In-hospital Intensive Care Unit Mortality Prediction Model

COMPUTING FOR DATA SCIENCES

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Contents

- **Impact**
- Problem Statement
- Methodology
- Challenges and Steps to overcome
- Implementation
- Program structure
- Results
- Improvement steps
- References

CONCEPT

- Using Artificial intelligence and predictive analytics in hospitals
- Huge amount of data generated in hospitals

Concerns

  - High Reliability is required
  - Highly domain knowledge centric field - reflected in methodology also

IMPACT

- Saves LIFE
- Focus resources on and only-on patients who need
- Data backed decision making for Doctors

Numbers

Expenditure on healthcare in India – 50 Billion USD

Number of Doctors – 7 lakhs

Average cost per survivor from ICU – Rs. 17,000

Nearly 40% of the people admitted to ICU have to borrow money or sell assets

Source:

*http://www.ijccm.org/article.asp?issn=0972-5229;year=2008;volume=12;issue=2;spage=55;epage=61;aulast=Jayaram

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- Improvement steps
- References

Predict risk of death(Mortality) in patients admitted in Intensive Care Unit (ICU) in a hospital.

5990 (simulated) patient records where each **patient record** had following **variables**:

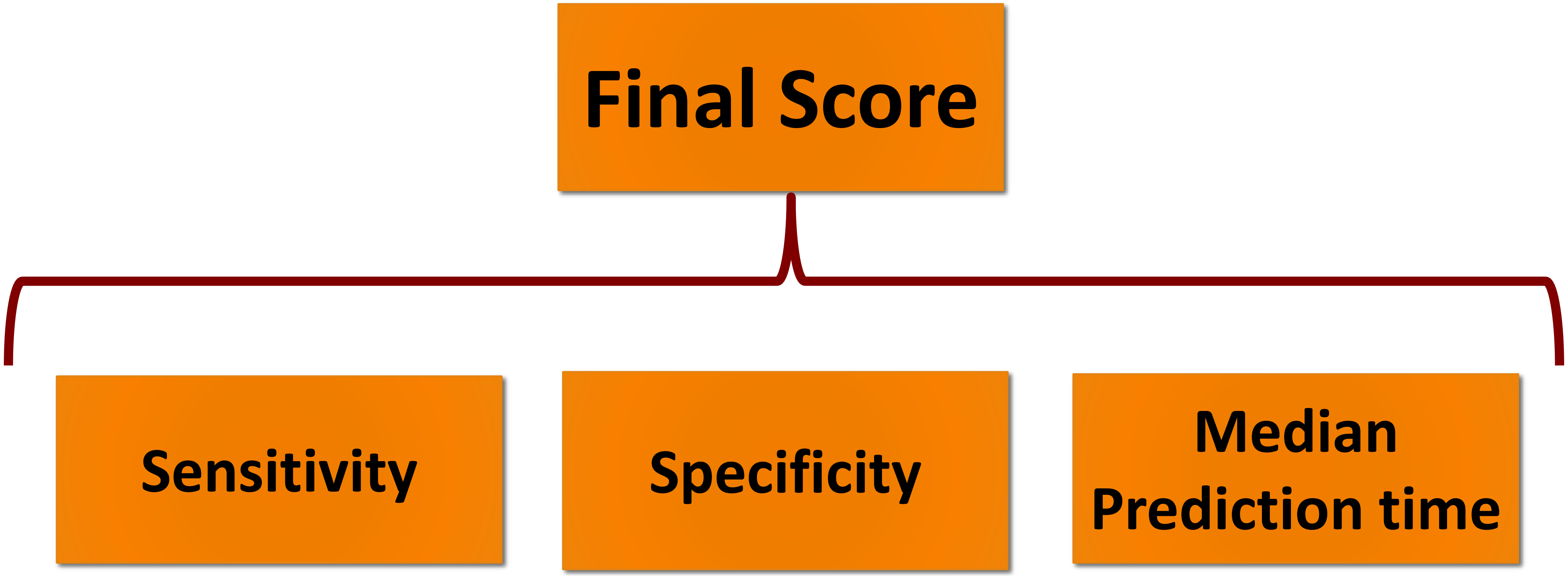
- **ID:** a unique identifier for each patient
- **Age**
- **6 Vitals:** Blood Pressure, Heart Rate, Respiration Rate, Oxygen Saturation, Temperature
- **25 Labs:** like Albumin, WBC Count, Hematocrit, Urine Output, etc.
- **Timestamps:** measurement time relative to first measurement for patient (First, timestamp 0)
- **ICU flag:** indicates whether a patient is in ICU or not at a given time
- **Mortality label:** indicates whether a patient survived or died (the label or outcome variable) at the end of hospital stay

