of structured patient data. ICU environments are particularly suitable for predictive modelling because physiological measurements and treatment events are continuously recorded.

Traditional severity scores summarize patient condition using predefined clinical rules. Although such scores are useful for risk stratification, they may not adapt to complex temporal interactions among variables. Machine learning models provide an alternative by learning relationships directly from historical observations.

Tree-based algorithms are widely used for structured clinical data because they can represent nonlinear relationships and interactions without requiring strong assumptions about the distribution of input variables. Random forests and gradient-boosting methods have consequently been applied to mortality prediction, length-of-stay estimation, and other hospital analytics tasks.

Deep learning has also become important for ICU time-series modelling. Recurrent architectures can process sequences of observations and identify changes in patient state. More recent temporal architectures can model long-range dependencies while reducing some limitations associated with recurrent processing.

Length-of-stay prediction is closely related to resource planning. Accurate estimation can assist hospital administrators in anticipating bed demand and can help clinical teams identify patients who may require prolonged intensive care. However, length of stay is influenced by both medical and operational factors, making it difficult to predict using a single variable.

The proposed study builds on these directions by combining temporal learning with a nonlinear tabular model. Instead of treating discharge classification and stay estimation as unrelated tasks, the proposed framework produces both outputs from a shared patient representation.

V. PROPOSED METHODOLOGY

The proposed system consists of six major stages:

- 1) ICU data acquisition,
- 2) preprocessing and quality control,
- 3) temporal feature construction,
- 4) hybrid predictive modelling,
- 5) joint prediction,
- 6) evaluation and decision support.

The complete architecture is illustrated in Fig. 1.

A. Data Acquisition

The framework is designed for structured ICU records containing physiological, laboratory, therapeutic, and clinical variables. Potential input variables include heart rate, respiratory rate, oxygen saturation, blood pressure, temperature, urine output, laboratory measurements, medication exposure, ventilatory support, and other relevant ICU observations.

Each patient record is represented as a sequence of observations collected during the ICU episode. Static variables such as age and admission characteristics can be stored separately and later combined with temporal features.

B. Data Preprocessing

Clinical datasets frequently contain missing values, abnormal measurements, inconsistent timestamps, and variables

