Commission on Excellence and Innovation in Health.

SALIENT: ED Machine Learning Sepsis Prediction

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Contents

1 About this document

This technical document has been developed as part of the 'Gen Med Project' by the Commission on Excellence and Innovation in Health (CEIH). The project forms part of a program of work that is funded through the Acute Models of Care Grant 2022 by the Medical Research Future Fund (MRFF). The project's primary goal is to reduce unwarranted clinical variation in general medicine, using a data analytics and machine learning approach.

Sepsis was identified as a focus area from early analysis that looked at high bed day consumption and high opportunity Diagnosis Related Groups (DRGs) that included shortness of breath as a symptom.

2 Document Revisions

No.	Date	Description	Person
0.1	30/10/24	First Draft Document describing the ED Sepsis Presentation ML model, and the various verification requirements for the model.	Iain Bertram

3 Introduction

A new adult sepsis pathway has been proposed for use with public hospitals within South Australia. This pathway is intended to identify patients who are at risk of developing Sepsis and initiating a standardised treatment programme. The patients are identified using Rapid Detection and Response (RDR) Observation Charts as implemented within the public hospital Electronic Medical Record (EMR) using the Sunrise Deteriorating Patient Reference Guide [1].

There are two pathways for flagging a patient as being at risk of Sepsis and requiring either review by a Senior Medical Officer or a Medical Emergency response. The Purple pathway is triggered if any of the patient's observations in the Rapid Detection and Response (RDR) are in the purple zone (Table 2). The Red pathway is triggered if there are two or more red zone observations.

This report describes the development of a Machine Learning (ML) model that can be used in place of these pathways. I.e. to develop machine learning models that identify people who will be admitted to hospital and will have a sepsis diagnosis (based on ICD-10 codes) on inpatient discharge based on measurement of the patient's vital signs.

Table 2: Rapid Detection and Response (RDR) Alert Triggers

Measure	Purple	Red	Yellow	Yellow	Red	Purple
		Low			High	
Respiration (breaths/min)	7		10	21	26	31
O_2 Saturation (%)	88	91	94	NA	NA	NA
O_2 Flow (L/min)	NA	NA	NA	5	7	8
Blood Pressure Systolic (mm Hg)	89	99	NA	170	180	200
Pulse Rate (beats/min)	39	49	59	100	120	140
Temperature (°C)		35	35.5	38.1	38.6	
Level of Consciousness	NA	NA	NA		2	3

4 Cohort

The data for this study was sourced from the South Australian Electronic Medical Record system (EMR). The data set is composed of Emergency Department (ED) presentations by an adult (age of at least 16 years) followed by an inpatient (IP) admission with sepsis diagnosis identified by the ICD-10 codes, Table 24 [1] (based on a journey, see appendix 7.1).

Specifically we only include the first ED presentation in a journey. The ED presentation must also be the first EoC in the journey. This excludes presentations that are part of the admission process when the patient is transferred from one hospital to another. It also excludes complex journeys such as a patient who is admitted via day procedure in hospital (e.g. Extracorporeal dialysis) We also require that at least three of the following vital signs are recorded in the EMR during the presentation: respiration, O_2 Saturation, systolic blood pressure, pulse rate and temperature[2] (Table 2).

The IP admission is required to be the first episode of care (EoC) after any ED presentations [3]. IP admissions where the patient does not leave the ED are excluded (these are identified by an IP discharge date/time within 60 minutes of the discharge date/time of the ED presentation and a location that includes the string “ED-Admin”.)

The training data set includes all presentations to Emergency Departments at metropolitan hospitals in the calendar year 2023 in which at least three observations of vital signs of interest have been made (see Table 2). There are 260,596 ED presentations with at least three vital signs recorded which included 2,557 presentations that resulted in an inpatient admission which includes at least one ICD-10 code matching a Sepsis diagnosis (of these 920 have sepsis as the primary, or first-listed, diagnosis). Note, 52,233 (16.7%) out of a total 312,829 ED presentations do not have at least three observations of vital signs recorded in the EMR and have been excluded from the analysis.

The first verification data set is created from all ED presentations at metropolitan hospitals in the calendar year 2024 in which at least three observations of vital signs of interest have been made. There are 263,594 ED presentations with at least three vital signs recorded which included 2,446 presentations that resulted in an inpatient admission which includes at least one ICD-10 code matching a Sepsis diagnosis (of these 912 have sepsis as the primary, or first-listed, diagnosis). Note, 46,250 (14.9%) out of a total 309,844 ED presentations do not have at least three observations of vital signs recorded in the EMR and have been excluded from the analysis.

