ICU Stroke Patients Mortality Prediction using Transformers: Enhanced Prediction and Factor Mining

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Abstract

This study explored applying advanced machine learning techniques to model mortality prediction in ICU stroke patients, utilising data from 4558 patients (842 deceased) in the MIMIC-IV. A comprehensive feature selection process was applied to facilitate factor mining. Several models including XGBoost, Logistic Regression, MLP and Transformers were experimented, with the Transformer beating previous baseline MLP by 7%. Features selected for the final model and their SHAP directional effects overwhelmingly aligned with existing literature, with 3 novel factors undercovered. Such results support the effectiveness of the Transformer model quantitatively and qualitatively for real-time mortality prediction of ICU stroke patients.

Keywords: Stroke, ICU Mortality, Deep Learning, Transformers, MIMIC-IV

1 Introduction

Stroke is a critical global health concern, contributing significantly to morbidity and mortality with approximately 4.5 million annual deaths worldwide; survivors often endure long-term disabilities [1]. Accurate prediction of stroke patient outcomes can enhance patient care, optimise healthcare resource allocation, and support clinical decision-making processes [2].

Advancements in deep learning have demonstrated substantial improvements in various healthcare applications [3,4], including mortality prediction in stroke patients [5]. This project aims to leverage the MIMIC-IV database to identify stroke patient cohorts with comprehensive features to analyse factors influencing mortality risk. We seek to enhance the performance of ICU stroke patient mortality predictions with state-of-the-art deep learning, aiming to produce a passive real-time death risk predictor that aids resource allocation and prioritisation in the ICU, and along the process uncover factors that contribute to stroke mortality in the ICU.

Our methodology encompasses the selection of relevant patient cohorts, feature extraction through digital phenotyping, and the evaluation of various models to determine the most effective approach [6]. The study focuses on identifying key predictors of mortality and examining the impact of critical factors such as medical procedures and vital sign metrics.

Our contributions are as follows:

1. Curate a new dataset for stroke ICU patients based on the MIMIC-IV dataset with open-sourced code for reproducibility;
2. Enhance mortality prediction performance (F1) of previous state-of-the-art model by 7%;
3. Uncover new factors that contribute to mortality risk, which were not highlighted in previous research.

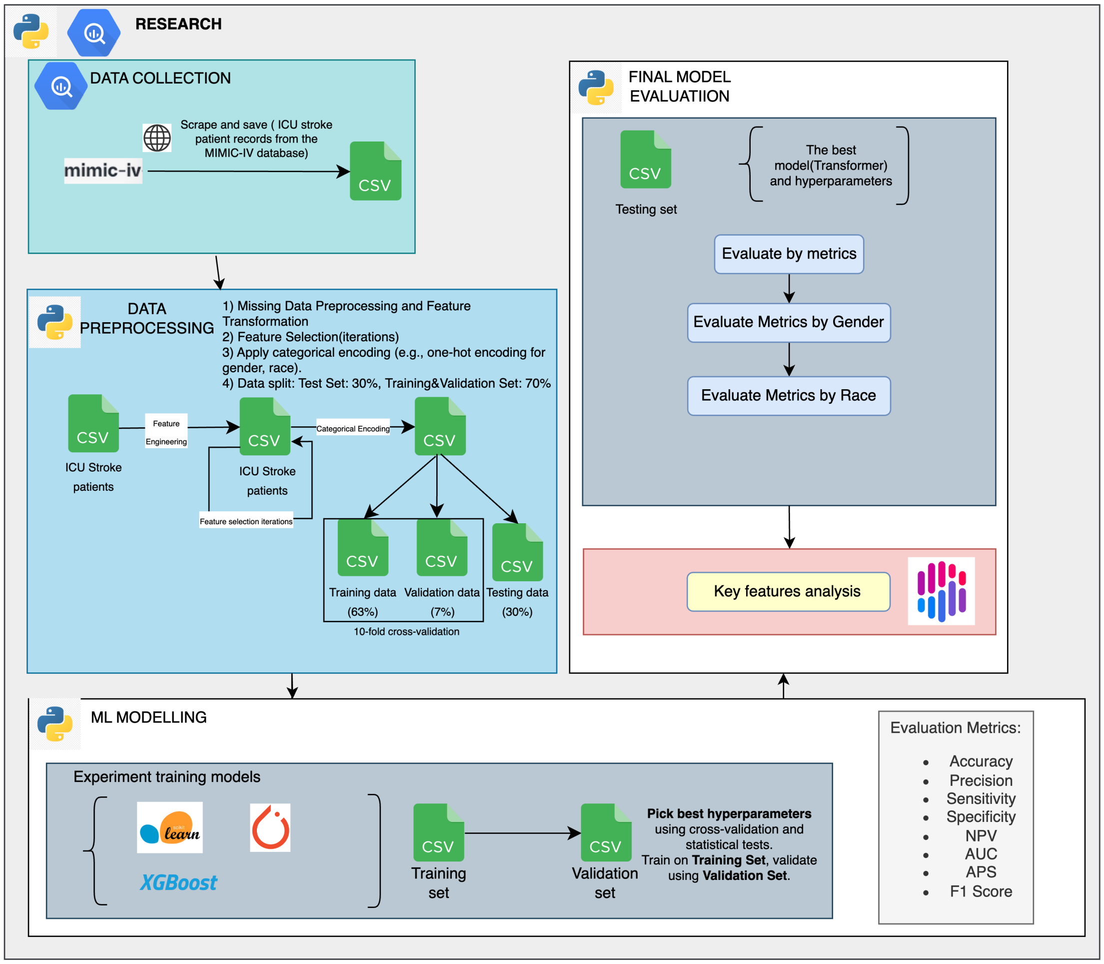


Figure 1. The overall pipeline of our study

2 Data Curation and Phenotyping

The primary data source for this study is the MIMIC-IV version 2.2 database, containing de-identified health-related data from over 70,000 ICU admissions at the Beth Israel Deaconess Medical Center between 2008 and 2019[7].

2.1 Patient Selection and ICD Codes

Patients diagnosed with stroke were identified using relevant ICD-9 and ICD-10 codes for cerebrovascular diseases (Table A.8). ICD codes were filtered using key terms commonly associated with stroke and cerebrovascular diseases. Specifically, we searched for codes that included terms such as "cerebral infarction", "stroke," "cerebral hemorrhage", "subarachnoid hemorrhage", and "intracranial hemorrhage". This comprehensive list ensures that we capture a broad range of stroke-related conditions, including ischemic stroke, hemorrhagic stroke, and other cerebrovascular events. We also filtered out terms that were irrelevant to an adult suffering the disease, such as "family history", "head trauma" and "newborn".

2.2 Feature Selection and Rationale

A comprehensive set of features relevant to stroke prognosis was identified and collected, guided by their clinical significance and documented impact on patient outcomes. This initial feature set was informed by established literature[8] and encompasses a wide range of variables, including treatment interventions, organ dysfunction measures, and procedural indicators.

We utilised three key categories of features from the MIMIC-IV dataset relevant to stroke prognosis: ICU vital signs (i.e. heart rate, blood pressure, oxygen saturation), lab test results, and surgical procedures. The selection of these features are based on their well-documented relevance in the literature to stroke outcomes.

Non-invasive "procedures" type features (i.e. imaging, lab tests, or meeting with patient family) were excluded as these features do not fundamentally impact the patient's clinical condition and do not align with our research's aim.

3 Methodology

3.1 Missing Data Pre-processing and Feature Transformation

The following pre-processing procedures were undertaken:

- Non-ICU patients or those discharged to hospice care were removed, as they did not align with the study aim.
- Features with more than 500 nulls were dropped to preserve sample size.
- All "procedure" features and "ventilation duration" were booleanised based on whether their value was null (not undergone).
- Feature "unique drugs" was 0-imputed as it is safe to assume patients with nan values had no drug administered.
- Categorical features "gender" and "race" were one-hot-encoded.
- Samples with any missing values in the remaining columns were dropped.

Table A.9 presents the full list of pre-processed features.

3.2 Feature Selection

The Mann-Whitney U test, Chi-Square test were conducted to evaluate the statistical significance of both continuous and categorical features' association with the target; non-significant features at a significant level of 0.05 were removed under the assumption that features with no association have no predictive power (Table 1 & 2). Spearman's correlation test was also conducted to remove correlated features that cause overfit, and only one of each highly correlated feature pairs ($|r| > 0.8$) were retained (Table 3 and Figure 2).

The final sample had 4558 samples, of which 842 (18.5%) were positive (death) and 3716 (81.5%) were negative (Figure A.7). See Table A.10 for full list of retained features for modelling and Table A.11 for their summary statistics.

The retained features were further selected through hyperparameter tuning: an XGB model is first fitted using the training sets of the pre-processed data, with its feature importance extracted to create a list of hyperparameter values for the hyperparameter **feature**: the first value is *{most important feature}*, the second value is *{most important feature, second most important feature}* etc, until the final value uses all retained features. One-hot-encoded features are constrained to appear together (i.e. if the *most important feature* was *Gender:Male*, then the first hyperparameter value of **features** will be *{Gender:Male, Gender:Female}* etc,.).