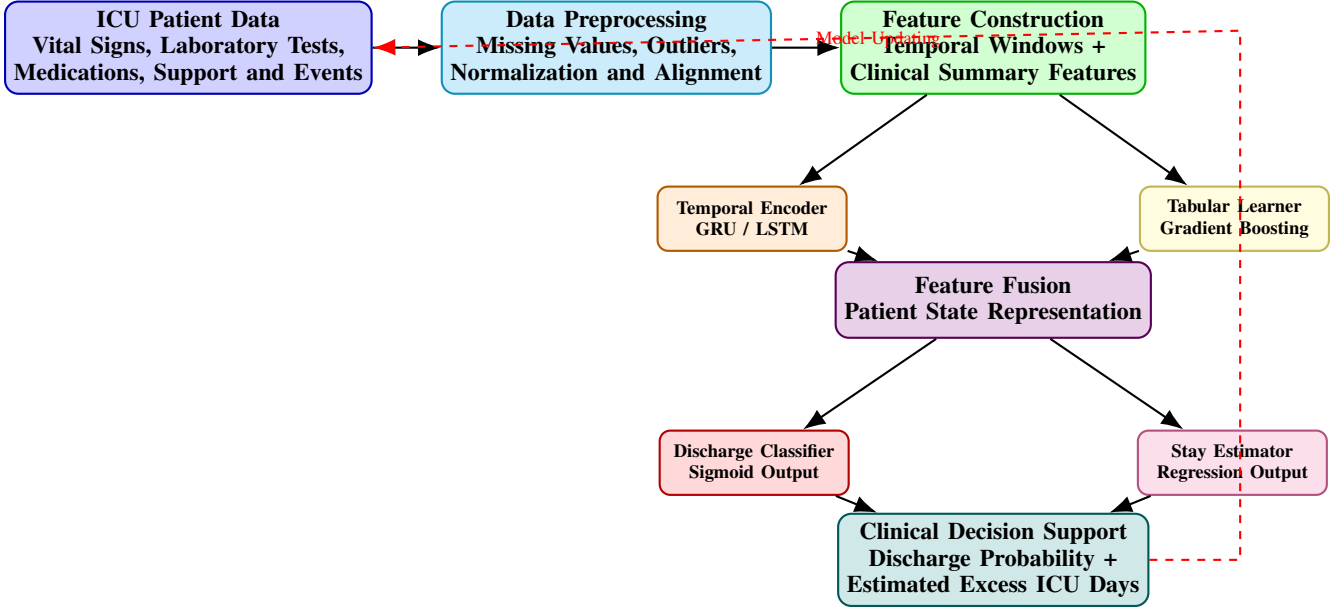


Fig. 1. Colored architecture of the proposed hybrid framework for ICU discharge-readiness prediction and excess ICU stay estimation.

recorded at different frequencies. The preprocessing stage therefore performs data quality checks before model training.

The major preprocessing operations include:

- removal or correction of invalid observations;
- treatment of missing values using suitable statistical or temporal methods;
- normalization of continuous variables;
- encoding of categorical variables;
- alignment of observations according to time;
- construction of fixed prediction windows.

The preprocessing process is designed to preserve clinically meaningful temporal changes instead of replacing the entire patient trajectory with a single summary value.

C. Feature Construction

Two categories of features are generated.

First, temporal features represent changes in physiological measurements. For a variable x , a temporal window can be represented as

$$X_t = [x_{t-k+1}, x_{t-k+2}, \dots, x_t], \quad (1)$$

where k denotes the number of observations included in the window.

Second, summary features describe patient status using statistics such as mean, minimum, maximum, standard deviation, recent trend, and measurement frequency.

These features are passed to separate temporal and tabular learning components.

D. Temporal Learning Component

The temporal component is designed to identify changes in patient condition across successive observations. A Gated Recurrent Unit (GRU) or Long Short-Term Memory (LSTM) network can be used to encode the patient trajectory.

For a GRU-based implementation, the hidden representation can be expressed as

$$h_t = GRU(x_t, h_{t-1}), \quad (2)$$

where x_t is the observation at time t and h_t represents the learned patient state.

The final hidden representation summarizes temporal information relevant to discharge readiness and prolonged ICU stay.

E. Tabular Learning Component

A gradient-boosting model is used as the second branch of the architecture. This component processes structured patient features and learns nonlinear relationships among variables.

Let the tabular representation be

$$z = [z_1, z_2, \dots, z_m], \quad (3)$$

where each z_i represents a clinical feature.

The tabular model produces an embedding

$$g(z) = T(z), \quad (4)$$

where T represents the trained nonlinear learner.

F. Feature Fusion

The outputs of the temporal and tabular branches are combined into a unified patient representation:

$$F = [h_T \| g(z)], \quad (5)$$

where h_T represents the final temporal state and $\|$ denotes vector concatenation.

The fused representation provides information about both the patient's recent trajectory and overall clinical condition.

G. Discharge Readiness Prediction

The classification branch estimates the probability of discharge readiness:

$$P(D = 1|F) = \frac{1}{1 + \exp[-(w^T F + b)]}, \quad (6)$$

where F is the fused representation, w is the learned parameter vector, and b is the bias term.

A probability threshold can then be selected to distinguish likely discharge-ready and not-yet-ready cases.

H. Excess ICU Stay Estimation

The regression branch estimates the expected number of additional ICU days:

$$\hat{E} = R(F), \quad (7)$$

where R represents the regression function and $\hat{E}$ is the predicted excess stay.

The predicted duration may be constrained to non-negative values because an excess stay cannot be less than zero.

