University of Glasgow | School of Computing Science

THE AWARDS 2020 | UNIVERSITY OF THE YEAR

Benchmark Deep Learning Models with EHR – Part 2

Dr. Fani Deligianni,

fani.deligianni@glasgow.ac.uk

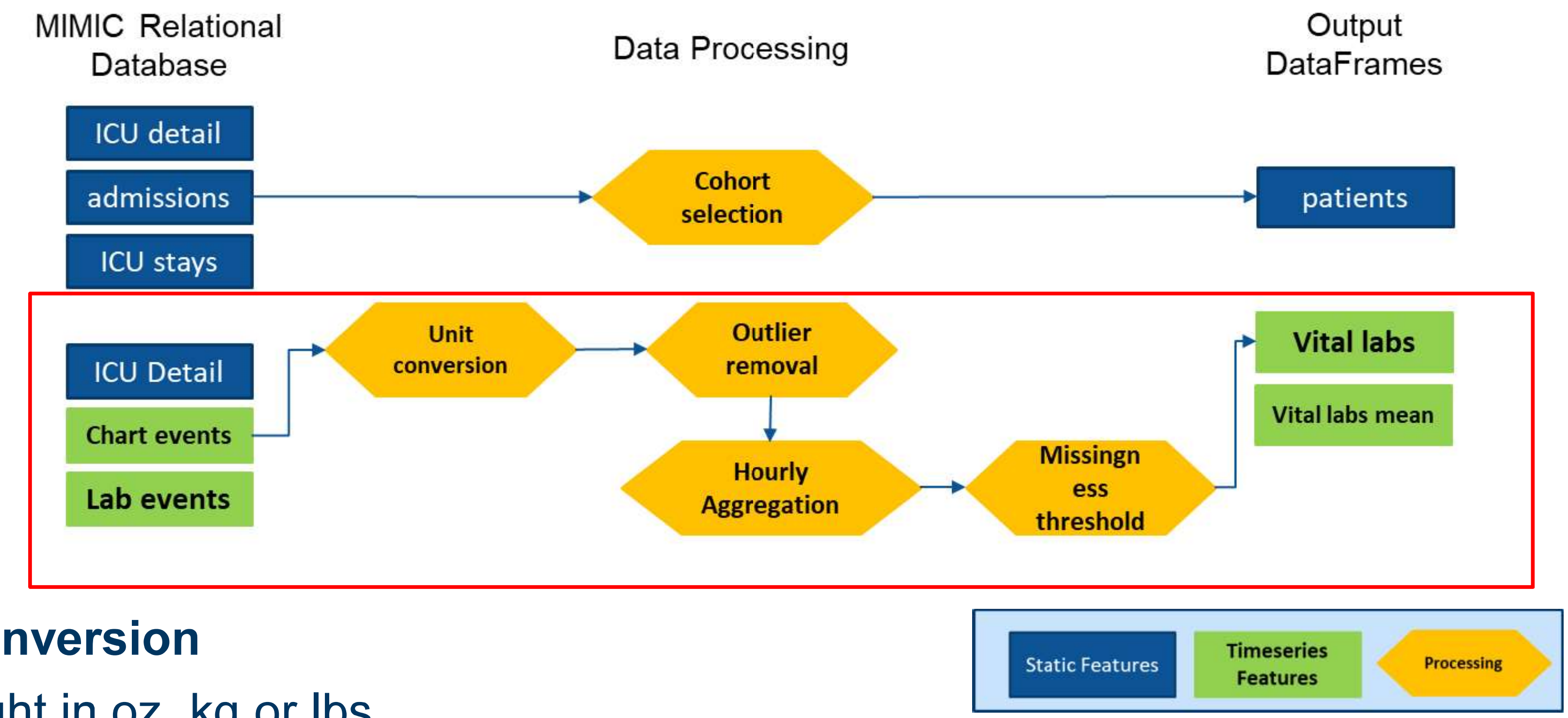
Lecturer (Assistant Professor)