The fraction of Sepsis cases that are not identified, ICD-10 A41.9, i.e. where pathology tests have not identified the infection agent, is 66.9% in the 2023 training data set and 69.4% in the 2024 verification data set (see Tables 25 & 26).

[1] We have removed infant Sepsis ICD-10 codes from the previous work.
[2] O_2 Flow and the sedation score are not included as these are not usually filled out if the patient is not receiving oxygen or is awake and aware.
[3] Note to self, need to look at joining transfers. See CAP and COPD analyses.

5 Validation Metrics

The performance of the ML model will evaluated in comparison with current scoring systems in terms of sensitivity/specificity and against the proposed adult sepsis pathway. The two scoring systems used are qSOFA and the SIRS criteria. In addition the fraction of patients who require ICU usage and patient mortality will also be examined.

5.1 qSOFSA

The quick Sequential Organ Failure Assessment (qSOFA) [2] is used to identify high-risk patients for in-hospital mortality with suspected infection outside the ICU. Two or more of the following criteria need to be met for a positive qSOFA:

- Glasgow Coma Scale < 15,
- Respiratory rate $\geq$ 22,
- Systolic Blood Pressure $\leq$ 100 mmHg.

5.2 Systemic Inflammatory Response Syndrome (SIRS)

There are multiple levels to the SIRS schema [3,4] relating to the severity of the response. The first is the basic SIRS criteria which requires at least two of the following conditions:

- T $<$ 36 °C or T $>$ 38 °C,
- Heart rate $>$ 90,
- Respiratory rate $>$ 20,
- White Blood Count $>$ 12

The second level is the Sepsis Criteria (SIRS + Source of Infection) which has not yet been implemented in this study as it requires searching the free text progress notes.

The third level is Severe Sepsis Criteria (Organ Dysfunction, Hypotension, or Hypoperfusion) which requires at least one of the following to be satisfied (we have excluded the drop in blood pressure as the patients being reviewed have just presented to the ED and usually only have one set of vital signs):

- Lactate Blood Gas $>$ 4,
- Systolic Blood Pressure $\leq$ 90.

5.3 Adult Sepsis Pathway

There are two pathways for flagging a patient as being at risk of Sepsis and requiring either review by a Senior Medical Officer or a Medical Emergency response. The Purple pathway is triggered if any of the patient's observations in the Rapid Detection and Response (RDR) are in the purple zone (Table 2). The Red pathway is triggered if there are two or more red zone observations.

5.4 ICU Usage

A stay in the ICU is identified by matching the patient's location to the ICU wards in the first episode of care (EoC) after inpatient admission. .

5.5 Mortality

Mortality is measured using the patients date of death and the date/time of the presentation at the ED. The mortality is calculated for death as an inpatient and at after admission are.

5.6 Triage Category

We categorise the patients based on the the triage category assigned on presentation at the emergency department. Patients with Sepsis, especially this in triage category 3, 4 or 5 can have there triage classification changed if they deteriorate while waiting to be seen.

5.7 Waiting Times

In order to understand the clinical workflow the various time stamps recorded in the ED status board will be analysed in order to measure the time waiting to be seen ('WTB'), the decision to admit, when ready for ward transfer.

5.8 Sepsis Patients

The demographics for the 2023 training sample are given in Table 3 amd for the 2024 validation data set in Table 4 The metrics for the 2023 training sample are given in Table 5 and for the 2024 validation sample Table 6. The outcomes for the 2023 training sample are give in Table 7 and for the 2024 validation sample Table 8.

Table 3: Demographics of the patients diagnosed with sepsis in 2023 training sample

Triage Category	EoC	Average Age	Indigenous	Female	Indeterminate	Unknown
1	239	74.2	6	111	0	0
2	1235	71.9	41	552	0	0
3	945	70.7	41	451	0	0
4	133	66.2	5	68	0	0
5	5	42.4	2	2	0	0
Total/Mean	2557	325	95	1184	0	0

Table 4: Demographics of the patients diagnosed with sepsis in 2024 validation sample

Triage Category	EoC	Average Age	Indigenous	Female	Indeterminate	Unknown
1	241	75.3	2	101	0	0
2	1210	71.9	44	451	0	0
3	838	70.1	32	344	0	0
4	157	69.8	11	61	0	0
Total/Mean	2446	71.5	89	957	0	0

Table 5: Metrics for the for patients diagnosed with sepsis in 2023 training sample

Triage Category	EoC	Average Age	>2 vital signs available	qSOFA Flag	SIRS Flag	SIRS Severe	Purple >0 Flag	Red >1 Flag
1	239	74.2	239	142	132	45	80	34
2	1235	71.9	1235	458	711	163	246	162
3	945	70.7	945	171	484	52	74	52
4	133	66.2	133	12	57	1	10	6
5	5	42.4	5	0	1	0	0	0
Total/Mean	2557	71.3	2557	783	1385	261	410	254