Table 1. Mann-Whitney U Test Results (p-values rounded to 3 decimal places)

Feature	p-value	Feature	p-value	Feature	p-value
anchor_age	0.000	creatinine	0.000	spo2	0.000
item_51006	0.000	bun	0.000	glucose	0.000
item_51221	0.000	urine_output_total	0.000	hospital_stay_duration	0.000
item_51222	0.000	pt	0.000	icu_stay_duration	0.008
item_51265	0.000	inr	0.000	systolic_bp	0.006
item_51301	0.000	systolic_bp	0.006	diastolic_bp	0.010
total_drugs	0.000	mean_arterial_pressure	0.002	heart_rate	0.000
unique_drugs	0.000	resp_rate	0.000	temperature	0.112
lods_score	0.000	potassium	0.001	sodium	0.317
oasis_score	0.000				

Table 2. Chi-Square Test Results (p-values rounded to 3 decimal places)

Feature	p-value	Feature	p-value	Feature	p-value
subject_id	0.493	procedure_225427	0.011	procedure_226475	0.007
hadm_id	0.493	procedure_225430	0.006	procedure_227194	0.000
ventilation_used	0.000	procedure_225432	0.009	procedure_227712	0.000
gender	0.647	procedure_225444	0.000	procedure_228125	0.000
mortality_status	0.000	procedure_225446	0.016	procedure_228127	0.000
admission_type	0.000	procedure_225451	0.000	procedure_228128	0.000
insurance	0.006	procedure_225454	0.000	procedure_228130	0.000
marital_status	0.000	procedure_225457	0.043	procedure_228715	0.005
race	0.000	procedure_225459	0.000	procedure_229298	0.002
procedure_221214	0.001	procedure_225464	0.001	procedure_229351	0.000
procedure_221216	0.666	procedure_225469	0.000	procedure_229380	0.000
procedure_221217	0.660	procedure_225470	0.018	procedure_229519	0.002
procedure_221223	0.000	procedure_225752	0.000	procedure_229580	0.000
procedure_221255	0.086	procedure_225792	0.000	procedure_229581	0.000
procedure_223253	0.000	procedure_225802	0.000	procedure_229582	0.000
procedure_224263	0.000	procedure_225817	0.034	procedure_229614	0.001
procedure_224264	0.757	procedure_226124	0.008	procedure_225399	1.000
procedure_224267	0.000	procedure_226236	0.020	procedure_225402	0.736
procedure_224268	0.094	procedure_225437	1.000	procedure_225433	0.418
procedure_224269	0.115	procedure_225439	0.831	procedure_225440	0.804
procedure_224270	0.000	procedure_225441	0.067	procedure_225462	0.278
procedure_224272	0.417	procedure_225448	0.135	procedure_225468	0.114
procedure_224274	0.000	procedure_225451	0.000	procedure_225457	0.043
procedure_224275	0.000	procedure_225454	0.000	procedure_225459	0.000
procedure_224276	0.000	procedure_225446	0.016	procedure_225464	0.001
procedure_224277	0.780	procedure_228127	0.000	procedure_229581	0.000

3.3 Data Partitioning and Modelling

10-fold cross-validation (10CV) was used to select hyperparameters for each model, based on the highest mean validation score. 30% of all data is held-out as test set, and hence each fold's train and val data are 63% and 7% of the original. All splits were stratified on gender and outcome to preserve the distribution of these features and improve the generalisability of results.

The Transformer[9] (Figure 3) is a powerful neural network architecture based on the attention mechanism. It has state-of-the-art signal encoding capabilities on large datasets. We experiment on the performance of transformers alongside well-known ML models such as Support Vector Machines (SVM), Logistic Regression (LogReg), Naive Bayes (NB), XGBoost (XGB) & Multi-Layer Perceptron (MLP) for this ICU stroke mortality problem.

A statistical-greedy algorithm is used for hyperparameter-tuning instead of RandomGridSearch, striking an optimum in the tradeoff between computation complexity while ensuring precision in finding the highest validation score combination. Best hyperparameters are presented in Table A.13.

All experiments were run on Python 3.10 on a Colab environment on a T4 GPU.

Table 3. Highly Correlated Pairs and Selected Features

Correlated Pair	r value	Dropped Feature
(item_51222, item_51221)	0.959	item_51222
(unique_drugs, total_drugs)	0.888	unique_drugs
(bun, item_51006)	1.000	bun
(inr, pt)	0.942	pt
(mean_arterial_pressure, diastolic_bp)	0.887	mean_arterial_pressure

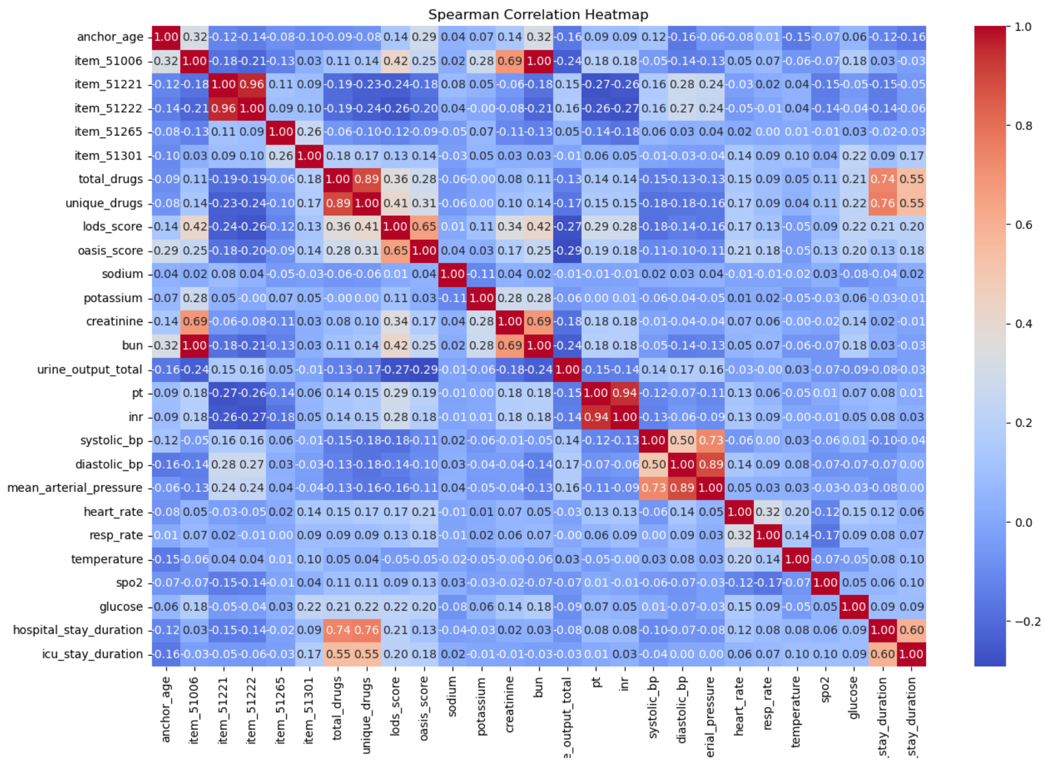


Figure 2. Spearman's Correlation between features

4 Results & Discussion

4.1 Model Evaluation

Since the dataset's outcome is imbalanced, the primary metric used to select and evaluate models is F1, the harmonic mean of precision and sensitivity. Medical systems should both reduce false positives and false negatives to avoid both alarm fatigue and misdiagnosis of positive cases[10], hence F1 is the optimal metric. Area-under-ROCCurve (AUC) and Average Precision (AP) are metrics to evaluate how well the model discriminates the outcomes at different probability thresholds. Other metrics like accuracy, specificity, NPV are also presented for reference.

The aforementioned metrics are defined as follows:

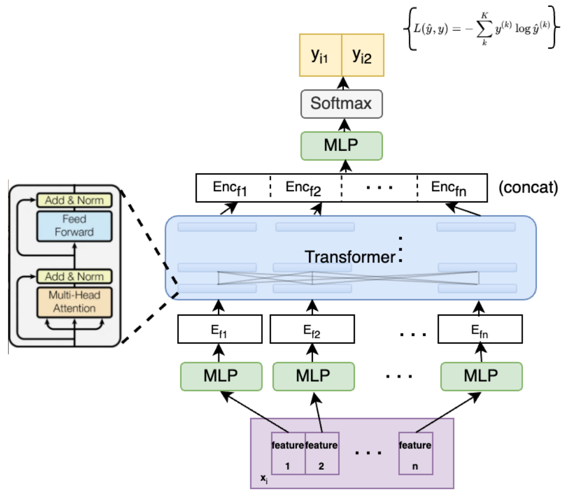


Figure 3. An encoder-only Transformer architecture, which better represents the transformer model used in this report compared to the encoder-decoder structure presented in the original paper, which is often misleading for readers.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{2}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

$$\text{Sensitivity (Recall)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{5}$$

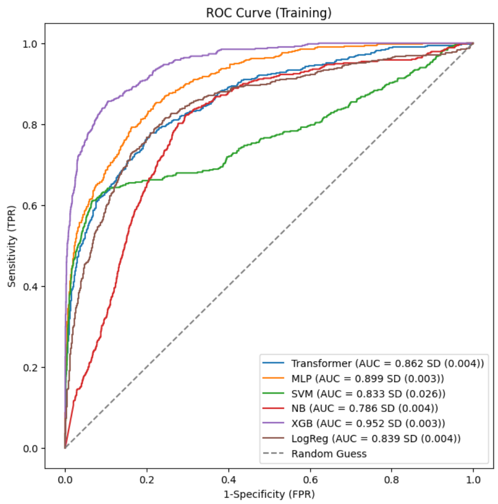
$$\text{Negative Predictive Value (NPV)} = \frac{\text{TN}}{\text{TN} + \text{FN}} \tag{6}$$

where: TP: True Positives; TN: True Negatives; FP: False Positives; FN: False Negatives

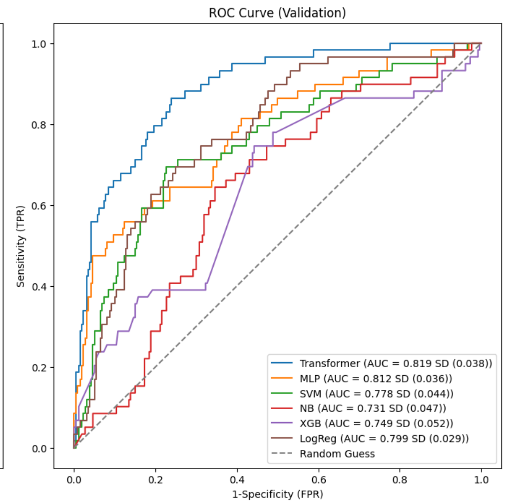
From Table 4, Transformers achieved the best mean validation F1 (0.548) compared to baseline (0), outperforming second best MLP (0.511) by 0.037. It achieved 3rd in precision (0.497) and 1st in sensitivity (0.664). If higher precision is required to avoid alarm fatigue, Logistic Regression is a better choice (0.665) but has much higher false negative with a weak sensitivity (0.076). Transformers also have the best AUC (0.819) and AP (0.563) scores, and hence are determined as the best model for mortality prediction in stroke ICU patients.

