Using Machine Learning to Refer Patients with Chronic Kidney Disease to Secondary Care

Lee Au-Yeung[1], Xianghua Xie[2], James Chess[3,4], Timothy Scale[3,4]

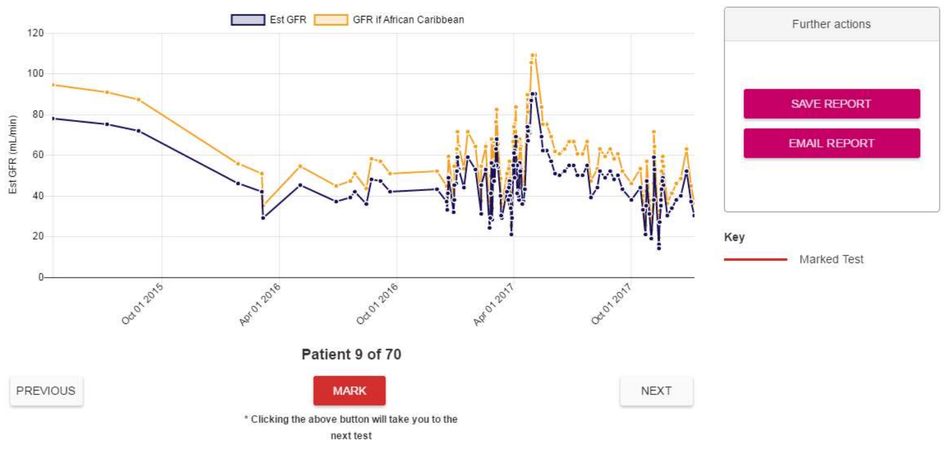
[1]Swansea University Medical School, [2]Department of Computer Science, Swansea University, [3]Swansea Bay Local Health Board , [4]Wales Kidney Research Unit

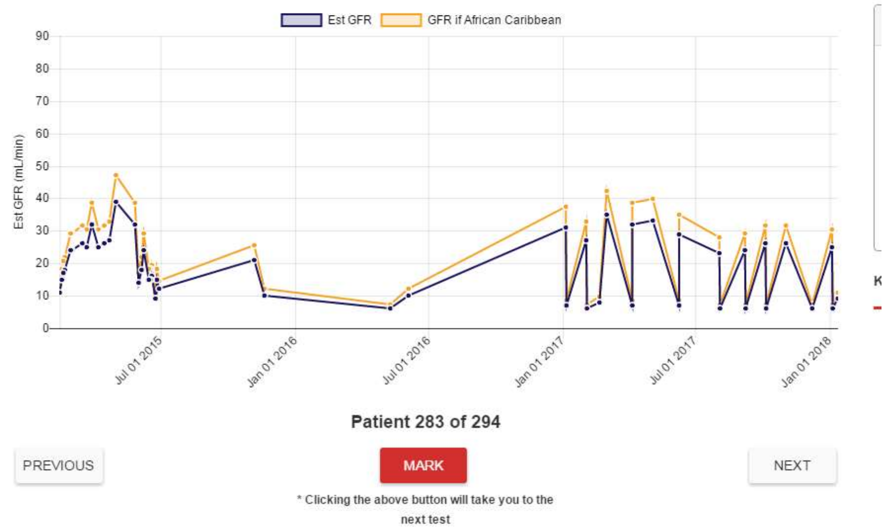
Introduction

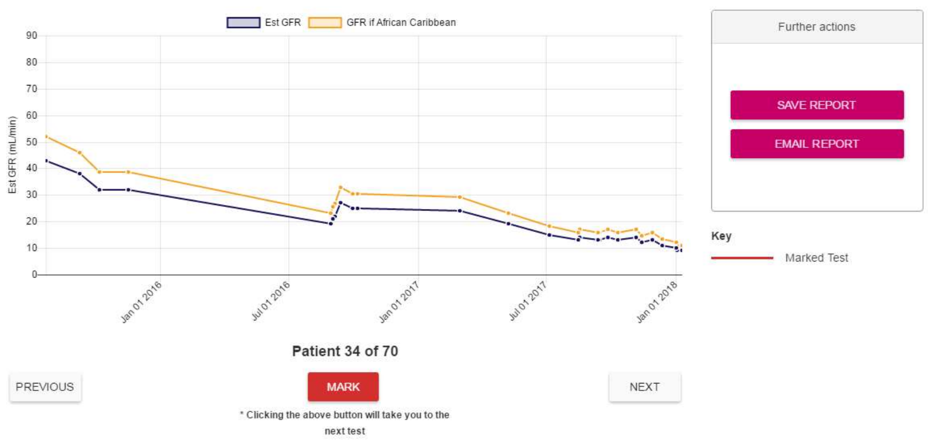
- Assist-CKD used by hospitals in England and Wales
  - Used 1 hour per week by 2 operators
  - Based on Clinical Judgement