Lead of the Computing Technologies for Healthcare Theme

https://www.gla.ac.uk/schools/computing/staff/fanideligianni

WORLD CHANGING GLASGOW

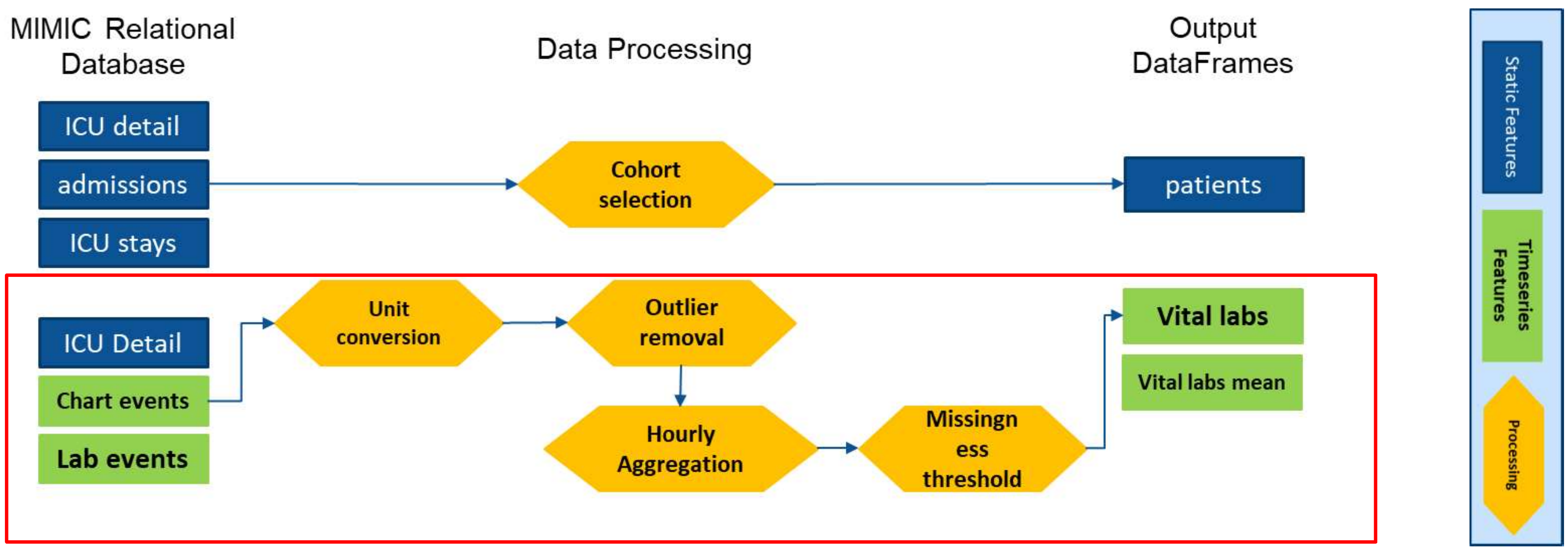
Unit Conversion



Unit Conversion

- Weight in oz, kg or lbs
- Fraction/Percentage
- Temperature in F/C
- Height in inches or meter