Observing the Validation ROC, PR and Decision Curve plots (Figure 4b, 4d, 4f), Transformers clearly outperforms other models, and also is the most well calibrated among the 6 models (Figure 4e). Delong tests measure statistical significance in the difference of AUC tests. Transformer's AUC is significantly greater than all models except for MLP (Table A.12); this aligns with ML literature that Transformers and deep learning have greater information encoding capabilities than non-deep models, given sufficient sample size.

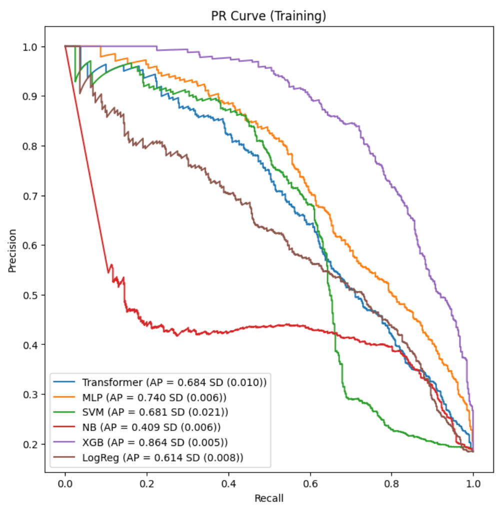
We trained transformers using the union of all 10CV data combined (70%) and evaluated its performance on the 30% test data (see Table 5, Figure 5 & A.8), achieving higher F1 (0.612), precision (0.724) and AP (0.871) but lower sensitivity (0.530) and AUC (0.707). This suggests that the model has generalised its performance onto a previously unobserved dataset; however, live clinical trials should be undertaken to validate this result further.



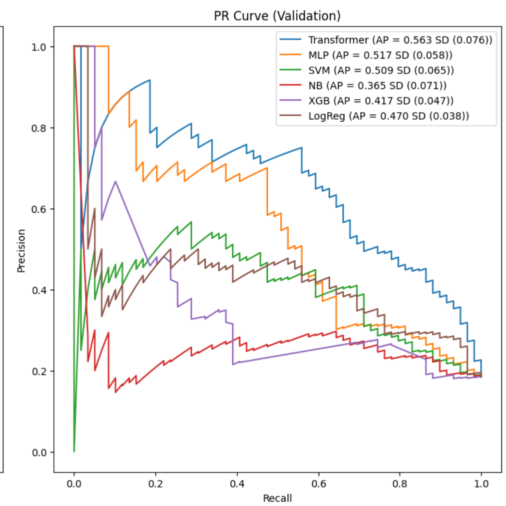
(a) Training ROC Curve of 6 models



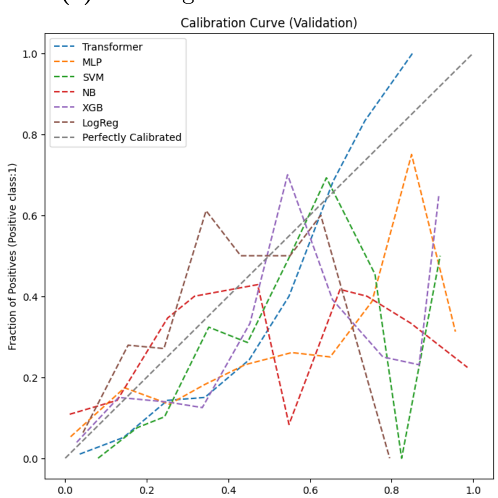
(b) Validation ROC Curve of 6 models



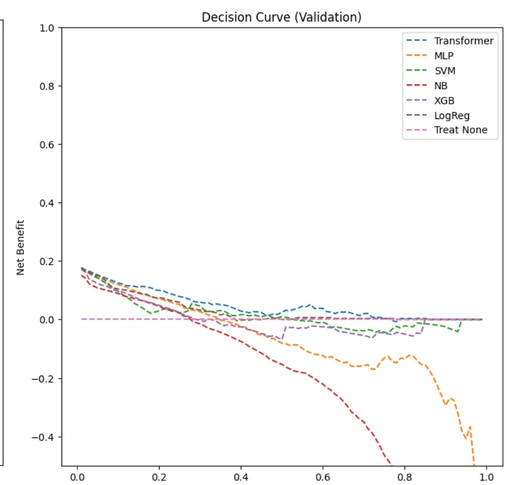
(c) Training PR Curve of 6 models



(d) Validation PR Curve of 6 models



(e) Validation Calibration Curve of 6 models



(f) Validation Decision Curve of 6 models

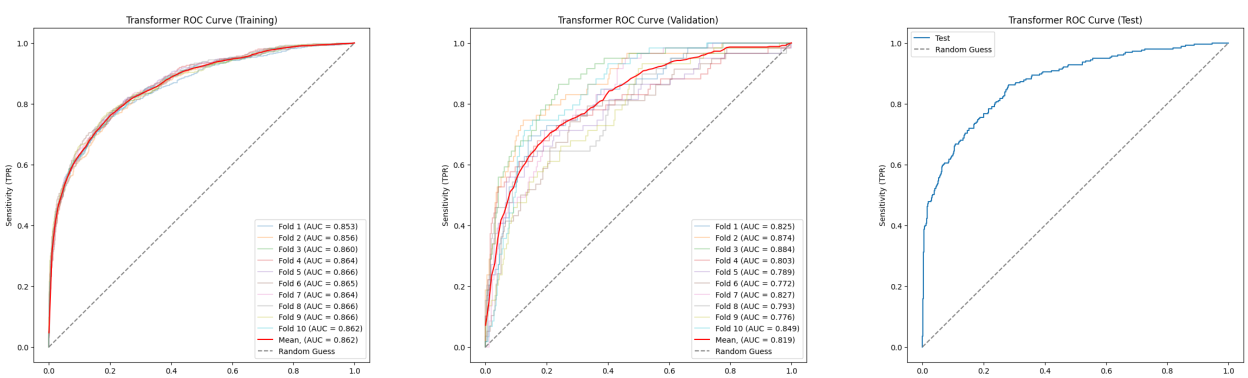
Figure 4. Key curves comparing 6 models

Table 4. Comparison of Key Metrics for 6 Models (Transformer, MLP, SVM, NB, XGB, LogReg) on Training and Validation Sets. Best metrics are bolded

Metric	Transformer	MLP	SVM	NB	XGB	LogReg
Training Set						
Accuracy	0.873 (±0.005)	0.883 (±0.002)	0.882 (±0.002)	0.693 (±0.022)	**0.918** (±0.002)	0.856 (±0.002)
Precision	0.808 (±0.045)	0.852 (±0.029)	0.808 (±0.029)	0.358 (±0.014)	**0.879** (±0.009)	0.706 (±0.008)
Sensitivity	0.413 (±0.060)	0.446 (±0.030)	0.479 (±0.029)	**0.830** (±0.024)	0.644 (±0.009)	0.375 (±0.010)
Specificity	0.977 (±0.010)	**0.982** (±0.005)	0.974 (±0.006)	0.662 (±0.032)	0.980 (±0.002)	0.965 (±0.001)
NPV	0.880 (±0.010)	0.887 (±0.005)	0.892 (±0.005)	**0.945** (±0.005)	0.924 (±0.002)	0.872 (±0.002)
AUC	0.862 (±0.004)	0.899 (±0.003)	0.833 (±0.026)	0.786 (±0.004)	**0.952** (±0.003)	0.839 (±0.004)
AP	0.684 (±0.010)	0.740 (±0.006)	0.681 (±0.021)	0.409 (±0.006)	**0.864** (±0.005)	0.614 (±0.008)
F1 Score	0.542 (±0.046)	0.584 (±0.020)	0.600 (±0.017)	0.500 (±0.011)	**0.743** (±0.008)	0.489 (±0.009)
Validation Set						
Accuracy	0.792 (±0.056)	0.768 (±0.039)	0.813 (±0.025)	0.735 (±0.033)	0.745 (±0.058)	**0.821** (±0.006)
Precision	0.497 (±0.130)	0.432 (±0.074)	0.503 (±0.069)	0.366 (±0.048)	0.405 (±0.073)	**0.665** (±0.151)
Sensitivity	**0.664** (±0.098)	0.655 (±0.111)	0.474 (±0.049)	0.579 (±0.099)	0.613 (±0.197)	0.076 (±0.032)
Specificity	0.822 (±0.085)	0.794 (±0.066)	0.889 (±0.036)	0.770 (±0.043)	0.774 (±0.105)	**0.990** (±0.009)
NPV	**0.916** (±0.016)	0.912 (±0.022)	0.882 (±0.008)	0.891 (±0.023)	0.903 (±0.033)	0.826 (±0.005)
AUC	**0.819** (±0.038)	0.812 (±0.036)	0.778 (±0.044)	0.731 (±0.047)	0.749 (±0.052)	0.799 (±0.029)
AP	**0.563** (±0.076)	0.517 (±0.058)	0.509 (±0.065)	0.365 (±0.071)	0.417 (±0.047)	0.470 (±0.038)
F1 Score	**0.548** (±0.053)	0.511 (±0.042)	0.484 (±0.036)	0.446 (±0.054)	0.459 (±0.080)	0.134 (±0.050)

Table 5. Train and Test Data Metrics for Transformer

Metric	Train Data	Test Data
Accuracy	0.871	0.876
Precision	0.704	0.724
Sensitivity	0.516	0.530
Specificity	0.951	0.954
NPV	0.897	0.899
AUC	0.686	0.707
APS	0.862	0.871
F1 Score	0.595	0.612
n	3190	1368



(a) Training ROC Curves **(b)** Validation ROC Curves **(c)** Testing ROC Curve

Figure 5. Transformer ROC Curves

4.1.1 Bias evaluation The test set performance results for each gender and race were also evaluated, with results presented in Tables 6 & 7. Key metrics for each gender have statistically insignificant differences, with male patients having slightly lower AUC and APs. The F1 scores for patients of each race are also largely the same for races with more than 10 patients. Thus we conclude there to be no significant model biases that significantly adversely affect either gender or race.