Table 6: Metrics for the for patients diagnosed with sepsis in 2024 validation sample

Triage Category	EoC	Average Age	>2 vital signs available	qSOFA Flag	SIRS Flag	SIRS Severe	Purple >0 Flag	Red >1 Flag
1	241	75.3	241	107	150	70	126	41
2	1210	71.9	1210	324	722	157	324	207
3	838	70.1	838	93	407	62	109	61
4	157	69.8	157	17	79	15	20	9
Total/Mean	2446	71.5	2446	541	1358	304	579	318

Table 7: Outcomes for the for patients diagnosed with sepsis in 2023 training sample

Triage Category	EoC	Average Age	ICU Stay	Died as IP	Died 30 days after admission
1	239	74.2	89	81	109
2	1235	71.9	400	208	292
3	945	70.7	247	135	176

Triage Category	EoC	Average Age	ICU Stay	Died as IP	Died 30 days after admission
4	133	66.2	39	23	26
5	5	42.4	2	0	0
Total/Mean	2557	71.3	777	447	603

Table 8: Outcomes for the for patients diagnosed with sepsis in 2024 validation sample

Triage Category	EoC	Average Age	ICU Stay	Died as IP	Died 30 days after admission
1	241	75.3	75	87	102
2	1210	71.9	344	206	232
3	838	70.1	227	126	135
4	157	69.8	39	15	21
Total/Mean	2446	71.5	685	434	490

Table 9: ED presentations for patients diagnosed with sepsis in 2023 training sample

Triage Category	FMC	LMH	MPH	NHS	QEH	RAH	Row Total
1	75	79	10	1	44	30	239
2	251	301	59	10	206	408	1235
3	151	216	116	27	179	256	945
4	21	32	14	5	29	32	133
5	1	3	0	0	1	0	5
Total	499	631	199	43	459	726	2557

Table 10: ED presentations for patients diagnosed with sepsis in 2024 validation sample

Triage Category	FMC	LMH	MPH	NHS	QEH	RAH	Row Total
1	93	41	10	3	60	34	241
2	263	283	78	20	225	341	1210
3	122	205	123	29	159	200	838
4	12	39	23	6	43	34	157
Total	490	568	234	58	487	609	2446

5.8.1 Discharge Disposition of Sepsis Patients

The discharge disposition from the ED of the patients diagnosed with Sepsis are listed in Tables 11 & 12. This shows the number of patients who are admitted directly as inpatients, who are admitted to the EECU and are transferred to another hospital, and those that died in the ED.

In addition there is a small cohort of patients who were not admitted included as patients "admitted" with Sepsis (12 in 2023 and 16 in 2024). This is caused by our journey definition. We have required the ED presentation to be the first in in a set of connected EoC. In this case the patient has represented at an ED within 6 hours of discharge and been admitted with Sepsis. We have used this journey definition so as not to double count patients who are transferred between hospitals.

If we examine timelines of the patient journeys for patients who were not admitted from the ED (Fig. 1) we we find four of the 12 patients were admitted (three of which were hospital transfers). A similar analysis of the 2024 validation sample finds at least five of the 16 patients were admitted.

Add patient timelines for some of these to the appendix.

Table 11: Discharge Disposition for the for patients diagnosed with sepsis in 2023 training sample

Triage Category	EoC	Average Age	Admit as Inpatient	Admit to EECU	Transfer to Other Hospital	Not admitted as inpatients	Died in the ED	Row Total
1	239	74.2	230	5	4	0	0	239
2	1235	71.9	1152	37	40	6	0	1235
3	945	70.7	798	69	74	4	0	945
4	133	66.2	107	17	7	2	0	133
5	5	42.4	5	0	0	0	0	5
Total/Mean	2557	71.3	2292	128	125	12	0	2557

Table 12: Discharge Disposition for the for patients diagnosed with sepsis in 2024 validation sample

Triage Category	EoC	Average Age	Admit as Inpatient	Admit to EECU	Transfer to Other Hospital	Not admitted as inpatients	Died in the ED	Row Total
1	241	75.3	229	7	5	0	0	241
2	1210	71.9	1111	39	53	7	0	1210
3	838	70.1	681	79	70	8	0	838
4	157	69.8	122	21	13	1	0	157
Total/Mean	2446	71.5	2143	146	141	16	0	2446