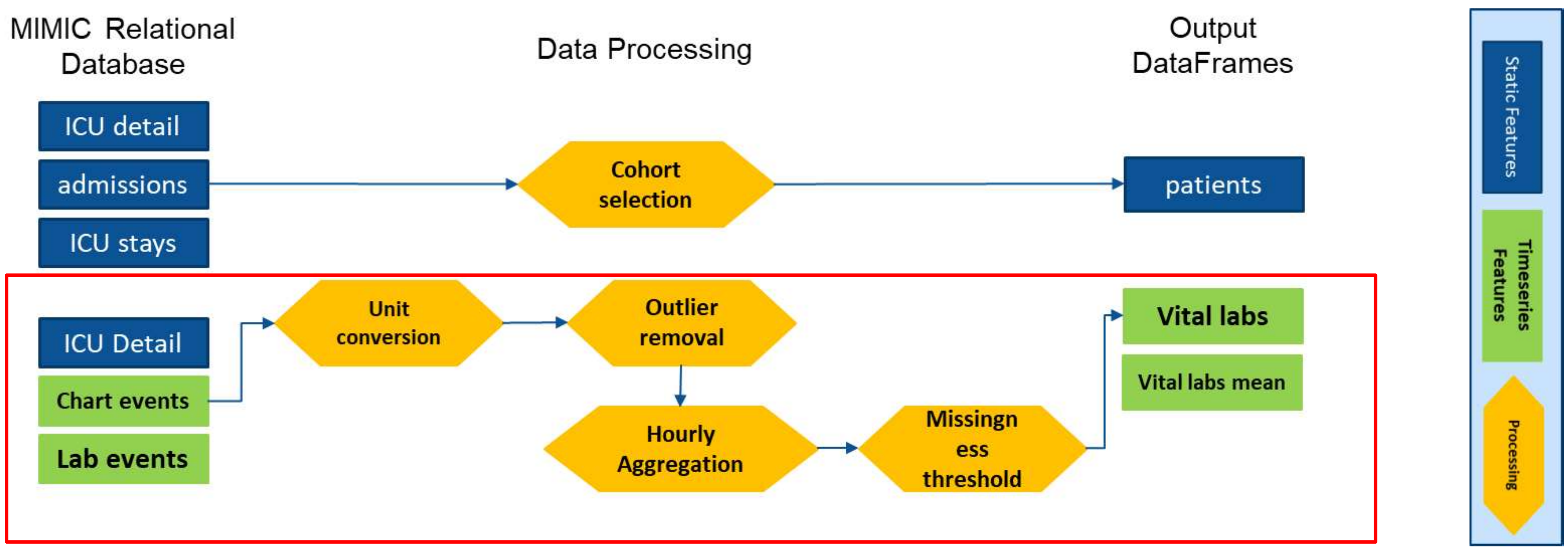
Remove outliers



Detect and remove outliers

- If the outlier falls outside of the threshold, it is treated as missing (set to NaN).
  - If a non-outlier falls outside physiological range, it is replaced with the nearest valid value