Table 6. Test Data Metrics by Gender for Transformer

Metric	Test Data (Male)	Test Data (Female)
Accuracy	0.876	0.874
Precision	0.703	0.725
Sensitivity	0.542	0.541
Specificity	0.949	0.952
NPV	0.904	0.899
AUC	0.689	0.722
APS	0.858	0.883
F1 Score	0.612	0.620
n	723	645

Table 7. Test Data Metrics by Race for Transformer

Metric	Asian	Black	Hispanic/Latino	Hispanic or Latino	Other	White
Accuracy	0.778	0.858	0.857	0.889	0.896	0.888
Precision	0.667	0.667	0.500	1.000	0.667	0.634
Sensitivity	0.400	0.381	0.500	0.800	0.333	0.500
Specificity	0.923	0.960	0.917	1.000	0.976	0.952
NPV	0.800	0.880	0.917	0.800	0.911	0.920
AUC	0.786	0.612	0.692	1.000	0.584	0.633
APS	0.923	0.883	0.884	1.000	0.778	0.847
F1 Score	0.500	0.485	0.500	0.889	0.444	0.559
n	18	120	42	9	48	830

4.2 Feature Analysis and Discussion

The final model used nine features, with SHAP analysis (Figure 6 & A.9) and referenced against the literature, ranked by their predictive importance.

Invasive Ventilation

Invasive ventilation refers to mechanical respiratory support for patients with compromised breathing functions. Our model's SHAP values indicate that invasive ventilation significantly increases mortality risk. This finding aligns with de Jonge et al.[11], who reported a 49% increase in one-year mortality among ischemic stroke patients requiring invasive ventilation.

Length of Hospital Stay

The SHAP values from our model show that shorter hospital stays (LoS) are associated with higher mortality risk, contradicting Somerford et al.[12] who found extended hospital stays correlated with higher mortality rates. We believe LoS may have accounted for confounding factors in previous studies, which are now correctly accounted for by other features, enabled by the transformer's superior encoding capabilities. Ultimately, mortality tends to occur quickly after admission for stroke ICU patients.

Logistic Organ Dysfunction System (LODS) Score

The LODS score quantifies the extent of a patient's organ dysfunction. Our model demonstrates that higher LODS scores are associated with increased mortality risk. This matches findings by Jin[13], indicating that greater organ dysfunction predicts higher mortality in critically ill stroke patients.

Ventilation Used

This refers to the use of both invasive and non-invasive ventilation support. SHAP values of our model suggest that ventilation use is linked to higher mortality risk, similar to findings on invasive ventilation.

Large Peripheral IV Catheter Used

This feature represents the utilisation of large-bore catheters in stroke patient management. Although routinely used, its direct relationship with stroke mortality is not established in the literature, making it a potentially novel predictive factor. SHAP analysis shows that its use is associated with decreased risk.

Dialysis—Continuous Renal Replacement Therapy (CRRT)

CRRT is initiated for acute kidney injury in stroke patients. Our model indicates that CRRT use is associated with increased mortality risk. Davenport[14] corroborates this by highlighting that standard dialysis can exacerbate brain swelling and injury in stroke patients, suggesting that patients requiring CRRT may have more severe complications.

External Ventricular Drain (EVD) Used

This neurosurgical procedure alleviates intracranial pressure in severe stroke cases. Our model shows that the use of EVDs is associated with higher mortality risk. Dey et al.[15] note that EVD use indicates significant neurological compromise and is associated with adverse outcomes.

Intraventricular Drain Inserted

An intraventricular drain relieves elevated intracranial pressure from hydrocephalus or hemorrhage. Similar to external drains, patients with an intraventricular drain showed higher SHAP values, indicating increased mortality. Fried et al.[16] also found intraventricular drains linked to higher mortality in severe intracranial conditions.

Removal of Temporary Pacemaker Wires

This procedure relates to the management of cardiac arrhythmias in stroke patients. Since existing literature has not linked this procedure to higher survival rates, it may be a novel predictive factor.

Summary

Most features and their direction of impact align with existing literature, providing domain-knowledge-based qualitative validation of our model. As such, we believe that the goal of producing a real-time mortality likelihood prediction model for stroke ICU patients - based on the procedures undertaken and other continuously updated metrics (LoS and LODS) - has been achieved.

Two novel predictive features were discovered as part of our study, and we found one feature to have the opposite direction of impact compared to literature.

4.3 Future Works

While our work is comprehensive, a further improvement would be to replicate the methodology on alternative datasets for result comparison and even conduct zero-shot inference (training with MIMIC data but evaluating on new dataset) to evaluate model robustness and generalisability of learned patterns.

The method of encoding vital signs (often recorded as a time series with each patient having a different number of observations) for tabular data has no consensus within the research community - our strategy to take the first observation aims to enforce feature homogeneity, but may be too crude, hence why none of the vital sign features were selected in the final model.

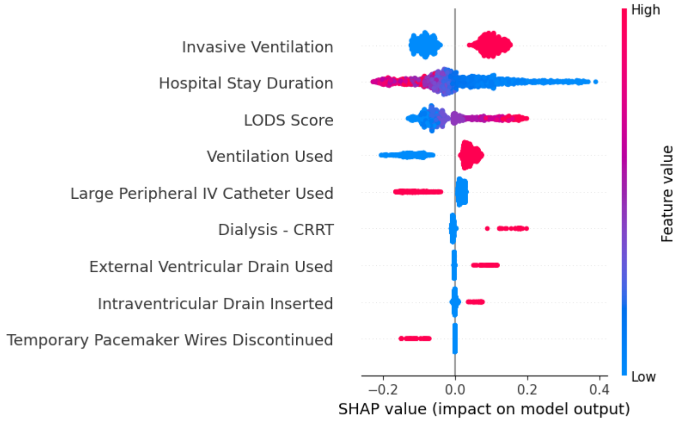


Figure 6. Transformer SHAP Summary Plot

5 Conclusion

In conclusion, this study demonstrates the potential of machine learning models in predicting mortality for ICU stroke patients. The model includes a combination of predictors from the literature and new insights uncovered during our analysis. The Transformer model achieved the highest performance, ranking first in Sensitivity, NPV, AUC, AP, and F1 Score. This proves its potential practical use as a robust real-time risk monitor in ICU settings.