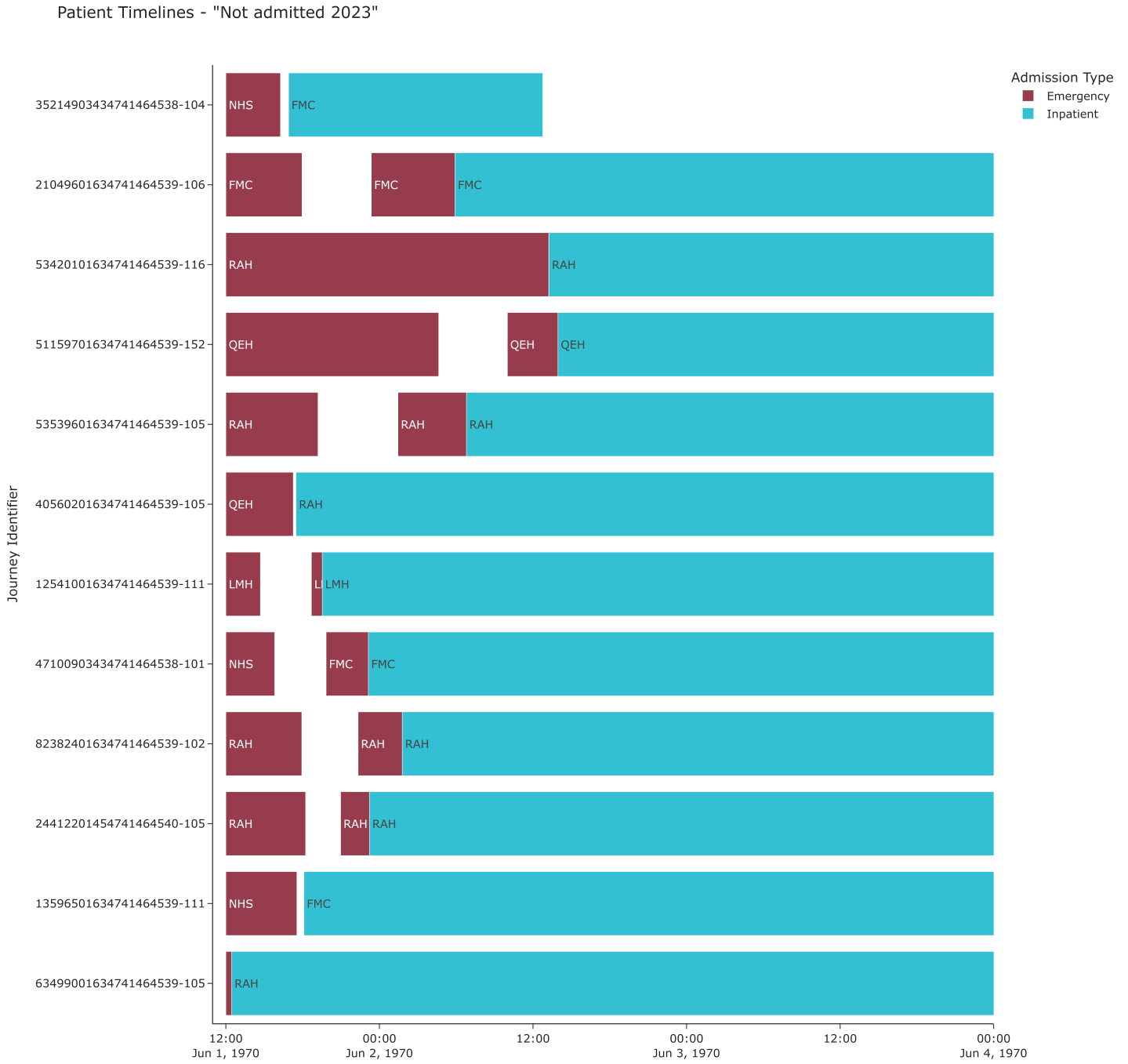

Figure 1: Journeys for patients diagnosed with sepsis with an ED discharge disposition consistent with not bing admitted in the 2023 training sample.

5.9 Patients without Sepsis

Table 13: Demographics of the patients diagnosed with sepsis in 2023 training sample

Triage Category	EoC	Average Age	Indigenous	Female	Indeterminate	Unknown
1	3901	58	262	1796	0	2
2	54363	57.7	2573	26586	5	5
3	126945	54.9	6370	69688	23	6
4	64936	49	3726	35166	13	7
5	7894	43.8	600	3733	0	1
Total/Mean	258039	263	13531	136969	41	21

Table 14: Demographics of the patients diagnosed with sepsis in 2024 validation sample

Triage Category	EoC	Average Age	Indigenous	Female	Indeterminate	Unknown
1	3745	57.1	242	1332	0	3
2	53951	57.6	2401	21084	2	3
3	126441	55	5606	54120	17	4
4	68531	49.4	3434	27502	6	3
5	8480	43.9	593	2993	1	1
Total/Mean	261148	53.7	12276	107031	26	14