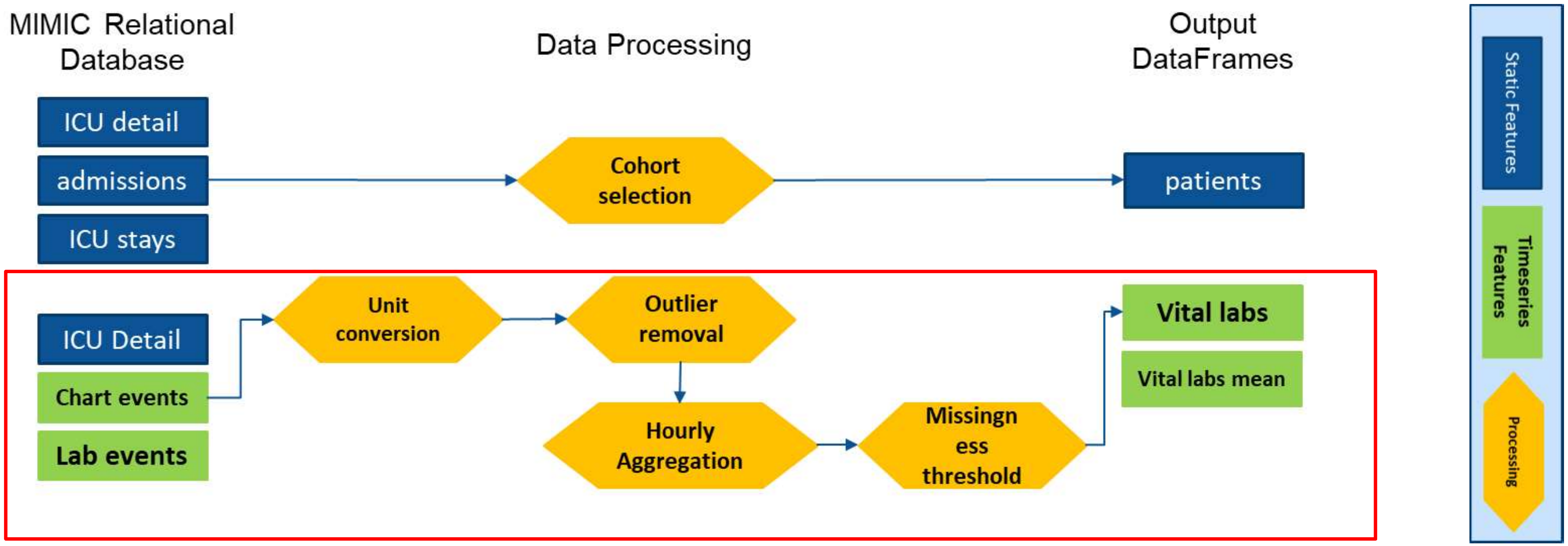
Data Aggregation



Re-organise the data

- Group the variable values within each hour
- Estimate the mean, median, standard deviation and count across all events

Imputation with Average Value



Imputation

- If the variable was measured for the subject, we fill the missing value with the average value across the subject
- If the variable was not measured for the subject for any hour, we fill the missing value with the average value of this variable across all subjects

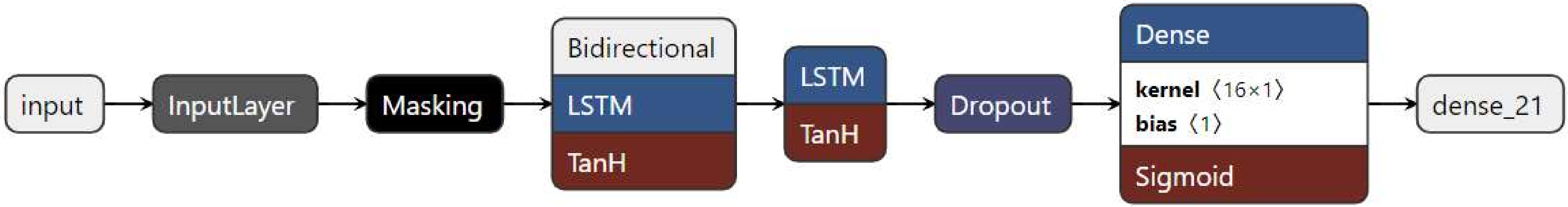
Example Data

Variable	Impute value	Unusable outliers	Valid range	Modelled as
Capillary refill rate	0.0	0.0 – 1.0	0.0 – 1.0	categorical
Diastolic blood pressure	59.0	0.0 – 375.0	0.0 – 375.0	continuous
Fraction inspired oxygen	0.21	0.2 – 1.1	0.21 – 1.0	continuous
Glascow coma scale eye opening	4	1.0 – 4.0	1.0 – 4.0	categorical
Glascow coma scale motor response	6	1.0 – 6.0	1.0 – 6.0	categorical
Glascow coma scale total	11	3.0 – 15.0	3.0 – 15.0	categorical
Glascow coma scale verbal response	4	1.0 – 5.0	1.0 – 5.0	categorical
Glucose	128.0	0.0 – 2200.0	33.0 – 2000.0	continuous
Heart rate	86	0.0 – 390.0	0.0 – 350.0	continuous
Height	170.0	0.0 – 275.0	0.0 – 240.0	continuous
Mean blood pressure	77.0	0.0 – 375.0	14.0 – 330.0	continuous
Oxygen saturation	98.0	0.0 – 150.0	0.0 – 100.0	continuous
Respiratory rate	19	0.0 – 330.0	0.0 – 300.0	continuous
Systolic blood pressure	118.0	0.0 – 375.0	0.0 – 375.0	continuous
Temperature	37.0	14.2 – 47.0	26.0 – 45.0	continuous
Weight	81.8	0.0 – 250.0	0.0 – 250.0	continuous
pH	7.4	6.3 – 10.0	6.3 – 8.4	continuous