Appendix

Table A.8. ICD Codes and Descriptions

ICD Code	Long Title
34660	Persistent migraine aura with cerebral infarction, without mention of intractable migraine without mention of status migrainosus
34661	Persistent migraine aura with cerebral infarction, with intractable migraine, so stated, without mention of status migrainosus
34662	Persistent migraine aura with cerebral infarction, without mention of intractable migraine with status migrainosus
34663	Persistent migraine aura with cerebral infarction, with intractable migraine, so stated, with status migrainosus
430	Subarachnoid hemorrhage
431	Intracerebral hemorrhage
4329	Unspecified intracranial hemorrhage
43300	Occlusion and stenosis of basilar artery without mention of cerebral infarction
43301	Occlusion and stenosis of basilar artery with cerebral infarction
43310	Occlusion and stenosis of carotid artery without mention of cerebral infarction
43311	Occlusion and stenosis of carotid artery with cerebral infarction
43320	Occlusion and stenosis of vertebral artery without mention of cerebral infarction
43321	Occlusion and stenosis of vertebral artery with cerebral infarction
43330	Occlusion and stenosis of multiple and bilateral precerebral arteries without mention of cerebral infarction
43331	Occlusion and stenosis of multiple and bilateral precerebral arteries with cerebral infarction
43380	Occlusion and stenosis of other specified precerebral artery without mention of cerebral infarction
43381	Occlusion and stenosis of other specified precerebral artery with cerebral infarction
43390	Occlusion and stenosis of unspecified precerebral artery without mention of cerebral infarction
43391	Occlusion and stenosis of unspecified precerebral artery with cerebral infarction
43400	Cerebral thrombosis without mention of cerebral infarction
43401	Cerebral thrombosis with cerebral infarction
43410	Cerebral embolism without mention of cerebral infarction
43411	Cerebral embolism with cerebral infarction
43490	Cerebral artery occlusion, unspecified without mention of cerebral infarction
43491	Cerebral artery occlusion, unspecified with cerebral infarction
7670	Subdural and cerebral hemorrhage
G436	Persistent migraine aura with cerebral infarction
G4360	Persistent migraine aura with cerebral infarction, not intractable
G43601	Persistent migraine aura with cerebral infarction, not intractable, with status migrainosus
G43609	Persistent migraine aura with cerebral infarction, not intractable, without status migrainosus
G4361	Persistent migraine aura with cerebral infarction, intractable
G43611	Persistent migraine aura with cerebral infarction, intractable, with status migrainosus
G43619	Persistent migraine aura with cerebral infarction, intractable, without status migrainosus
G463	Brain stem stroke syndrome
G464	Cerebellar stroke syndrome
I60	Nontraumatic subarachnoid hemorrhage
I600	Nontraumatic subarachnoid hemorrhage from carotid siphon and bifurcation
I6000	Nontraumatic subarachnoid hemorrhage from unspecified carotid siphon and bifurcation
I6001	Nontraumatic subarachnoid hemorrhage from right carotid siphon and bifurcation
I6002	Nontraumatic subarachnoid hemorrhage from left carotid siphon and bifurcation
I601	Nontraumatic subarachnoid hemorrhage from middle cerebral artery
I6010	Nontraumatic subarachnoid hemorrhage from unspecified middle cerebral artery
I6011	Nontraumatic subarachnoid hemorrhage from right middle cerebral artery
I6012	Nontraumatic subarachnoid hemorrhage from left middle cerebral artery
I602	Nontraumatic subarachnoid hemorrhage from anterior communicating artery
I6020	Nontraumatic subarachnoid hemorrhage from unspecified anterior communicating artery
I6021	Nontraumatic subarachnoid hemorrhage from right anterior communicating artery
I6022	Nontraumatic subarachnoid hemorrhage from left anterior communicating artery
I603	Nontraumatic subarachnoid hemorrhage from posterior communicating artery
I6030	Nontraumatic subarachnoid hemorrhage from unspecified posterior communicating artery
I6031	Nontraumatic subarachnoid hemorrhage from right posterior communicating artery
I6032	Nontraumatic subarachnoid hemorrhage from left posterior communicating artery
I604	Nontraumatic subarachnoid hemorrhage from basilar artery
I605	Nontraumatic subarachnoid hemorrhage from vertebral artery
I6050	Nontraumatic subarachnoid hemorrhage from unspecified vertebral artery
I6051	Nontraumatic subarachnoid hemorrhage from right vertebral artery
I6052	Nontraumatic subarachnoid hemorrhage from left vertebral artery
I606	Nontraumatic subarachnoid hemorrhage from other intracranial arteries
I607	Nontraumatic subarachnoid hemorrhage from unspecified intracranial artery
I608	Other nontraumatic subarachnoid hemorrhage
I609	Nontraumatic subarachnoid hemorrhage, unspecified
I61	Nontraumatic intracerebral hemorrhage
I610	Nontraumatic intracerebral hemorrhage in hemisphere, subcortical
I611	Nontraumatic intracerebral hemorrhage in hemisphere, cortical
I612	Nontraumatic intracerebral hemorrhage in hemisphere, unspecified
I613	Nontraumatic intracerebral hemorrhage in brain stem
I614	Nontraumatic intracerebral hemorrhage in cerebellum

Continued on next page

Table A.8 – continued from previous page

ICD Code	Long Title
I615	Nontraumatic intracerebral hemorrhage, intraventricular
I616	Nontraumatic intracerebral hemorrhage, multiple localized
I618	Other nontraumatic intracerebral hemorrhage
I619	Nontraumatic intracerebral hemorrhage, unspecified
I62	Other and unspecified nontraumatic intracranial hemorrhage
I629	Nontraumatic intracranial hemorrhage, unspecified
I63	Cerebral infarction
I630	Cerebral infarction due to thrombosis of precerebral arteries
I6300	Cerebral infarction due to thrombosis of unspecified precerebral artery
I6301	Cerebral infarction due to thrombosis of vertebral artery
I63011	Cerebral infarction due to thrombosis of right vertebral artery
I63012	Cerebral infarction due to thrombosis of left vertebral artery
I63013	Cerebral infarction due to thrombosis of bilateral vertebral arteries
I63019	Cerebral infarction due to thrombosis of unspecified vertebral artery
I6302	Cerebral infarction due to thrombosis of basilar artery
I6303	Cerebral infarction due to thrombosis of carotid artery
I63031	Cerebral infarction due to thrombosis of right carotid artery
I63032	Cerebral infarction due to thrombosis of left carotid artery
I63033	Cerebral infarction due to thrombosis of bilateral carotid arteries
I63039	Cerebral infarction due to thrombosis of unspecified carotid artery
I6309	Cerebral infarction due to thrombosis of other precerebral artery
I631	Cerebral infarction due to embolism of precerebral arteries
I6310	Cerebral infarction due to embolism of unspecified precerebral artery
I6311	Cerebral infarction due to embolism of vertebral artery
I63111	Cerebral infarction due to embolism of right vertebral artery
I63112	Cerebral infarction due to embolism of left vertebral artery
I63113	Cerebral infarction due to embolism of bilateral vertebral arteries
I63119	Cerebral infarction due to embolism of unspecified vertebral artery
I6312	Cerebral infarction due to embolism of basilar artery
I6313	Cerebral infarction due to embolism of carotid artery
I63131	Cerebral infarction due to embolism of right carotid artery
I63132	Cerebral infarction due to embolism of left carotid artery
I63133	Cerebral infarction due to embolism of bilateral carotid arteries
I63139	Cerebral infarction due to embolism of unspecified carotid artery
I6319	Cerebral infarction due to embolism of other precerebral artery
I632	Cerebral infarction due to unspecified occlusion or stenosis of precerebral arteries
I6320	Cerebral infarction due to unspecified occlusion or stenosis of unspecified precerebral arteries
I6321	Cerebral infarction due to unspecified occlusion or stenosis of vertebral arteries
I63211	Cerebral infarction due to unspecified occlusion or stenosis of right vertebral artery
I63212	Cerebral infarction due to unspecified occlusion or stenosis of left vertebral artery
I63213	Cerebral infarction due to unspecified occlusion or stenosis of bilateral vertebral arteries
I63219	Cerebral infarction due to unspecified occlusion or stenosis of unspecified vertebral artery
I6322	Cerebral infarction due to unspecified occlusion or stenosis of basilar artery
I6323	Cerebral infarction due to unspecified occlusion or stenosis of carotid arteries
I63231	Cerebral infarction due to unspecified occlusion or stenosis of right carotid arteries
I63232	Cerebral infarction due to unspecified occlusion or stenosis of left carotid arteries
I63233	Cerebral infarction due to unspecified occlusion or stenosis of bilateral carotid arteries
I63239	Cerebral infarction due to unspecified occlusion or stenosis of unspecified carotid artery
I6329	Cerebral infarction due to unspecified occlusion or stenosis of other precerebral arteries
I633	Cerebral infarction due to thrombosis of cerebral arteries
I6330	Cerebral infarction due to thrombosis of unspecified cerebral artery
I6331	Cerebral infarction due to thrombosis of middle cerebral artery
I63311	Cerebral infarction due to thrombosis of right middle cerebral artery
I63312	Cerebral infarction due to thrombosis of left middle cerebral artery
I63313	Cerebral infarction due to thrombosis of bilateral middle cerebral arteries
I63319	Cerebral infarction due to thrombosis of unspecified middle cerebral artery
I6332	Cerebral infarction due to thrombosis of anterior cerebral artery
I63321	Cerebral infarction due to thrombosis of right anterior cerebral artery
I63322	Cerebral infarction due to thrombosis of left anterior cerebral artery
I63323	Cerebral infarction due to thrombosis of bilateral anterior cerebral arteries
I63329	Cerebral infarction due to thrombosis of unspecified anterior cerebral artery
I6333	Cerebral infarction due to thrombosis of posterior cerebral artery
I63331	Cerebral infarction due to thrombosis of right posterior cerebral artery
I63332	Cerebral infarction due to thrombosis of left posterior cerebral artery
I63333	Cerebral infarction due to thrombosis of bilateral posterior cerebral arteries
I63339	Cerebral infarction due to thrombosis of unspecified posterior cerebral artery
I6334	Cerebral infarction due to thrombosis of cerebellar artery
I63341	Cerebral infarction due to thrombosis of right cerebellar artery
I63342	Cerebral infarction due to thrombosis of left cerebellar artery
I63343	Cerebral infarction due to thrombosis of bilateral cerebellar arteries
I63349	Cerebral infarction due to thrombosis of unspecified cerebellar artery
I6339	Cerebral infarction due to thrombosis of other cerebral artery
I634	Cerebral infarction due to embolism of cerebral arteries
I6340	Cerebral infarction due to embolism of unspecified cerebral artery
I6341	Cerebral infarction due to embolism of middle cerebral artery
I63411	Cerebral infarction due to embolism of right middle cerebral artery
I63412	Cerebral infarction due to embolism of left middle cerebral artery
I63413	Cerebral infarction due to embolism of bilateral middle cerebral arteries

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Table A.8 – continued from previous page