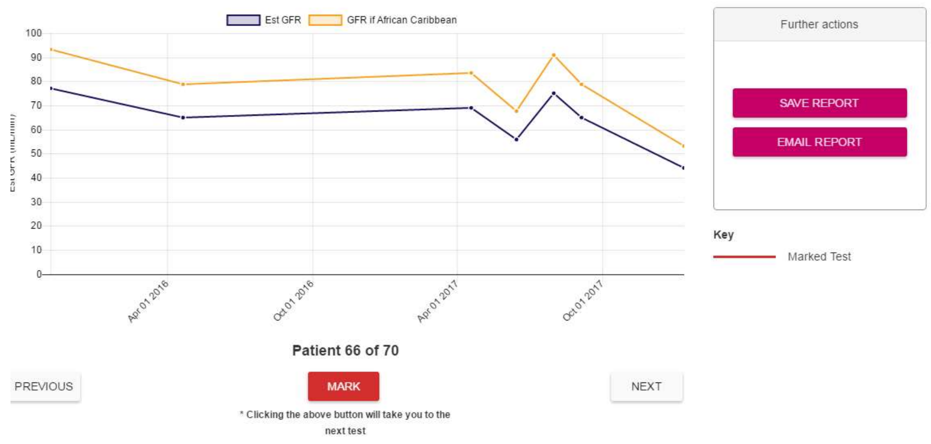
- Variables
  - eGFR – estimated Glomerular Filtration rate.
  - Age
  - Gender


Est GFR
GFR if African Caribbean
100
90
80
70
60
50
40
30
20
10
0
Est GFR (mL/min)
Oct 01 2015
Apr 01 2016
Oct 01 2016
Apr 01 2017
Oct 01 2017
Patient 2 of 70
PREVIOUS
MARK
NEXT
* Clicking the above button will take you to the next test
Further actions
SAVE REPORT
EMAIL REPORT
Key
Marked Test


Est GFR
GFR if African Caribbean
Est GFR (mL/min)
Oct 01 2015
Apr 01 2016
Oct 01 2016
Apr 01 2017
Oct 01 2017
Further actions
SAVE REPORT
EMAIL REPORT
Key
Marked Test
Patient 9 of 70
PREVIOUS
MARK
NEXT
* Clicking the above button will take you to the next test


Est GFR
GFR if African Caribbean
Est GFR (mL/min)
Jul 01 2015
Jan 01 2016
Jul 01 2016
Jan 01 2017
Jul 01 2017
Jan 01 2018
Patient 283 of 294
PREVIOUS
MARK
NEXT
* Clicking the above button will take you to the next test


Est GFR
GFR if African Caribbean
Est GFR (mL/min)
Jan 01 2016
Jul 01 2016
Jan 01 2017
Jul 01 2017
Jan 01 2018
Further actions
SAVE REPORT
EMAIL REPORT
Key
Marked Test
Patient 34 of 70
PREVIOUS
MARK
NEXT
* Clicking the above button will take you to the next test

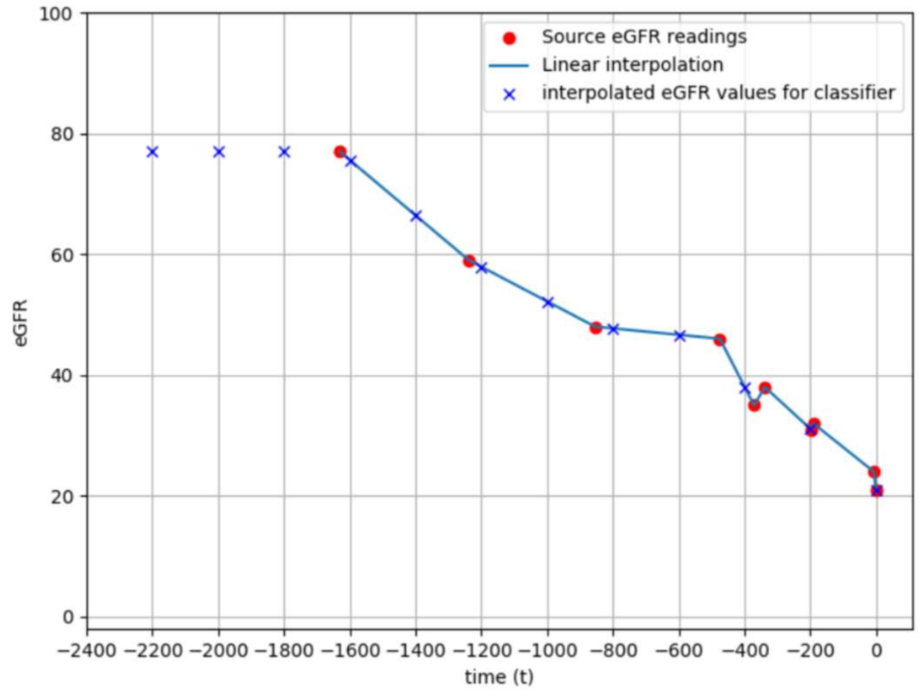

Est GFR
GFR if African Caribbean
Apr 01 2016
Oct 01 2016
Apr 01 2017
Oct 01 2017
Further actions
SAVE REPORT
EMAIL REPORT
Key
Marked Test
Patient 66 of 70
PREVIOUS
MARK
NEXT
* Clicking the above button will take you to the next test