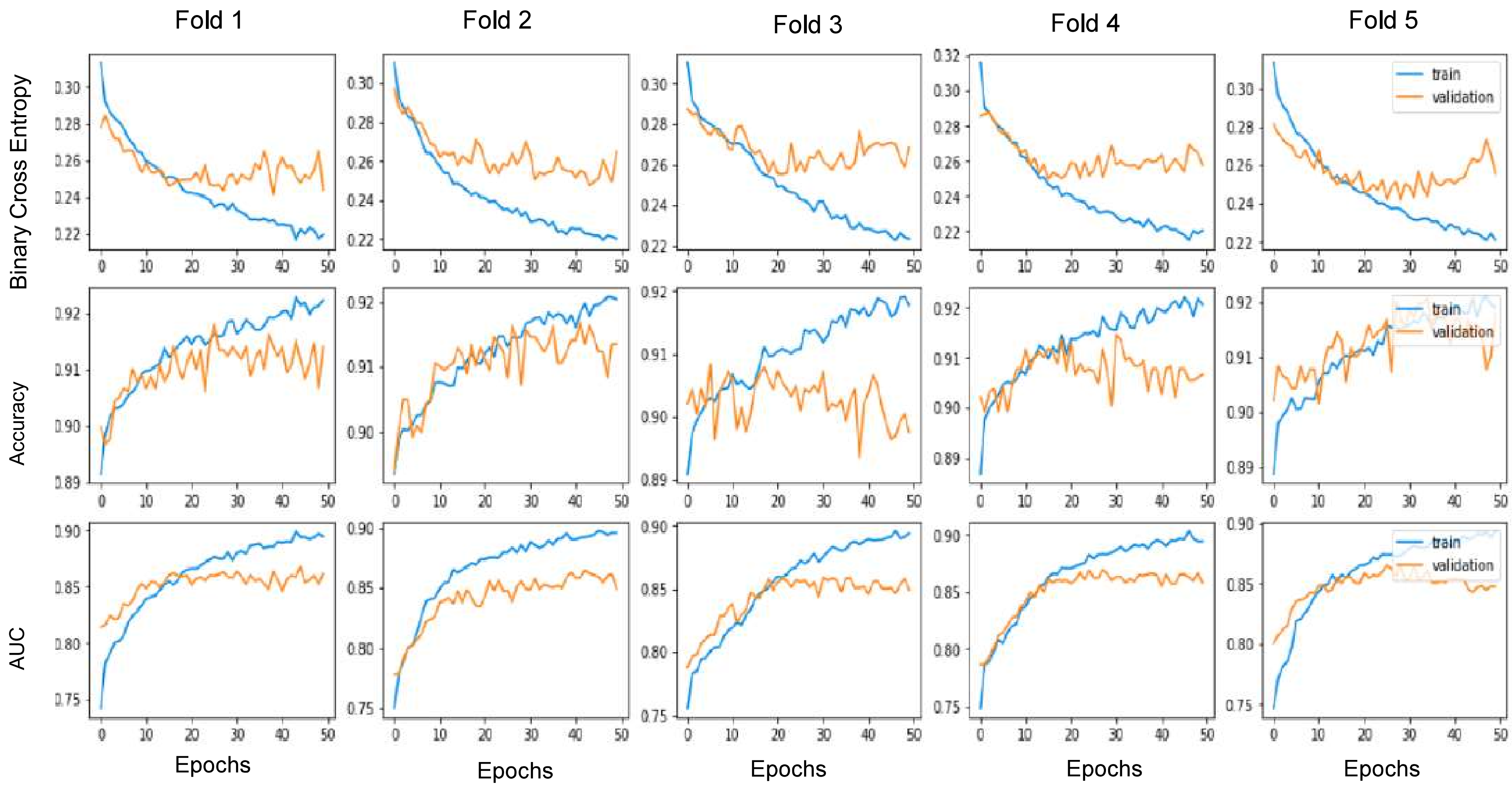
Example Data

			LEVEL2	Diastolic blood pressure				Fraction inspired oxygen			
			Aggregation Function	count	mean	median	std	count	mean	median	std
icustay_id	subject_id	hadm_id	hours_in								
200003	27513	163557	0	1.0	49.000000	49.0	NaN	0.0	NaN	NaN	NaN
			1	3.0	52.000000	47.0	11.357817	0.0	NaN	NaN	NaN
			2	3.0	52.333333	47.0	9.237604	0.0	NaN	NaN	NaN
			3	2.0	60.500000	60.5	13.435029	0.0	NaN	NaN	NaN
			4	2.0	61.000000	61.0	0.000000	0.0	NaN	NaN	NaN