ICD Code	Long Title
I63419	Cerebral infarction due to embolism of unspecified middle cerebral artery
I6342	Cerebral infarction due to embolism of anterior cerebral artery
I63421	Cerebral infarction due to embolism of right anterior cerebral artery
I63422	Cerebral infarction due to embolism of left anterior cerebral artery
I63423	Cerebral infarction due to embolism of bilateral anterior cerebral arteries
I63429	Cerebral infarction due to embolism of unspecified anterior cerebral artery
I6343	Cerebral infarction due to embolism of posterior cerebral artery
I63431	Cerebral infarction due to embolism of right posterior cerebral artery
I63432	Cerebral infarction due to embolism of left posterior cerebral artery
I63433	Cerebral infarction due to embolism of bilateral posterior cerebral arteries
I63439	Cerebral infarction due to embolism of unspecified posterior cerebral artery
I6344	Cerebral infarction due to embolism of cerebellar artery
I63441	Cerebral infarction due to embolism of right cerebellar artery
I63442	Cerebral infarction due to embolism of left cerebellar artery
I63443	Cerebral infarction due to embolism of bilateral cerebellar arteries
I63449	Cerebral infarction due to embolism of unspecified cerebellar artery
I6349	Cerebral infarction due to embolism of other cerebral artery
I635	Cerebral infarction due to unspecified occlusion or stenosis of cerebral arteries
I6350	Cerebral infarction due to unspecified occlusion or stenosis of unspecified cerebral artery
I6351	Cerebral infarction due to unspecified occlusion or stenosis of middle cerebral artery
I63511	Cerebral infarction due to unspecified occlusion or stenosis of right middle cerebral artery
I63512	Cerebral infarction due to unspecified occlusion or stenosis of left middle cerebral artery
I63513	Cerebral infarction due to unspecified occlusion or stenosis of bilateral middle cerebral arteries
I63519	Cerebral infarction due to unspecified occlusion or stenosis of unspecified middle cerebral artery
I6352	Cerebral infarction due to unspecified occlusion or stenosis of anterior cerebral artery
I63521	Cerebral infarction due to unspecified occlusion or stenosis of right anterior cerebral artery
I63522	Cerebral infarction due to unspecified occlusion or stenosis of left anterior cerebral artery
I63523	Cerebral infarction due to unspecified occlusion or stenosis of bilateral anterior cerebral arteries
I63529	Cerebral infarction due to unspecified occlusion or stenosis of unspecified anterior cerebral artery
I6353	Cerebral infarction due to unspecified occlusion or stenosis of posterior cerebral artery
I63531	Cerebral infarction due to unspecified occlusion or stenosis of right posterior cerebral artery
I63532	Cerebral infarction due to unspecified occlusion or stenosis of left posterior cerebral artery
I63533	Cerebral infarction due to unspecified occlusion or stenosis of bilateral posterior cerebral arteries
I63539	Cerebral infarction due to unspecified occlusion or stenosis of unspecified posterior cerebral artery
I6354	Cerebral infarction due to unspecified occlusion or stenosis of cerebellar artery
I63541	Cerebral infarction due to unspecified occlusion or stenosis of right cerebellar artery
I63542	Cerebral infarction due to unspecified occlusion or stenosis of left cerebellar artery
I63543	Cerebral infarction due to unspecified occlusion or stenosis of bilateral cerebellar arteries
I63549	Cerebral infarction due to unspecified occlusion or stenosis of unspecified cerebellar artery
I6359	Cerebral infarction due to unspecified occlusion or stenosis of other cerebral artery
I636	Cerebral infarction due to cerebral venous thrombosis, nonpyogenic
I638	Other cerebral infarction
I6381	Other cerebral infarction due to occlusion or stenosis of small artery
I6389	Other cerebral infarction
I639	Cerebral infarction, unspecified

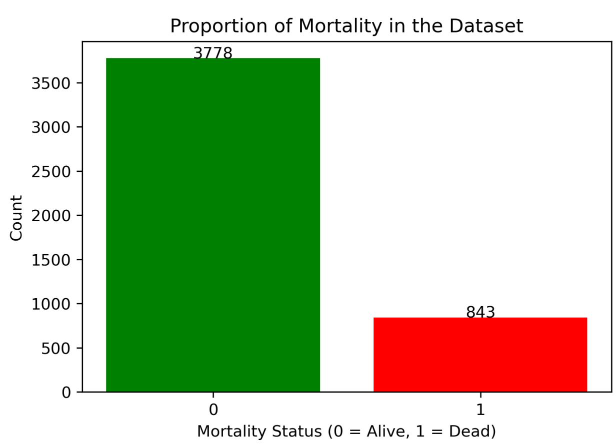

Figure A.7. This is the caption for the image.

Table A.9. Pre-processed Features and Actions Applied

Feature	Action	Reason (if Removed)
item__50863	Removed	Too many nulls
item__50878	Removed	Too many nulls
item__50885	Removed	Too many nulls
item__51237	Removed	Too many nulls
item__51274	Removed	Too many nulls
item__51275	Removed	Too many nulls
ph	Removed	Too many nulls
PaO2	Removed	Too many nulls
calcium	Removed	Too many nulls
ptt	Removed	Too many nulls
PaCO2	Removed	Too many nulls
procedure__223253	Removed	Non-invasive surgery procedure
procedure__225817	Removed	Non-invasive surgery procedure
procedure__228125	Removed	Non-invasive surgery procedure
procedure__221214	Removed	Non-invasive surgery procedure
procedure__228127	Removed	Non-invasive surgery procedure
procedure__228128	Removed	Non-invasive surgery procedure
procedure__228130	Removed	Non-invasive surgery procedure
procedure__228715	Removed	Non-invasive surgery procedure
procedure__225401	Removed	Non-invasive surgery procedure
procedure__225427	Removed	Non-invasive surgery procedure
procedure__225432	Removed	Non-invasive surgery procedure
procedure__225444	Removed	Non-invasive surgery procedure
procedure__225451	Removed	Non-invasive surgery procedure
procedure__225454	Removed	Non-invasive surgery procedure
procedure__225457	Removed	Non-invasive surgery procedure
procedure__225459	Removed	Non-invasive surgery procedure
procedure__225469	Removed	Non-invasive surgery procedure
procedure__225470	Removed	Non-invasive surgery procedure
procedure__229581	Removed	Non-invasive surgery procedure
procedure__229582	Removed	Non-invasive surgery procedure
procedure__229614	Removed	Non-invasive surgery procedure
item__51221	Removed	High Spearman's Correlation with another feature
item__51006	Removed	High Spearman's Correlation with another feature
total__drugs	Removed	High Spearman's Correlation with another feature
inr	Removed	High Spearman's Correlation with another feature
diastolic__bp	Removed	High Spearman's Correlation with another feature
sodium	Removed	Insignificant Mann-Whitney U test
temperature	Removed	Insignificant Mann-Whitney U test
procedure__221216	Removed	Insignificant Chi-square test
procedure__221217	Removed	Insignificant Chi-square test
procedure__221255	Removed	Insignificant Chi-square test
procedure__224264	Removed	Insignificant Chi-square test
procedure__224268	Removed	Insignificant Chi-square test
procedure__224269	Removed	Insignificant Chi-square test
procedure__224272	Removed	Insignificant Chi-square test
procedure__224277	Removed	Insignificant Chi-square test
procedure__224560	Removed	Insignificant Chi-square test
procedure__225202	Removed	Insignificant Chi-square test
procedure__225204	Removed	Insignificant Chi-square test
procedure__225399	Removed	Insignificant Chi-square test
procedure__225402	Removed	Insignificant Chi-square test
procedure__225433	Removed	Insignificant Chi-square test
procedure__225437	Removed	Insignificant Chi-square test
procedure__225439	Removed	Insignificant Chi-square test
procedure__225440	Removed	Insignificant Chi-square test
procedure__225441	Removed	Insignificant Chi-square test
procedure__225448	Removed	Insignificant Chi-square test
procedure__225462	Removed	Insignificant Chi-square test
procedure__225468	Removed	Insignificant Chi-square test
procedure__225789	Removed	Insignificant Chi-square test
procedure__225794	Removed	Insignificant Chi-square test
procedure__225805	Removed	Insignificant Chi-square test
procedure__225814	Removed	Insignificant Chi-square test
procedure__225966	Removed	Insignificant Chi-square test
procedure__227719	Removed	Insignificant Chi-square test
procedure__228129	Removed	Insignificant Chi-square test
procedure__229526	Removed	Insignificant Chi-square test
procedure__229532	Removed	Insignificant Chi-square test
unique__drugs	Zero Imputation of Null	-
ventilation__duration	Booleanised (NA/Not NA)	-
procedure__221223	Booleanised (NA/Not NA)	-
procedure__224263	Booleanised (NA/Not NA)	-
procedure__224267	Booleanised (NA/Not NA)	-
procedure__224270	Booleanised (NA/Not NA)	-
procedure__224274	Booleanised (NA/Not NA)	-
procedure__224275	Booleanised (NA/Not NA)	-

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Table A.9 – continued from previous page

Feature	Action	Reason (if Removed)
procedure__224276	Booleanised (NA/Not NA)	-
procedure__224385	Booleanised (NA/Not NA)	-
procedure__225400	Booleanised (NA/Not NA)	-
procedure__225430	Booleanised (NA/Not NA)	-
procedure__225446	Booleanised (NA/Not NA)	-
procedure__225464	Booleanised (NA/Not NA)	-
procedure__225752	Booleanised (NA/Not NA)	-
procedure__225792	Booleanised (NA/Not NA)	-
procedure__225802	Booleanised (NA/Not NA)	-
procedure__226124	Booleanised (NA/Not NA)	-
procedure__226236	Booleanised (NA/Not NA)	-
procedure__226475	Booleanised (NA/Not NA)	-
procedure__227194	Booleanised (NA/Not NA)	-
procedure__227712	Booleanised (NA/Not NA)	-
procedure__229298	Booleanised (NA/Not NA)	-
procedure__229351	Booleanised (NA/Not NA)	-
procedure__229380	Booleanised (NA/Not NA)	-
procedure__229519	Booleanised (NA/Not NA)	-
procedure__229580	Booleanised (NA/Not NA)	-
gender	One-hot encode	-
race	One-hot encode	-