<table>
<tr><th>Patient ID</th><th>Age</th><th>Time Stamp</th><th>ICU Flag</th><th colspan="2">Vital lab measurement (6 Col)</th><th colspan="2">Labs measurements (25 Col)</th><th>Mortality Label (Only in train dataset)</th></tr>
<tr><td>P1</td><td rowspan="3">30</td><td>0</td><td>0</td><td></td><td></td><td></td><td></td><td rowspan="3">0</td></tr>
<tr><td>P1</td><td>T2</td><td>1</td><td></td><td></td><td></td><td></td></tr>
<tr><td>P1</td><td>T3</td><td>1</td><td></td><td></td><td></td><td></td></tr>
<tr><td>P2</td><td rowspan="4">80</td><td>0</td><td>0</td><td></td><td></td><td></td><td></td><td rowspan="4">1</td></tr>
<tr><td>P2</td><td>T5</td><td>0</td><td></td><td></td><td></td><td></td></tr>
<tr><td>P2</td><td>T2</td><td>1</td><td></td><td></td><td></td><td></td></tr>
<tr><td>P2</td><td>T7</td><td>1</td><td></td><td></td><td></td><td></td></tr>
</table>

Constraints

- Prediction only for patients in ICU
- Prediction for all time stamps of the patient
- Only history data of patient for prediction
- Overall prediction – at least one 1 for final prediction 1

Performance Metrics



Performance Metrics

Actual Outcome	**Prediction**	
Dead	Dead	**True Positive(TP)**
Dead	Alive	False Negative(FN)
Alive	Dead	False Positive(FP)
Alive	Alive	True Negative(TN)

Sensitivity =
TP / (TP + FN)

Specificity =
TN / (TN + FP)

Problem Discussion - Metrics

Median Prediction Time:

Only for true positives:

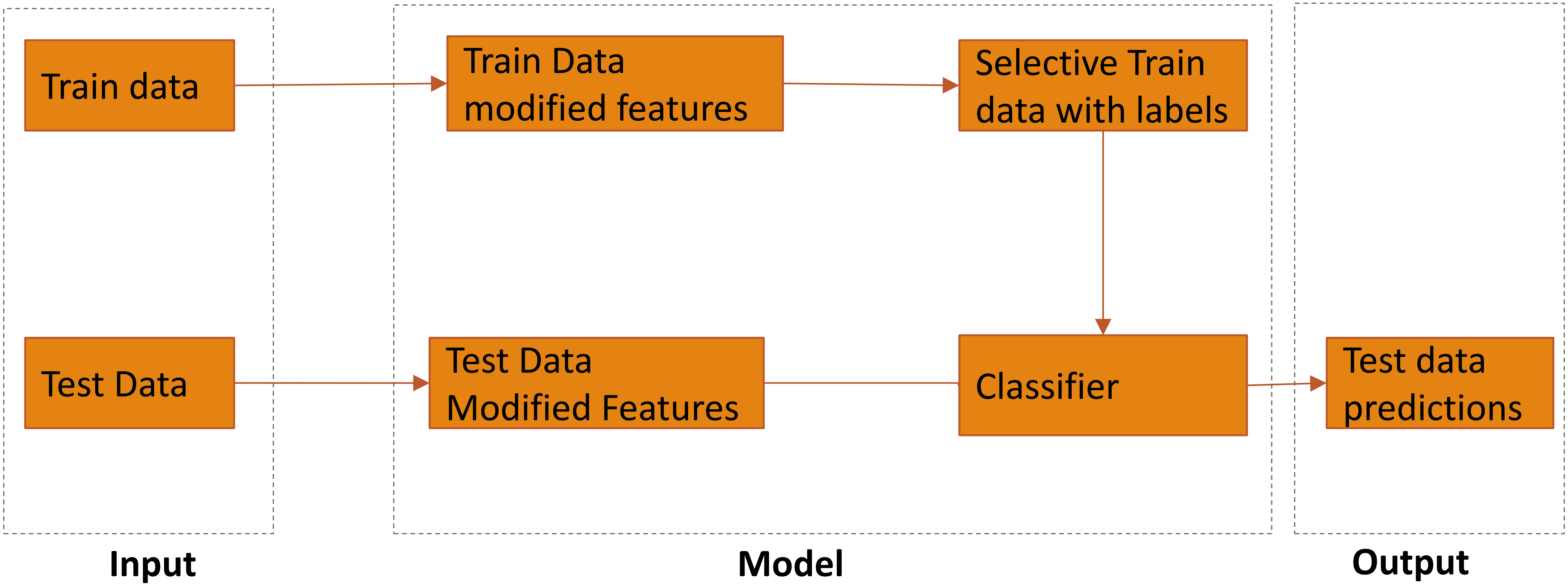
Patient ID	Time Stamp	Prediction
1	0	0
1	2000	0
1	5893	0
1	6137	1
1	7889	1
1	9578	0
1	10345	0