Challenges

- Data is very sparse with blood test sampling frequency very low
- Irregularly sampled data
- The data is temporal data

Feature Extraction Method

- Construct feature matrix that can be used by classification algorithms
  - Use linear interpolation between readings
  - Align readings to latest or earliest reading
  - Age and Sex variables concatenated to feature matrix
    - Sex is converted to a numerical code M = 0, Female = 1



Imputation by linear interpolation. Aligned to latest reading.

Feature Extraction Method

Feature Matrix

	impted eGFR$_1$	...	imputed eGFR$_n$	Age	Sex
Patient$_1$	55	:	30	89	1
Patient$_2$	54	:	25	32	0
Patient$_3$	53	:	45	48	1
:	:	:	:	:	:
Patient$_n$	:	:	:	:	:

Classification Algorithms

- Logistic Regression
- Artificial Neural Network
- Support Vector Machine

Results: Best Classification Model Descriptions

#	Classifier and Feature Set Description	Date Algin
1	**SVM(LK)** matrix of interpolated eGFR at equal chronological time intervals, interpolation by value between 2 real readings, including age	L
2	**SVM(LK)** matrix of interpolated eGFR at equal chronological time intervals, interpolation by value between 2 real readings, including age and sex	L
3	**ANN (1024,256,2)** matrix of interpolated eGFR at equal chronological time intervals, interpolation by value between 2 real readings, including age	L
4	**LogReg** matrix of interpolated eGFR at equal chronological time intervals, interpolation by value between 2 real readings, including age	L
5	**LogReg** matrix of interpolated eGFR at equal chronological time intervals, interpolation by value between 2 real readings, including age and sex	L
6	**ANN (1024,256,2)** matrix of interpolated eGFR at equal chronological time intervals, interpolation by value between 2 real readings	L
7	**LogReg** matrix of interpolated eGFR at equal chronological time intervals, interpolation by value between 2 real readings	L
8	**ANN (512,64,2)** matrix of interpolated eGFR at equal chronological time intervals, interpolation by value between 2 real readings, including sex	L
9	**LogReg** matrix of interpolated eGFR at equal chronological time intervals, interpolation by value between 2 real readings, including sex	L
10	**ANN (512,64,2)** matrix of interpolated eGFR at equal chronological time intervals, interpolation by value between 2 real readings	L

Results: k-Fold x-Validation

Model #	Avg Training Time (s)	Avg Overall Accuracy	Avg Sensitivity	Avg Specificity
1	1.95	90.64%	81.40%	93.37%
2	1.94	89.54%	91.86%	88.83%
3	37.48	89.11%	72.09%	94.07%
4	1.43	88.01%	88.95%	87.61%
5	1.38	87.96%	88.37%	87.78%
6	21.8	87.64%	87.79%	87.61%
7	1.32	87.53%	88.95%	87.09%
8	18.49	87.34%	86.63%	87.43%
9	1.47	87.18%	88.95%	86.74%
10	22.45	86.91%	81.98%	88.31%

Results: Bootstrap Testing

Model #	Avg Training Time (s)	Avg Overall Accuracy	Avg Sensitivity	Avg Specificity
5	6.47	88.48%	86.67%	89.02%
9	6.71	88.14%	86.50%	88.63%
4	6.42	88.09%	86.03%	88.71%
7	6.5	88.05%	86.08%	88.64%
8	48.21	87.12%	88.36%	86.74%
6	31.93	86.94%	89.01%	86.31%
10	15.21	86.60%	89.74%	85.65%
3	15.69	86.61%	89.30%	85.81%
1	0.4	85.29%	85.51%	85.23%
2	0.39	84.78%	80.29%	86.14%

Results: Summary

We are able to achieve an overall accuracy of

- 88.48% using logistic regression,
- 87.12% using Artificial Neural Network and
- 85.29% using Support Vector Machine.

ANNs performed with the highest sensitivity at 89.74% compared to 86.67% for logistic regression and 85.51% for SVM.

Conclusions

- Support Vector Machines didn't perform consistently in this application
- Logistic regression performed the most consistently
  and gave the best overall results under more rigorous bootstrap testing
- Artificial Neural Networks performed with the highest sensitivity.
  This is a very desirable property for use in a clinical setting.

Future Work

Enhanced Feature Extraction:

- Search for ideal imputation time interval
- Experiment with Convolutional Neural Networks
- Test with more data

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Uned Ymchwil Arennol Cymru
Wales Kidney Research Unit

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QUESTIONS?