Table A.10. Features Used for Modelling

Features Used for Modeling	(cont.)	(cont.)	(cont.)
gender	procedure__224267	procedure__225400	potassium
anchor__age	procedure__224270	procedure__225430	creatinine
race	procedure__224274	procedure__225446	bun
item__51222	procedure__224275	procedure__225464	urine__output__total
item__51265	procedure__224276	procedure__225752	pt
item__51301	procedure__224385	procedure__225792	systolic__bp
unique__drugs	procedure__225400	procedure__225802	mean__arterial__pressure
lods__score	procedure__225430	procedure__226124	heart__rate
oasis__score	procedure__225446	procedure__226236	resp__rate
procedure__221223	procedure__225464	procedure__226475	spo2
procedure__224263	procedure__225752	procedure__227194	glucose
procedure__224267	procedure__225792	procedure__227712	hospital__stay__duration
procedure__224270	procedure__225802	procedure__229298	icu__stay__duration
procedure__224274	procedure__226124	procedure__229351	ventilation__duration
procedure__224275	procedure__226236	procedure__229380	
procedure__224276	procedure__226475	procedure__229519	
procedure__224385	procedure__227194	procedure__229580	

Table A.11. Summary statistics for continuous features (mean, std, median, and variance)

feature	mean	std	50% (median)	var
anchor__age	66.542307	15.466533	68.000000	239.213632
item__51222	11.998550	2.146820	12.200000	4.608836
item__51265	218.244103	92.577887	208.000000	8570.665076
item__51301	11.208894	9.429523	9.900000	88.915910
unique__drugs	41.457477	20.045635	38.000000	401.827466
lods__score	3.900671	2.779307	3.000000	7.724547
oasis__score	31.609392	8.318081	31.000000	69.190466
potassium	4.055529	0.645771	4.000000	0.417020
creatinine	1.151872	1.165178	0.900000	1.357640
bun	20.962129	14.868532	17.000000	221.073241
urine__output__total	289.629582	269.938461	200.000000	72866.772824
pt	14.083294	6.983031	12.700000	48.762721
systolic__bp	135.943302	25.274618	136.000000	638.806308
mean__arterial__pressure	90.524526	18.809346	89.000000	353.791486
heart__rate	83.127894	18.212023	81.000000	331.677795
resp__rate	18.731335	5.452643	18.000000	29.731321
spo2	97.390824	3.270231	98.000000	10.694409
glucose	146.822636	67.766657	129.000000	4592.319825
hospital__stay__duration	12.067076	12.601333	8.463889	158.793584
icu__stay__duration	5.630679	6.746169	3.121632	45.510793

Table A.13. Optimised hyperparameters (and features) for different models

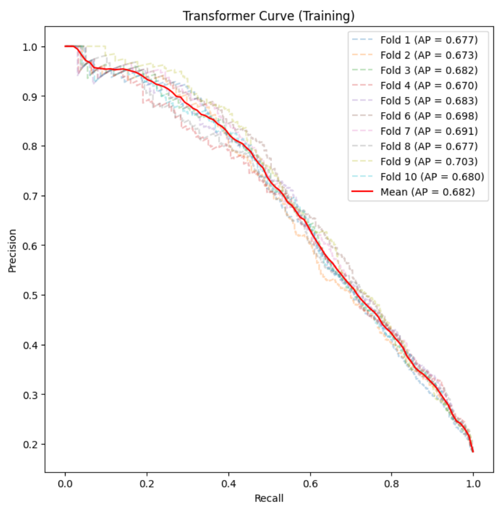
Model	Hyperparameter	Value
Transformer	hidden__dim	32
	num__transformer__layers	3

Model	Hyperparameter	Value
	num_mlp_layers	1
	dropout	0
	batch_size	128
	nhead	8
	epochs	10
	lr	0.001
	batchnorm	False
	grad_clip	True
	features	{'procedure_225792', 'ventilation_used', 'procedure_226475', 'lods_score', 'procedure_225802', 'hospital_stay_duration', 'procedure_224276', 'procedure_229519', 'procedure_226236'}
MLP	hidden_dim	64
	hidden_layers	2
	dropout	0.1
	batch_size	64
	epochs	10
	lr	0.01
	batchnorm	True
	grad_clip	True
	features	{'procedure_225792', 'ventilation_used', 'procedure_226475', 'lods_score', 'procedure_225802', 'hospital_stay_duration', 'procedure_224276', 'procedure_229519', 'procedure_226236', 'race_AMERICAN INDIAN/ALASKA NATIVE', 'race_ASIAN', 'race_ASIAN - ASIAN INDIAN', 'race_ASIAN - CHINESE', 'race_ASIAN - KOREAN', 'race_ASIAN - SOUTH EAST ASIAN', 'race_BLACK/AFRICAN', 'race_BLACK/AFRICAN AMERICAN', 'race_BLACK/CAPE VERDEAN', 'race_BLACK/CARIBBEAN ISLAND', 'race_HISPANIC OR LATINO', 'race_HISPANIC/LATINO - CENTRAL AMERICAN', 'race_HISPANIC/LATINO - COLUMBIAN', 'race_HISPANIC/LATINO - CUBAN', 'race_HISPANIC/LATINO - DOMINICAN', 'race_HISPANIC/LATINO - GUATEMALAN', 'race_HISPANIC/LATINO - HONDURAN', 'race_HISPANIC/LATINO - MEXICAN', 'race_HISPANIC/LATINO - PUERTO RICAN', 'race_HISPANIC/LATINO - SALVADORAN', 'race_MULTIPLE RACE/ETHNICITY', 'race_NATIVE HAWAIIAN OR OTHER PACIFIC ISLANDER', 'race_OTHER', 'race_PATIENT DECLINED TO ANSWER', 'race_PORTUGUESE', 'race_SOUTH AMERICAN', 'race_UNABLE TO OBTAIN', 'race_WHITE', 'race_WHITE - BRAZILIAN', 'race_WHITE - EASTERN EUROPEAN', 'race_WHITE - OTHER EUROPEAN', 'race_WHITE - RUSSIAN', 'race_UNKNOWN'}
SVC	C	10
	tol	0.0001
	max_iter	800
	gamma	scale
	features	{'procedure_225792', 'ventilation_used', 'procedure_226475', 'lods_score', 'procedure_225802', 'hospital_stay_duration', 'procedure_224276'}
Gaussian Naive Bayes	var_smoothing	0.001
	features	{'procedure_225792', 'ventilation_used', 'procedure_226475', 'lods_score', 'procedure_225802', 'hospital_stay_duration', 'procedure_224276', 'procedure_229519', 'procedure_226236', 'race_AMERICAN INDIAN/ALASKA NATIVE', 'race_ASIAN', 'race_ASIAN - ASIAN INDIAN', 'race_ASIAN - CHINESE', 'race_ASIAN - KOREAN', 'race_ASIAN - SOUTH EAST ASIAN', 'race_BLACK/AFRICAN', 'race_BLACK/AFRICAN AMERICAN', 'race_BLACK/CAPE VERDEAN', 'race_BLACK/CARIBBEAN ISLAND', 'race_HISPANIC OR LATINO', 'race_HISPANIC/LATINO - CENTRAL AMERICAN', 'race_HISPANIC/LATINO - COLUMBIAN', 'race_HISPANIC/LATINO - CUBAN', 'race_HISPANIC/LATINO - DOMINICAN', 'race_HISPANIC/LATINO - GUATEMALAN', 'race_HISPANIC/LATINO - HONDURAN', 'race_HISPANIC/LATINO - MEXICAN', 'race_HISPANIC/LATINO - PUERTO RICAN', 'race_HISPANIC/LATINO - SALVADORAN', 'race_MULTIPLE RACE/ETHNICITY', 'race_NATIVE HAWAIIAN OR OTHER PACIFIC ISLANDER', 'race_OTHER', 'race_PATIENT DECLINED TO ANSWER', 'race_PORTUGUESE', 'race_SOUTH AMERICAN', 'race_UNABLE TO OBTAIN', 'race_WHITE', 'race_WHITE - BRAZILIAN', 'race_WHITE - EASTERN EUROPEAN', 'race_WHITE - OTHER EUROPEAN', 'race_WHITE - RUSSIAN', 'race_UNKNOWN', 'oasis_score', 'procedure_224267', 'icu_stay_duration', 'procedure_229580', 'procedure_224270', 'procedure_225446', 'procedure_225400', 'procedure_221223', 'unique_drugs', 'procedure_227712', 'procedure_224263', 'creatinine', 'heart_rate'}
Logistic Regression	C	10
	max_iter	1600
	penalty	l1
	tol	1e-05