I. Joint Optimization

The two outputs can be optimized using a combined objective:

$$\mathcal{L} = \lambda_c \mathcal{L}_{\text{classification}} + \lambda_r \mathcal{L}_{\text{regression}}, \quad (8)$$

where λ_c and λ_r control the contribution of the classification and regression objectives.

Binary cross-entropy can be used for discharge classification:

$$\mathcal{L}_{\text{classification}} = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]. \quad (9)$$

Mean squared error can be used for excess-stay estimation:

$$\mathcal{L}_{\text{regression}} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2. \quad (10)$$

VI. ALGORITHM

Algorithm 1: Hybrid ICU Discharge and Excess-Stay Prediction

- 1) Collect ICU observations for each patient.
- 2) Check the records for invalid, duplicated, or inconsistent observations.
- 3) Handle missing values and normalize numerical variables.
- 4) Arrange physiological measurements according to their timestamps.
- 5) Construct temporal windows and summary clinical features.
- 6) Pass sequential observations through the temporal encoder.

- 7) Pass structured clinical features through the tabular learning branch.
- 8) Fuse the outputs of both branches.
- 9) Calculate the probability of ICU discharge readiness.
- 10) Estimate the expected excess ICU stay.
- 11) Evaluate the predictions using classification and regression metrics.
- 12) Present the results as clinical decision-support information.

VII. PERFORMANCE EVALUATION

The proposed framework uses separate metrics for the classification and regression tasks.

A. Classification Metrics

Accuracy is calculated as

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}. \quad (11)$$

Precision is given by

$$\text{Precision} = \frac{TP}{TP + FP}. \quad (12)$$

Recall is calculated as

$$\text{Recall} = \frac{TP}{TP + FN}. \quad (13)$$

The F1-score is defined as

$$F1 = 2 \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \quad (14)$$

AUROC can additionally be used to evaluate discrimination across different probability thresholds.

B. Regression Metrics

Mean Absolute Error is

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|. \quad (15)$$

Root Mean Squared Error is

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}. \quad (16)$$

Lower MAE and RMSE values indicate more accurate excess-stay estimation.

VIII. PERFORMANCE COMPARISON

Table I provides an illustrative comparison of the modelling approaches. The numerical values are placeholders and should be replaced with experimentally obtained results after training and testing the models on the selected dataset.

IX. RESULT VISUALIZATION

Figure 2 presents an illustrative visualization of classification performance.

TABLE I
ILLUSTRATIVE MODEL COMPARISON

Model	Accuracy	Precision	Recall	F1
Logistic Regression	82.4	81.8	80.9	81.3
Random Forest	87.6	86.9	86.2	86.5
LSTM	89.3	88.7	88.1	88.4
Hybrid Model	93.1	92.6	92.0	92.3

Values are illustrative and are not claimed as experimental results.

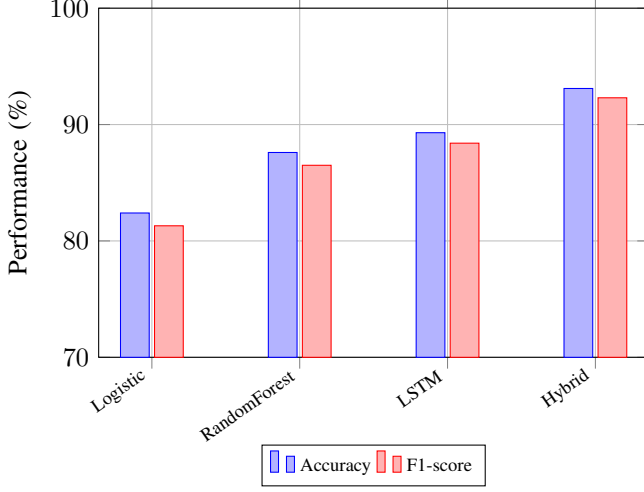


Fig. 2. Illustrative comparison of classification performance.