Median prediction Time

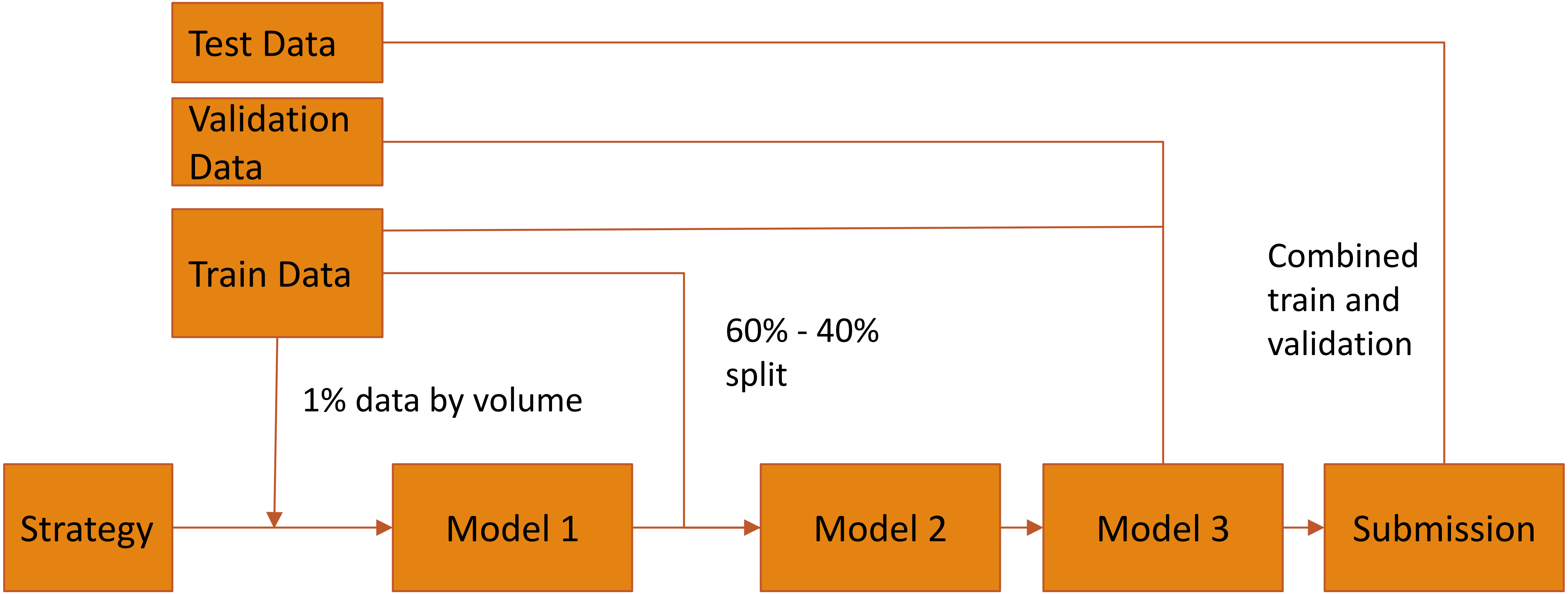
$$
\text{Score} = 100 * \{ 0.75 * \text{Sensitivity} + 0.2 * \text{Median Prediction time clipped at } 72 + 0.05 * (\text{Specificity} - 0.99) \}
$$

- Impact
- Problem Statement
- **Methodology**
- Challenges and Steps to overcome
- Implementation
- Program structure
- Results
- Improvement steps
- References

Methodology



Project Stages



- Impact
- Problem Statement
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- **Challenges and Steps to overcome**
- Implementation
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Challenges