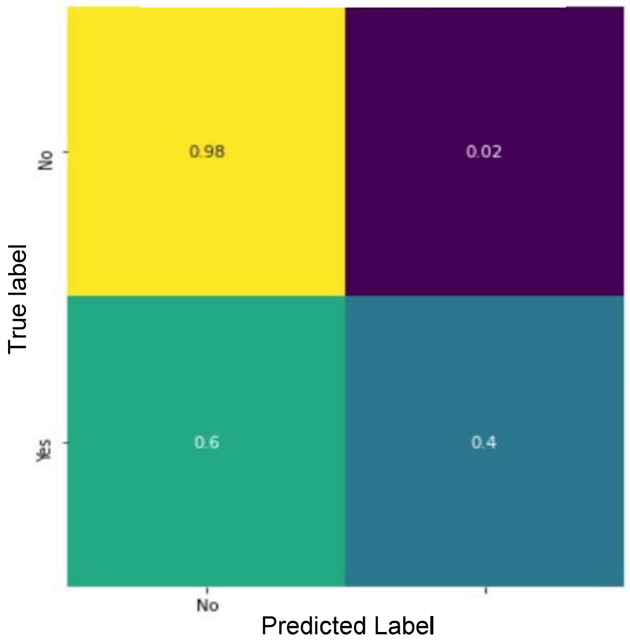
Deep Learning Model

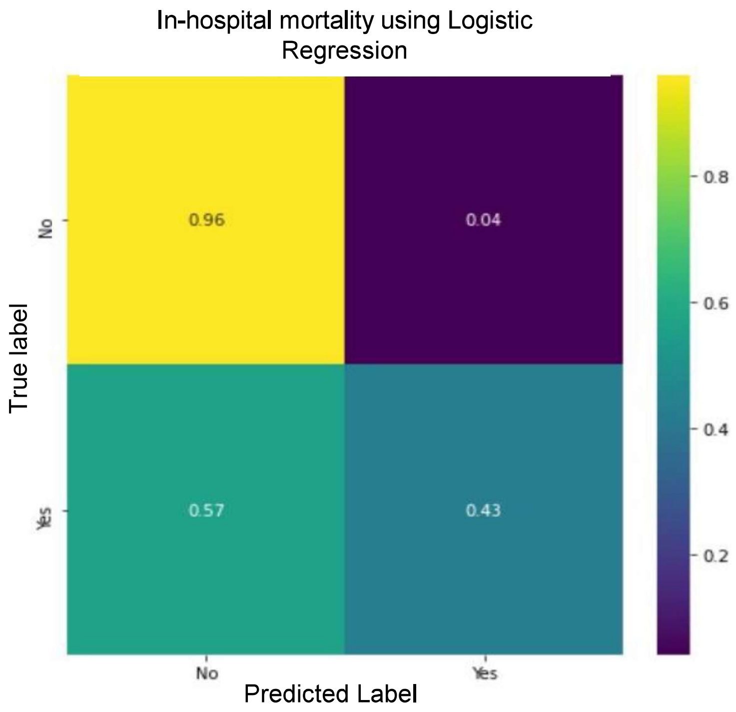


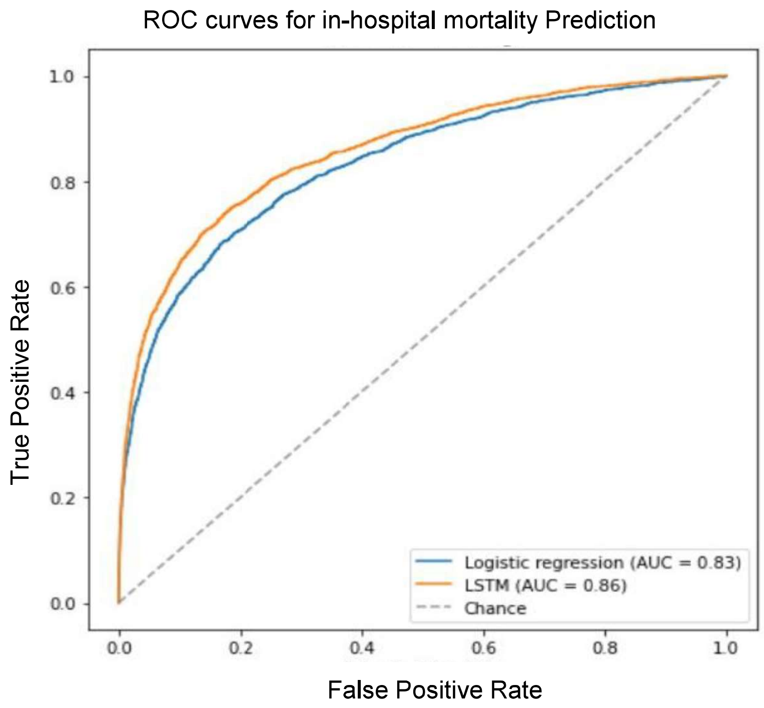
Model Selection



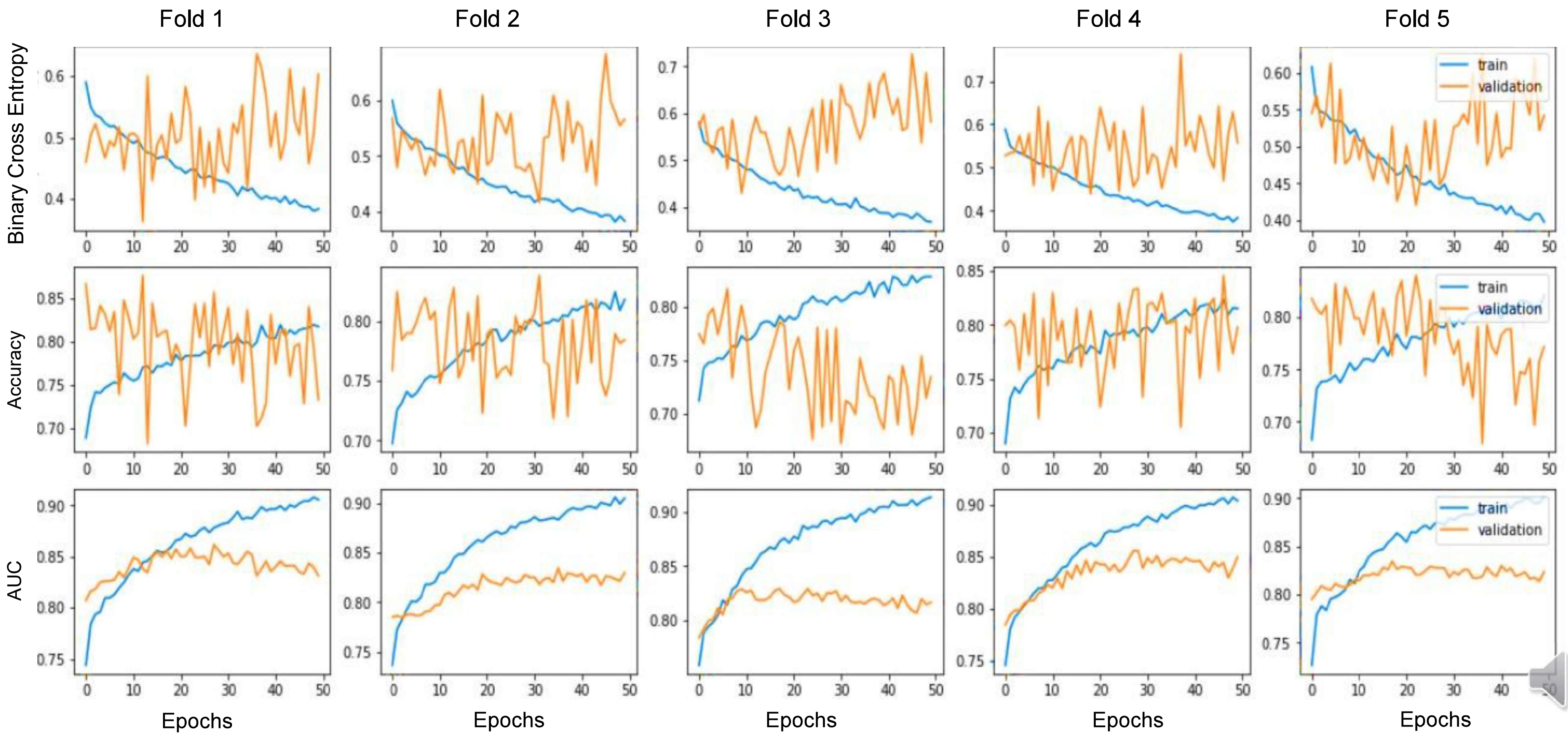
Imbalanced Classes



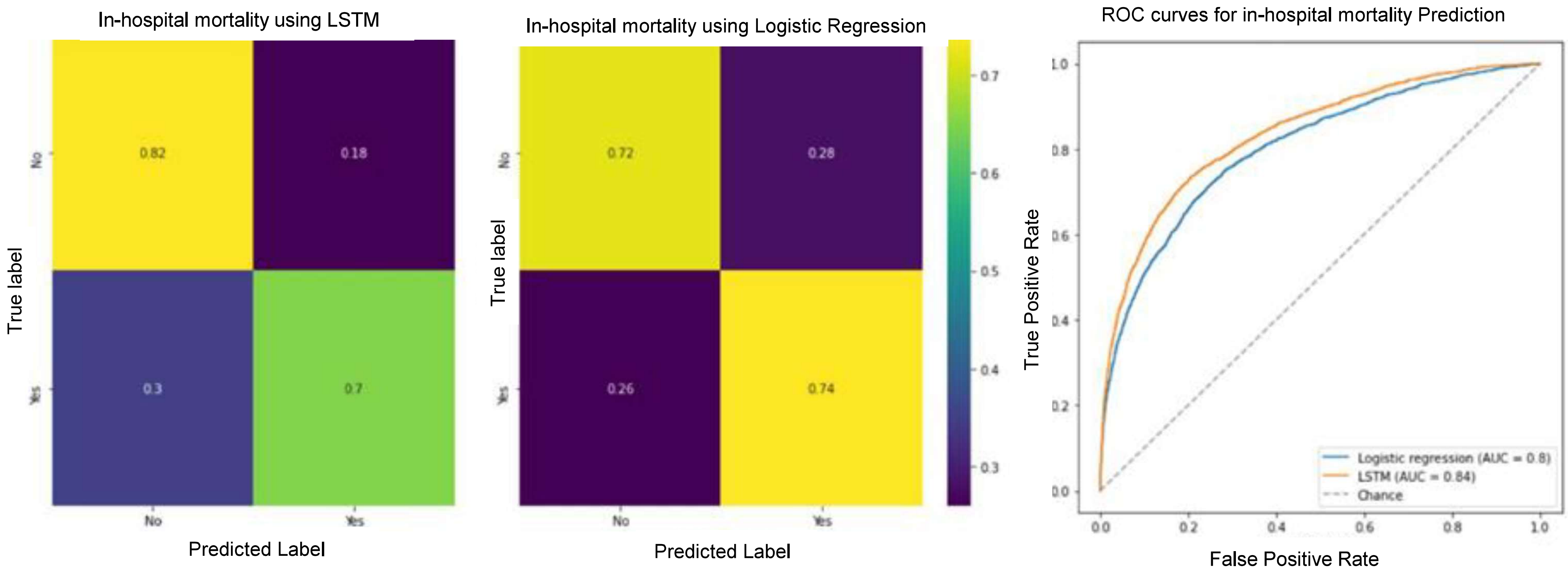




Model Selection



Model Validation



Summary

- Benchmark deep learning algorithm on EHR
- Preprocessing can affect the performance of the machine learning models
- Imbalanced class data can severely affect classification ability
- Overview of several performance metrics is required
- Baseline models are important to understand how our models perform with relation to state-of-the art

References

- Johnson et al. ‘MIMIC-III, a freely accessible critical care database’, Scientific Data, 2016.
- Wang et al. ‘MIMIC-Extract: A Data Extraction, Preprocessing, and Representation Pipeline for MIMIC-III’. https://arxiv.org/abs/1907.08322, 2019.
- Harutyunyan et al. ‘Multitask learning and benchmarking with clinical time series data’, Scientific Data, 2019.