Table 15: Metrics for the for patients diagnosed with sepsis in 2023 training sample

Triage Category	EoC	Average Age	>2 vital signs available	qSOFA Flag	SIRS Flag	SIRS Severe	Purple >0 Flag	Red >1 Flag
1	3901	58	3901	687	1458	219	653	200
2	54363	57.7	54363	3185	15895	615	2799	1059
3	126945	54.9	126945	2653	29872	420	1997	725
4	64936	49	64936	422	11597	82	545	127
5	7894	43.8	7894	16	1347	2	43	10
Total/Mean	258039	53.7	258039	6963	60169	1338	6037	2121

Table 16: Metrics for the for patients diagnosed with sepsis in 2024 validation sample

Triage Category	EoC	Average Age	>2 vital signs available	qSOFA Flag	SIRS Flag	SIRS Severe	Purple >0 Flag	Red >1 Flag
1	3745	57.1	3745	399	1451	201	923	273
2	53951	57.6	53951	2058	15911	656	4093	1626
3	126441	55	126441	1571	29467	483	2355	874
4	68531	49.4	68531	285	12338	86	545	185
5	8480	43.9	8480	6	1476	4	35	16
Total/Mean	261148	53.7	261148	4319	60643	1430	7951	2974

Table 17: Outcomes for the for patients not diagnosed with sepsis in 2023 training sample

Triage Category	EoC	Average Age	ICU Stay	Died as IP	Died 30 days after admission
1	3901	58	422	183	394
2	54363	57.7	1106	726	1849
3	126945	54.9	851	633	2148
4	64936	49	142	95	387
5	7894	43.8	6	0	11
Total/Mean	258039	53.7	2527	1637	4789

Table 18: Outcomes for the for patients not diagnosed with sepsis in 2024 validation sample

Triage Category	EoC	Average Age	ICU Stay	Died as IP	Died 30 days after admission
1	3745	57.1	312	198	304
2	53951	57.6	1060	690	1469
3	126441	55	800	641	1785
4	68531	49.4	123	93	379
5	8480	43.9	4	3	14
Total/Mean	261148	53.7	2299	1625	3951

Table 19: ED presentations for patients not diagnosed with sepsis in 2023 training sample

Triage Category	FMC	LMH	MPH	NHS	QEH	RAH	Row Total
1	1216	910	136	56	418	1165	3901

Triage Category	FMC	LMH	MPH	NHS	QEH	RAH	Row Total
2	13323	11041	4277	3991	5536	16195	54363
3	25718	21568	14875	13752	19051	31981	126945
4	10627	12288	6281	9984	11947	13809	64936
5	1210	2836	502	1092	555	1699	7894
Total	52094	48643	26071	28875	37507	64849	258039

Table 20: ED presentations for patients not diagnosed with sepsis in 2024 validation sample

Triage Category	FMC	LMH	MPH	NHS	QEH	RAH	Row Total
1	1104	645	141	129	558	1168	3745
2	14287	10055	4313	3836	5613	15847	53951
3	24700	20873	17377	13302	19625	30564	126441
4	9911	14281	7913	10058	14007	12361	68531
5	1049	3212	890	1384	689	1256	8480
Total	51051	49066	30634	28709	40492	61196	261148

5.9.1 Discharge Disposition of Patients without Sepsis

Table 21: Discharge Disposition for the for patients not diagnosed with sepsis in 2023 training sample

Triage Category	EoC	Average Age	Admit as Inpatient	Admit to EECU	Transfer to Other Hospital	Not admitted as inpatients	Died in the ED	Row Total
1	3901	58	2471	400	52	960	15	3898
2	54363	57.7	21150	8340	1399	23271	38	54198
3	126945	54.9	33495	19663	2607	70100	18	125883
4	64936	49	8943	6863	712	46164	1	62683
5	7894	43.8	565	371	38	6320	0	7294
Total/Mean	258039	53.7	66624	35637	4808	146815	72	253956

Table 22: Discharge Disposition for the for patients not diagnosed with sepsis in 2024 validation sample

Triage Category	EoC	Average Age	Admit as Inpatient	Admit to EECU	Transfer to Other Hospital	Not admitted as inpatients	Died in the ED	Row Total
1	3745	57.1	2223	543	93	859	18	3736
2	53951	57.6	21128	10441	1486	20722	28	53805
3	126441	55	31544	23671	2897	66744	25	124881
4	68531	49.4	8902	8787	907	46915	1	65512
5	8480	43.9	511	488	48	6744	0	7791
Total/Mean	261148	53.7	64308	43930	5431	141984	72	255725