1. Healthcare Variables
2. Missing Values (more than 95% values missing)
3. Train data label assignment
4. Large Data Size (approx. 6 Lakh rows)
5. Minimum score on two-of-the-three metrics
6. Limited attempts submission on test dataset

Healthcare Variables

- Non – linear relation to mortality
- Effective in combinations (e.g. Oxygen Saturation, Carbon Dioxide)
- Depends highly on person to person (e.g. smokers and non-smokers)
- Mortality v/s Morbidity
- Exhaustive Coverage of all mortality reasons is difficult

Overcoming

- Consulted doctors
- Literature review
- Verified using Rpart

Missing Values

- More than 95% data missing
- Data missing for different time stamps for the same patient

```
For every
patient-timestamp{
        for every feature{
                if current value is missing{
                        fill with worst value in last 24 hours
                        else : fill with worst value since ICU entry
                        else : fill with worst value since hospital entry
                        else  : fill with the normal value for the feature
                        }
                }
        }
```

Train Data Label Assignment

- Mortality label only given for patients not patient-timestamp combination
- Aggressive v/s Conservative model

Case		Label Assigned
Patient who ultimately died	Combination of best value of features from Non-ICU Data	0
	Combination of Worst value of features from ICU Data	1
Patient who was alive after ICU	Combination of best value of features from Non-ICU Data	0
	Combination of Worst value of features from ICU Data	0

Large Data Size

- Approx. 6 Lakh rows
- Approx. Feature development time on test set – 35 Hours on PC
- Multiple data slicing involved

Overcome

- Used small but representative dataset while coding (approx. 1% of full dataset)
- Distributed Feature development task on different computers

Minimum score on metrics

- Minimum specificity = 0.99 & Minimum Median Prediction Time – 5 hours
- Specificity v/s Sensitivity tradeoff
- Specificity v/s Median Prediction Time Tradeoff
- Low sensitivity leading to high run-run variation in Median Prediction Time

Overcome

- Vary train data label weights
- Conducted many runs to get the optimum score model parameters

Limited attempts submission on test dataset

- Only 3 submission per team on test data
- High run-to-run variation in metrics
- Model invalid if the minimum metric not achieved

Overcome

- Using Model parameter values which resulted in lower run-to-run variation
- Using conservative parameter values to reduce risk and hence compromising on the final score

- Impact
- Problem Statement
- Methodology
- Challenges and Steps to overcome
- **Implementation**
- Program structure
- Results
- Improvement steps
- References

Implementation

- Language – Python, R

- Packages - numpy, pandas, Scikit-learn, os, csv, rpart, e1071

- Some important functions - merge, subset, rpart, crossValidation, RandomForestClassifier, KNeighborsClassifier, svm

- Impact
- Problem Statement
- Methodology
- Challenges and Steps to overcome
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- **Program structure**
- Results
- Improvement steps
- References

Program Structure for train data

```
For every patient in training data
{ if patient died
  {
        Extracting modified feature from non-icu data of the current patient
        Extracting modified features from icu data of the current patient
  }
  Else
  {
        Extracting modified feature from non-icu data of the current patient
        Extracting modified features from icu data of the current patient
  }
}
```

Program Structure for test data

For every patient timestamp in test data

```
{ if patient in ICU
  {
          Creating modified feature for the current patient timestamp using his/her historical data
  }
}
```