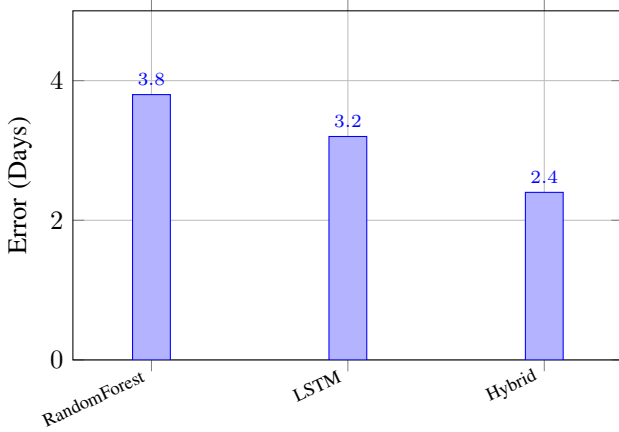


Fig. 3. Illustrative MAE comparison for excess ICU stay estimation.

X. DISCUSSION

The proposed architecture combines two complementary sources of information. The temporal branch focuses on the evolution of patient condition, whereas the tabular branch captures nonlinear interactions among summarized clinical variables.

This combination is useful because ICU discharge decisions are influenced by both recent trends and the patient's broader clinical state. For example, a single oxygen saturation measurement may not provide sufficient information about respiratory stability. A sequence showing persistent improvement or deterioration can provide additional evidence.

The excess-stay prediction component adds another dimension to the decision-support process. Instead of providing only a binary discharge recommendation, the framework can estimate whether additional ICU occupancy is likely and approximately quantify its duration.

The outputs should be interpreted as predictive information rather than autonomous medical decisions. Clinical professionals must consider factors that may not be represented in the available dataset, including bedside assessment, treatment goals, family preferences, and institutional protocols.

XI. NOVELTY AND KEY CONTRIBUTIONS

The proposed framework introduces several aspects that distinguish it from a single-task ICU prediction system.

- **Dual prediction objective:** The framework addresses discharge readiness and excess ICU duration within one predictive architecture.
- **Temporal-tabular integration:** Longitudinal physiological observations are combined with structured clinical summaries.
- **Patient-state representation:** The fusion layer creates a unified representation of the patient's current clinical condition.
- **Resource-aware prediction:** Excess-stay estimation can provide information useful for ICU capacity and bed planning.
- **Flexible hybrid architecture:** The temporal component and tabular learner can be replaced or improved independently as better models become available.
- **Decision-support orientation:** The system is designed to provide predictions that assist clinicians rather than automatically determine patient discharge.
- **Extendable framework:** The architecture can incorporate additional information such as clinical notes, imaging information, medication trajectories, and other hospital data.

XII. SCOPE OF THE WORK

The scope of the proposed research includes the development of a computational framework for analysing ICU patient records and generating two predictive outputs.

The work covers:

- prediction of near-term ICU discharge readiness;
- estimation of excess ICU stay duration;
- processing of time-dependent physiological observations;
- analysis of laboratory and clinical variables;
- integration of temporal and tabular machine learning;
- performance evaluation using classification and regression metrics;
- visualization of prediction results;
- potential support for ICU resource planning;
- development of an interpretable decision-support workflow.

The current framework is primarily focused on structured ICU information. Direct autonomous clinical decision making, regulatory certification, and replacement of physician judgment are outside the intended scope.

XIII. LIMITATIONS

The proposed framework has several limitations that should be considered during implementation and evaluation.

- 1) **Data quality:** Clinical datasets may contain missing, noisy, delayed, or incorrectly recorded observations. Poor data quality can affect model reliability.
- 2) **Dataset bias:** A model trained using data from one hospital may not perform equally well in another institution because clinical protocols and patient populations can differ.
- 3) **Temporal irregularity:** ICU measurements are not always collected at uniform intervals. Irregular sampling can make temporal modelling difficult.
- 4) **Class imbalance:** The number of patients ready for discharge may differ considerably from the number of patients who are not ready, creating an imbalance problem.
- 5) **Clinical complexity:** Some discharge decisions depend on information that may not be captured in structured datasets.
- 6) **Interpretability:** Complex hybrid models may be difficult to interpret compared with simple rule-based approaches.
- 7) **Generalization:** A model that performs well on historical records may experience reduced performance when clinical practices or patient populations change.
- 8) **Prediction uncertainty:** Both discharge probability and excess-stay estimates contain uncertainty and should therefore be accompanied by appropriate confidence information.
- 9) **Privacy and security:** ICU records contain sensitive health information. Data processing must follow applicable privacy, security, and governance requirements.
- 10) **Clinical validation:** Extensive external and prospective validation is necessary before such a system can be considered for routine clinical use.