5.10 Variable Distributions

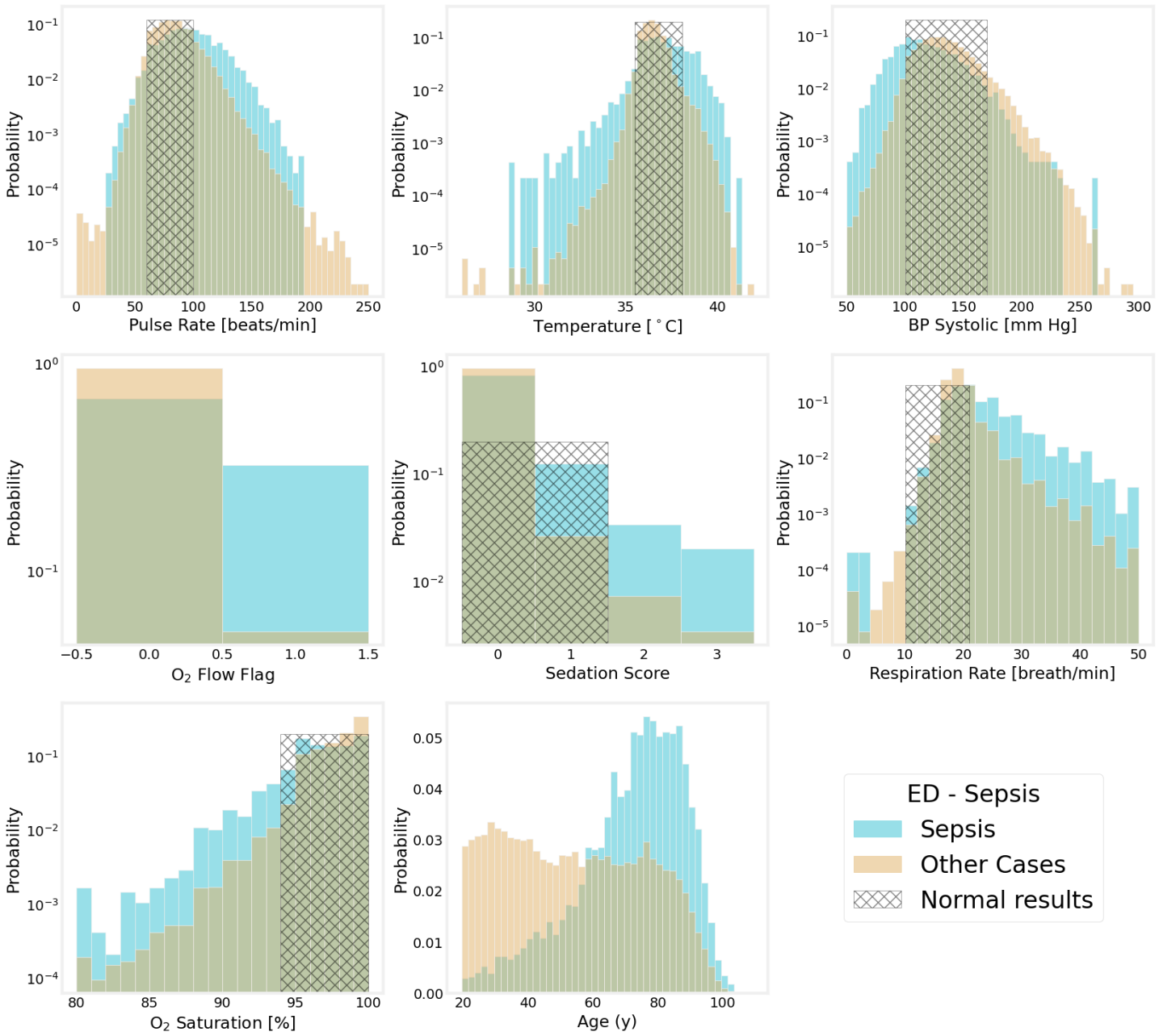

Figure 2: Results for Sthe various observations used in the Machine Learning models. The data for patients with a Sepsis admission (light blue) and without Sepsis (yellow). The rectangles outlined in black contain normal results as taken from the Deteriorating Patient Reference Guide [1].

6 Machine Learning

The data described in the earlier section is used to train and validate diagnosis classifier models Sepsis. The data is prepared by setting any missing measurement from in the data set with the defaults listed in Table 23. Numerical variables are transformed on to the range $[0, 1]$. Categorical values are passed through the One Hot Encoder algorithm [6] to turn them into a complete set of logical variables.

The data set is split into training and validation sets using an 80:20% split. An XG Boost model [7] is optimised by randomly scanning through the possible model settings and minimising the false positive rate for a true positive rate of 85%. The optimized model is then tested on the validation samples.

Table 23: Data used in the ML models. If no result has been recorded the default value is assigned. If the default is NA (not applicable) then there is no default value.