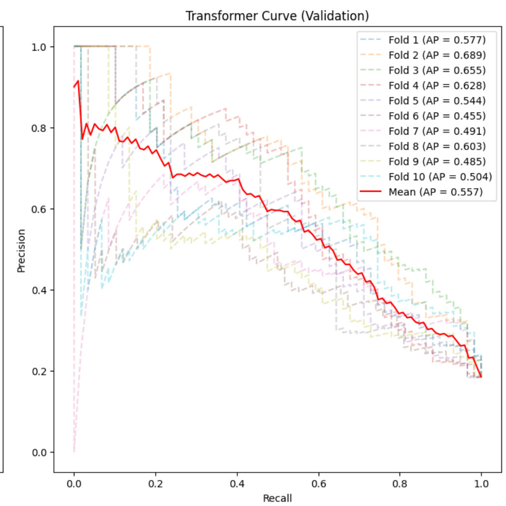
Model	Hyperparameter	Value
	features	{'procedure__225792', 'ventilation__used', 'procedure__226475', 'lods_score', 'procedure__225802', 'hospital_stay_duration', 'procedure__224276', 'procedure__229519', 'procedure__226236', 'race__AMERICAN INDIAN/ALASKA NATIVE', 'race__ASIAN', 'race__ASIAN - ASIAN INDIAN', 'race__ASIAN - CHINESE', 'race__ASIAN - KOREAN', 'race__ASIAN - SOUTH EAST ASIAN', 'race__BLACK/AFRICAN', 'race__BLACK/AFRICAN AMERICAN', 'race__BLACK/CAPE VERDEAN', 'race__BLACK/CARIBBEAN ISLAND', 'race__HISPANIC OR LATINO', 'race__HISPANIC/LATINO - CENTRAL AMERICAN', 'race__HISPANIC/LATINO - COLUMBIAN', 'race__HISPANIC/LATINO - CUBAN', 'race__HISPANIC/LATINO - DOMINICAN', 'race__HISPANIC/LATINO - GUATEMALAN', 'race__HISPANIC/LATINO - HONDURAN', 'race__HISPANIC/LATINO - MEXICAN', 'race__HISPANIC/LATINO - PUERTO RICAN', 'race__HISPANIC/LATINO - SALVADORAN', 'race__MULTIPLE RACE/ETHNICITY', 'race__NATIVE HAWAIIAN OR OTHER PACIFIC ISLANDER', 'race__OTHER', 'race__PATIENT DECLINED TO ANSWER', 'race__PORTUGUESE', 'race__SOUTH AMERICAN', 'race__UNABLE TO OBTAIN', 'race__WHITE', 'race__WHITE - BRAZILIAN', 'race__WHITE - EASTERN EUROPEAN', 'race__WHITE - OTHER EUROPEAN', 'race__WHITE - RUSSIAN', 'race__UNKNOWN'}
XGBoost	n_estimators	50
	max_depth	3
	subsample	1
	colsample_bytree	0.85
	gamma	1e-08
	eta	1
	features	{'procedure__225792', 'ventilation__used', 'procedure__226475', 'lods_score', 'procedure__225802', 'hospital_stay_duration', 'procedure__224276', 'procedure__229519', 'procedure__226236', 'race__AMERICAN INDIAN/ALASKA NATIVE', 'race__ASIAN', 'race__ASIAN - ASIAN INDIAN', 'race__ASIAN - CHINESE', 'race__ASIAN - KOREAN', 'race__ASIAN - SOUTH EAST ASIAN', 'race__BLACK/AFRICAN', 'race__BLACK/AFRICAN AMERICAN', 'race__BLACK/CAPE VERDEAN', 'race__BLACK/CARIBBEAN ISLAND', 'race__HISPANIC OR LATINO', 'race__HISPANIC/LATINO - CENTRAL AMERICAN', 'race__HISPANIC/LATINO - COLUMBIAN', 'race__HISPANIC/LATINO - CUBAN', 'race__HISPANIC/LATINO - DOMINICAN', 'race__HISPANIC/LATINO - GUATEMALAN', 'race__HISPANIC/LATINO - HONDURAN', 'race__HISPANIC/LATINO - MEXICAN', 'race__HISPANIC/LATINO - PUERTO RICAN', 'race__HISPANIC/LATINO - SALVADORAN', 'race__MULTIPLE RACE/ETHNICITY', 'race__NATIVE HAWAIIAN OR OTHER PACIFIC ISLANDER', 'race__OTHER', 'race__PATIENT DECLINED TO ANSWER', 'race__PORTUGUESE', 'race__SOUTH AMERICAN', 'race__UNABLE TO OBTAIN', 'race__WHITE', 'race__WHITE - BRAZILIAN', 'race__WHITE - EASTERN EUROPEAN', 'race__WHITE - OTHER EUROPEAN', 'race__WHITE - RUSSIAN', 'race__UNKNOWN', 'oasis_score', 'procedure__224267'}

Table A.12. DeLong Test P-Values for Model Comparisons

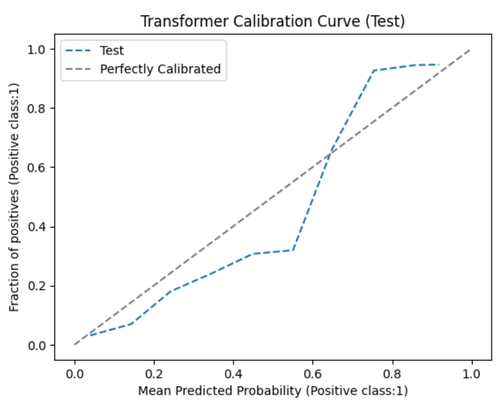
Model	Transformer	MLP	SVM	NB	XGB	LogReg
Transformer	N/A	0.836	0.000	0.000	0.006	0.001
MLP	0.836	N/A	0.001	0.000	0.011	0.000
SVM	0.000	0.001	N/A	0.351	0.280	0.138
NB	0.000	0.000	0.351	N/A	0.022	0.002
XGB	0.006	0.011	0.280	0.022	N/A	0.754
LogReg	0.001	0.000	0.138	0.002	0.754	N/A



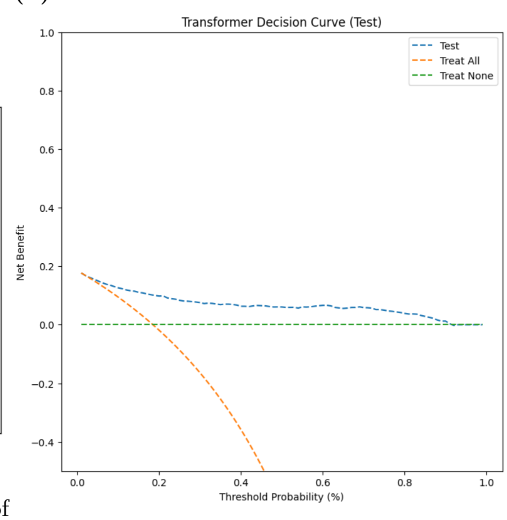
(a) Transformer 10CV Training PR Curves



(b) Transformer 10CV Validation PR Curves

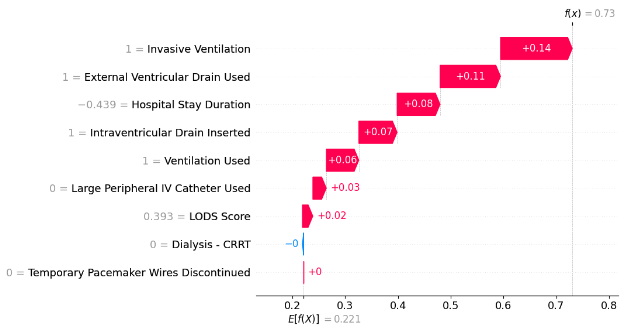


(c) Test Decision Calibration Curve of Transformer

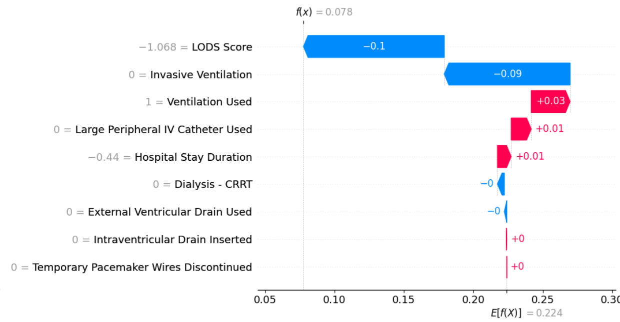


(d) Test Decision Curve of Transformer

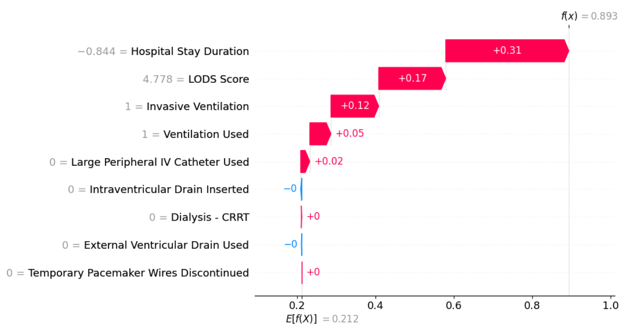
Figure A.8. Transformer PR/Decision/Calibration curves



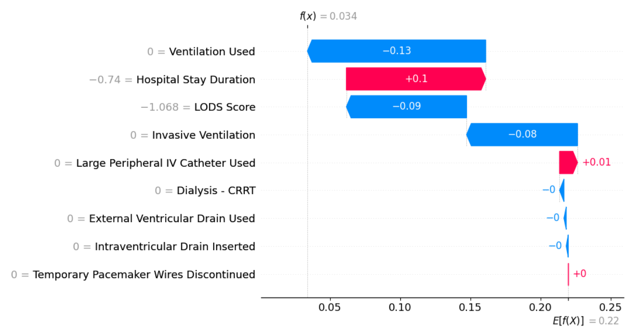
(a) ExtraRFC instance 1 Waterfall Plot



(b) ExtraRFC instance 2 Waterfall Plot



(c) ExtraRFC instance 3 Waterfall Plot



(d) ExtraRFC instance 4 Waterfall Plot

Figure A.9. ExtraRFC example Waterfall Plots

A Table of Contributions

Table 14. CRediT - Contributor Roles Taxonomy

	Jiayuan	**Lang**	**Xinyi**	**Zixuan**
Conceptualisation	■	■	■	■
Data curation	■		■	
Formal Analysis		■		■
Funding acquisition				
Investigation	■		■	■
Methodology		■		
Project administration		■		
Resources				
Software	■	■	■	■
Supervision				
Validation	■	■	■	■
Visualization	■	■	■	■
Writing – original draft	■	■	■	■
Writing – review & editing	■	■	■	■

B GitHub Repository

For the open-sourced dataset and project code, please refer to our GitHub repository:
https://github.com/TGChenZP/COMP90089__GroupWork___Py

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