XIV. FUTURE RESEARCH DIRECTIONS

Several extensions can improve the proposed framework.

First, transformer-based models can be incorporated to analyse clinical notes and other unstructured medical text. Such information may contain details that are unavailable in structured variables.

Second, uncertainty-aware prediction can be investigated so that the system reports prediction intervals rather than only point estimates for excess stay.

Third, explainable AI techniques can be integrated to identify the clinical variables and temporal patterns that contribute most strongly to each prediction.

Fourth, federated learning can be explored to enable collaboration across hospitals while reducing the need to centralize sensitive patient data.

Finally, prospective clinical evaluation can determine whether the predictions improve discharge planning, reduce avoidable ICU occupancy, and maintain patient safety.

XV. CONCLUSION

This paper presented a hybrid framework for predicting ICU discharge readiness and estimating excess ICU stay duration. The proposed architecture combines temporal patient information with structured clinical features and generates two complementary outputs: a probability of near-term discharge readiness and an estimate of additional ICU duration.

The central idea is to represent both the current clinical state and the trajectory of patient recovery. Such a representation can provide more useful information than relying on a single severity score or a fixed length-of-stay threshold.

The framework has potential applications in clinical decision support, personalized discharge planning, and ICU resource management. However, reliable deployment requires careful validation, attention to data quality, protection of patient privacy, and appropriate interpretation by clinical professionals.

Future research will focus on multimodal clinical data, explainable prediction, uncertainty estimation, federated learning, and prospective validation across multiple healthcare institutions.

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REFERENCES

- [1] A. E. W. Johnson *et al.*, "MIMIC-III, a freely accessible critical care database," *Scientific Data*, vol. 3, 2016.
- [2] T. J. Pollard *et al.*, "The eICU Collaborative Research Database, a freely available multi-center database for critical care research," *Scientific Data*, vol. 5, 2018.
- [3] A. Rajkomar *et al.*, "Scalable and accurate deep learning with electronic health records," *npj Digital Medicine*, vol. 1, 2018.
- [4] H. Harutyunyan, H. Khachatrian, D. C. Kale, and A. Galstyan, "Multi-task learning and benchmarking with clinical time series data," *Scientific Data*, vol. 6, 2019.
- [5] Z. Che, S. Purushotham, K. Cho, D. Sontag, and Y. Liu, "Recurrent neural networks for multivariate time series with missing values," *Scientific Reports*, vol. 8, 2018.
- [6] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [7] K. Cho *et al.*, "Learning phrase representations using RNN encoder-decoder for statistical machine translation," in *Proc. EMNLP*, 2014, pp. 1724–1734.
- [8] L. Breiman, "Random forests," *Machine Learning*, vol. 45, pp. 5–32, 2001.
- [9] J. H. Friedman, "Greedy function approximation: A gradient boosting machine," *Annals of Statistics*, vol. 29, no. 5, pp. 1189–1232, 2001.
- [10] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. ACM SIGKDD*, 2016, pp. 785–794.
- [11] A. Vaswani *et al.*, "Attention is all you need," in *Advances in Neural Information Processing Systems*, vol. 30, 2017.
- [12] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proc. NAACL-HLT*, 2019, pp. 4171–4186.
- [13] E. J. Topol, *Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again*. Basic Books, 2019.
- [14] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016.
- [15] C. Molnar, *Interpretable Machine Learning*. 2022.