Property or Result	Default
Age	NA
Sex	NA
Respiration (breaths/min)	15
O2 Saturation (%)	98
Blood Pressure Systolic (mm Hg)	120
Pulse Rate (beats/min)	80
Temperature (°C)	37.5
Level of Consciousness	0

6.1 ML Metrics

Standard machine learning quality metrics are calculated where N is the size of the cohort, TP is the number of true positives, TN is the number if true negatives, FP is the number of false positives, TN is the number if false negatives, N_{sepsis} is the number of patients with a sepsis diagnosis and $N_{\text{not sepsis}} = N - N_{\text{sepsis}}$ is the number of patients who do not have sepsis:

$$\text{Accuracy} = A = \frac{\text{TP} + \text{TN}}{N} \tag{1}$$

$$\text{Precision} = P = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = R = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$F_1 = \frac{2PR}{P + R} \tag{4}$$

$$\text{Sensitivity} = \frac{\text{TP}}{N_{\text{sepsis}}} \tag{5}$$

$$\text{Specificity} = \frac{\text{TN}}{N_{\text{not sepsis}}} \tag{6}$$

6.2 Variation Across Subgroups

The performance of the ML model for different subgroups of the patient cohort will be verified for - the patient's gender, - indigenous status, - the hospital, - age groups, - triage categories. The true positive and true negative rates will be compared across these subgroups.

6.3 Optimisation

Several strategies for optimising the ML model will be explored.

The first will be the cohort composition and will compare patients with a minimum of three of the following vital signs are recorded in the EMR during the presentation: respiration, O_2 Saturation, systolic blood pressure, pulse rate and temperature and patients where all five are recorded.

The second will look at variations in the data included in the model. For example is the patients age included, do we use the O_2 flow to create a categorical true false value etc.

The third variation will be the variable used in fitting the model. The variables to be optimized are: - minimising the false positive rate for a true positive rate of 85%, - maximising the sensitivity for a specificity of 95%.

7 Appendices

7.1 Patient Journey

Descriptions and variable names listed below are based on the SA Health EMR. Episodes of Care are joined into a journey if they meet the following criteria. If the value is set to zero, the EoC is part of the same journey.

1. Check if the previous CHARTGUID entry (for the same CLIENTGUID order by discharge datetime) is the same as the current CHARTGUID.
   If yes, set the value to 0.
2. Check if the time difference between the previous discharge datetime (for the same) and current admission datetime is within 6 hours (either before or after).
   If yes, set the value to 0.
3. Check if the time difference between the previous discharge datetime (for the same CLIENTGUID) and current admission datetime is within 24 hours (either before or after) and the 'previous_discharge_disposition' (for the same CLIENTGUID order by admission datetime) is in this list ('IP Other hosp - Down', 'IP Other hosp - Up', 'IP Other Hospital - DOWN','IP Other Hospital - UP').
   If yes, set the value to 0.
4. Check if the previous discharge datetime (for the same CLIENTGUID order by discharge datetime) is before the current admission datetime and the previous admission datetime (for the same CLIENTGUID order by admission datetime) date is after the current admission datetime.
   If yes, set the value to 0.
5. Check if the time difference between the previous discharge datetime (for the same CLIENTGUID order by admission datetime) and current admission datetime is within 24 hours (either before or after) and the previous episode_of_care(for the same CLIENTGUID order by admission datetime) is 'Rehabilitation' and the current episode_of_care is 'Hospital at Home - Rehab at Home'.
   If yes, set the value to 0.
6. Check if the time difference between the previous admission datetime (for the same CLIENTGUID order by admission datetime) and current admission datetime is within 24 hours (either before or after) and the previous TYPECODE (for the same CLIENTGUID order by admitdate asc) is 'Emergency' and the current source_of_referral is 'IP Casualty-Emergency' and the current TYPECODE is 'Inpatient'.
   If yes, set the value to 0.

If none of the above conditions are met start a new journey.

7.2 Sepsis ICD-10 Codes

Table 24: Sepsis Diagnosis Codes (from APC Reference Table_corrected - ICD-10-AM 11th edition 2019)