Train classifier using the extracted modified feature matrix

Predicting mortality for every timestamp (in test data) when patient is in ICU

Code Snippet

```
def score_mean_blood_pressure(systolic_bp,diastolic_bp):
        if not pd.isnull(systolic_bp):
                if not pd.isnull(diastolic_bp):
                        mean_bp = (systolic_bp + diastolic_bp)/2
                        if mean_bp <= 39:
                                return 23
                        elif mean_bp>39 and mean_bp<60:
                                return 15
                        elif mean_bp>=60 and mean_bp<70:
                                return 7
                        elif mean_bp>=70 and mean_bp<80:
                                return 6
                        elif mean_bp>=80 and mean_bp<100:
                                return 0
                        elif mean_bp>=100 and mean_bp<120:
                                return 4
                        elif mean_bp>=120 and mean_bp<130:
                                return 7
                        elif mean_bp>=130 and mean_bp<140:
                                return 9
                        elif mean_bp>=140:
                                return 10
```

```
#Mean BP modified feature for Non-ICU of current patient if he/she finally died
pressure_data = data_sub[['V1','V2']]
score_list = []
for index,row in pressure_data.iterrows():
        systolic_bp = float(row['V1'])
        diastolic_bp = float(row['V2'])
        if not pd.isnull(systolic_bp):
                if not pd.isnull(diastolic_bp):
                        mean_bp = score_mean_blood_pressure(systolic_bp,diastolic_bp)
                        score_list.append(mean_bp)
if not score_list:
        mean_bp_non_icu_score = 0
else:
        mean_bp_non_icu_score = min(score_list)
```

```python
#Mean BP modified feature
systolic_current_value = float(row['V1'])
diastolic_current_value = float(row['V2'])
if ((pd.isnull(systolic_current_value)) or (pd.isnull(diastolic_current_value))):
    if timestamp>0:
        data_sub = val_df[(val_df.ID == patient_id) & (val_df.TIME < timestamp)]
        bp_data_history = data_sub[['V1','V2']]
        if timestamp < (3600*24):
            score_list = []
            for index,row_1 in bp_data_history.iterrows():
                systolic_bp = float(row_1['V1'])
                diastolic_bp = float(row_1['V2'])
                if (pd.isnull(systolic_bp)) or (pd.isnull(diastolic_bp)):
                    score_list.append(0)
                else:
                    mean_bp = score_mean_blood_pressure(systolic_bp,diastolic_bp)
                    score_list.append(mean_bp)
                if not score_list:
                    mean_bp_score = 0
                else:
                    mean_bp_score = max(score_list)
        else:
            timestamp_less_24 = timestamp - (3600*24)
            data_sub = val_df[(val_df.ID == patient_id) & (val_df.TIME < timestamp) & (val_df.TIME > timestamp_less_24)]
            bp_data_history = data_sub[['V1','V2']]
            score_list = []
            for index,row_2 in bp_data_history.iterrows():
                systolic_bp = float(row_2['V1'])
                diastolic_bp = float(row_2['V2'])
                if (pd.isnull(systolic_bp)) or (pd.isnull(diastolic_bp)):
                    score_list.append(0)
                else:
                    mean_bp = score_mean_blood_pressure(systolic_bp,diastolic_bp)
                    score_list.append(mean_bp)
                if not score_list:
                    data_sub = val_df[(val_df.ID == patient_id) & (val_df.TIME < timestamp)]
                    bp_data_history = data_sub[['V1','V2']]
                    score_list = []
                    for index,row in bp_data_history.iterrows():
                        systolic_bp = float(row_2['V1'])
                        diastolic_bp = float(row_2['V2'])
                        if (pd.isnull(systolic_bp)) or (pd.isnull(diastolic_bp)):
                            score_list.append(0)
                        else:
                            mean_bp = score_mean_blood_pressure(systolic_bp,diastolic_bp)
                            score_list.append(mean_bp)
                    if not score_list:
                        mean_bp_score = 0
                    else:
                        mean_bp_score = max(score_list)
                else:
                    mean_bp_score = max(score_list)
    else:
        mean_bp_score = 0
else:
    mean_bp_score = score_mean_blood_pressure(systolic_current_value,diastolic_current_value)
```

- Impact
- Problem Statement
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- References

Results

Upload solution here:

Output.csv:	output.csv (2.36 MiB)	Validation Passed	Score: 0.250372	Uploads Remaining: 2

Median Prediction time (hrs) 1937.68111111
Average Prediction time (hrs) 1937.68111111
Sensitivity : 0.0243902439024
Specificity : 0.996415770609

Workfiles: run_model.7z (6.54 kiB)

- Better results with Random Forest Classifier than KNN and SVM

- Impact
- Problem Statement
- Methodology
- Challenges and Steps to overcome
- Implementation
- Program structure
- Results
- **Improvement steps**
- References

Improvement Steps

- Different classifiers; tweaking depth and sample weight

- KNN - lower run to run variance Vs Random forest - higher median prediction time

- Added train and validation data as training data for prediction on test data

- Impact
- Problem Statement
- Methodology
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- Implementation
- Program structure
- Results
- Improvement steps
- **References**

References

- Literature
  - Published approaches from Physionet challenge 2012
  - National Centre for Biotechnology Information (NCBI)
  - Journal of intensive care
- Doctors consulted
  - Dr. Priyanka Singh
  - Dr. Tejaswi
  - Dr. Ram Kiran
- www.stackoverflow.com
- Hackerrank Discussion forum
- Discussions with classmates (Pradeep Mooda, Avinash Kumar)
- Lord Google ☺

Questions?