Code	Diagnosis	Code	Diagnosis
A021	Salmonella sepsis	A412	Sepsis due to unsp staphylococcus
A227	Anthrax sepsis	A413	Sepsis dt Haemophilus influenzae
A267	Erysipelothrix sepsis	A414	Sepsis due to anaerobes
A327	Listerial sepsis	A415	Sepsis dt oth & unsp gram neg organisms
A40	Streptococcal sepsis	A4150	Sepsis dt unsp Gram neg organisms
A400	Sepsis dt streptococcus group A	A4151	Sepsis dt Escherichia coli [E coli]
A401	Sepsis dt streptococcus group B	A4152	Sepsis due to Pseudomonas
A402	Sepsis dt streptococcus grp D & enteroc	A4158	Sepsis dt other gram neg organisms
A403	Sepsis dt Streptococcus pneumoniae	A418	Other specified sepsis
A408	Other streptococcal sepsis	A419	Sepsis, unspecified
A409	Streptococcal sepsis unspecified	A427	Actinomycotic sepsis
A41	Other sepsis	B377	Candidal sepsis
A410	Sepsis due to Staphylococcus aureus	O85	Puerperal sepsis
A411	Sepsis dt other spec staphylococcus		

7.3 ICD-10 Breakdown of Samples

Table 25: ICD-10 Codes for the 2023 Training data sample

Top Level	Number	Decsription	2nd Level	Number	Description	3rd Level	Number	Description
A02.1	5	Salmonella sepsis						
A40	197	Streptococcal sepsis	A40.0	38	Sepsis dt streptococcus group A			
			A40.1	25	Sepsis dt streptococcus group B			
			A40.2	52	Sepsis dt streptococcus group D			
			A40.3	22	Sepsis dt Streptococcus pneumoniae			
			A40.8	61	Other streptococcal sepsis			
			A40.9	4	Streptococcal sepsis unspecified			
A41	2349	Other sepsis	A41.0	106	Sepsis due to Staphylococcus aureus			
			A41.1	39	Sepsis dt other spec staphylococcus			
			A41.2	8	Sepsis due to unsp staphylococcus			
			A41.3	2	Sepsis dt Haemophilus influenzae			
			A41.4	14	Sepsis due to anaerobes			
			A41.5	405	Sepsis dt oth & unsp gram neg organisms	A41.50	12	Sepsis dt unsp Gram neg organisms
						A41.51	262	Sepsis dt Escherichia coli (E coli)
						A41.52	45	Sepsis due to Pseudomonas
						A41.58	100	Sepsis dt other gram neg organisms
			A41.8	86	Other specified sepsis			
			A41.9	1710	Sepsis, unspecified			
A42.7	1	Actinomycotic sepsis						
B37.7	22	Candidal sepsis						
O85	11	Puerperal sepsis						

Table 26: ICD-10 Codes for the 2024 Verification data sample

Top Level	Number	Decsription	2nd Level	Number	Description	3rd Level	Number	Description
A02.1	4	Salmonella sepsis						
A40	186	Streptococcal sepsis	A40.0	25	Sepsis dt streptococcus group A			
			A40.1	29	Sepsis dt streptococcus group B			
			A40.2	46	Sepsis dt streptococcus group D			
			A40.3	31	Sepsis dt Streptococcus pneumoniae			
			A40.8	47	Other streptococcal sepsis			
			A40.9	13	Streptococcal sepsis unspecified			
A41	2256	Other sepsis	A41.0	97	Sepsis due to Staphylococcus aureus			
			A41.1	37	Sepsis dt other spec staphylococcus			
			A41.2	2	Sepsis due to unsp staphylococcus			
			A41.3	1	Sepsis dt Haemophilus influenzae			
			A41.4	9	Sepsis due to anaerobes			
			A41.5	349	Sepsis dt oth & unsp gram neg organisms	A41.50	9	Sepsis dt unsp Gram neg organisms
						A41.51	234	Sepsis dt Escherichia coli (E coli)
						A41.52	27	Sepsis due to Pseudomonas
						A41.58	86	Sepsis dt other gram neg organisms
			A41.8	70	Other specified sepsis			
			A41.9	1698	Sepsis, unspecified			
A42.7	0	Actinomycotic sepsis						
B37.7	16	Candidal sepsis						
O85	9	Puerperal sepsis						

OFFICIAL: Sensitive

8 SQL Commands

8.1 ED Presentations

```
create or replace view DEV_DAP_CAE05_DB.SEPSIS.VW_ED_VISIT()
as SELECT * FROM (
SELECT ROW_NUMBER() OVER (PARTITION BY JOURNEY_ID ORDER BY ADMITDTM) ED_SEQ_BY_JOURNEY,
* FROM (
SELECT * FROM DEV_DAP_CAE05_DB.JNY.TB_PATIENT_JOURNEY_MAPPING_NEW  AS VISIT
WHERE visit.HOSPITAL IN (SELECT * FROM DEV_DAP_CAE05_DB.SEPSIS.VW_CONFIG_HOSPITAL)
AND TYPECODE = 'Emergency'
AND AGEONADMIT > 15
AND VISIT.ADMITDTM between '2023-01-01'  and DATEADD(month,-1,to_date(getdate())))))
WHERE ED_SEQ_BY_JOURNEY=1
```

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