Evaluating the risk of acute kidney failure in pre-existing diabetic patients

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Abstract

This study harnesses the power of machine learning techniques to anticipate the onset of Acute Kidney Injury (AKI) within a 7-day horizon in patients with pre-existing diabetes. The research unfolds against the backdrop of electronic health records extracted from the MIMIC-IV (Medical Information Mart for Intensive Care) database, encompassing data from patients admitted to the critical care units of Beth Israel Deaconess Medical Centre between 2008 and 2023. Mixed results were uncovered, with promising results shown for the Harding Voting, Gradient Boosting Trees and Random Forest models.

1 Introduction

Acute kidney injury (AKI) is a critical concern in the healthcare field, marked by a sudden and often severe decline in kidney function. This complex condition is associated with significant health risks and mortality, making it a focal point in clinical research and practice. AKI is also intricately linked with patients that suffer from Chronic Kidney Disease (CKD), with studies suggesting that their aetiology being remarkably similiar.[3] Among the various factors that increase the likelihood of AKI, pre-existing diabetes mellitus stands out as a prominent contributor.

Diabetes mellitus, a chronic metabolic disorder characterized by high blood sugar levels, presents a substantial global health challenge, affecting a significant portion of the population. The prevalence of diabetes is continually rising.[14] In 2021, the global prevalence of diabetes of adults aged between 25 to 75 was estimated to be 10.5% (536.6 million people), with it expected to rise to 12.2% (783.2 million) by the year 2045. This rise has largely been attributed to the ageing population. However, there are also other factors such as improvements in medical care and increasing incidence within specific countries that also act as important drivers in higher prevalence.[2,10] This only underscores the pressing need to comprehend its relationship with AKI due to the serious consequences associated.

The objective of this research is to systematically investigate and assess the intricacies of AKI risk in the context of pre-existing diabetes. It is known that AKI occurs in 15% of hospital patients, yet ¡50% of these results are recorded in electronic health records (EHRs) and best practises are also performed inconsistently.[15] We aim to train and analyse the performance of a multitude of machine learning models to predict the onset of AKI within 7 days of vital sign recordings. This is to better aid healthcare professionals in early intervention and personalised case for diabetes, mitigating kidney complications.

2 Method

2.1 Data Source

The chosen data source for this project would be the latest version of MIMIC-IV (Medical Information Mart for Intensive Care).[7] MIMIC comprises of deidentified health-related dataset from patients admitted to the critical care units of Beth Israel Deaconess Medical Centre from the years 2008 to 2023. Within this dataset, we plan to identify patients who developed acute kidney injury within those that suffer from diabetes.

2.2 Algorithm Development

We used the following definitions of acute kidney injury and diabetes as the diagnostic criteria to identify the relevant patients.

1. Acute Kidney Injury (AKI):

   Using the criteria defined in the 2012 Kidney Disease: Improving Global Outcomes (KDIGO), we used serum creatinine levels and urine output.[9] ICD diagnostics codes were also used to substantiate these measures.

   - Serum Creatinine: $\geq$ 1.5 times baseline OR $\geq$ 0.3 mg/dL increase
   - Urine output: $\leq$ 0.5 mL/kg/h for $\leq$ 6 hours
   - ICD Diagnosis Code: N179, Acute kidney failure, unspecified (Version 10)

2. Diabetes:

   There are a number of diagnostic tests that can be administered following the Royal Australian College of General Practitioners diabetes guidelines.[4] We will specifically be targeting the Hb1Ac test for its non-fasting requirements and general blood glucose levels.

   - Glycated Hemoglobin(Hb1Ac): $\geq$ 6.5%
   - Blood Glucose Level: $>$ 125 mg/dL

If any readings satisfied the above diabetes diagnostic criteria, these patients were then included within the diabetes patient cohort. This is summarised in Figure 1. In a similiar fashion, to pinpoint diabetic patients who then experience AKI within 7 days of an abnormal glucose reading we use the above AKI diagnostic criteria to identify these patients. This is summarised in Figure 2.

The algorithm used a combination of diagnostics codes, laboratory results and medications taken. The tables 1 and 2 below shows some of the lab item codes used to identify blood glucose levels and Hb1Ac tests.

3 Results

A visual comparison of the performance of various classification models and ensemble techniques in identifying the risk factors unique to

Lab Item Code (d_items)	Description
220621	Serum Glucose
225662	Glucose (Finger Stick)
226537	Glucose (Whole Blood)

Table 1: Glucose Measurement Codes for MIMIC icu module

Lab Item Code (d_labitems)	Description
50809	Glucose (Blood Gas)
50931	Glucose (Chemistry)
52027	Glucose (Whole Blood)
52569	Glucose (Chemistry)

Table 2: Glucose Measurement Codes for MIMIC hosp module

Acute Kidney Injury (AKI) in patients with preexisting Diabetes Mellitus. The models considered for evaluation include Logistic Regression, Support Vector Classification (Linear Kernel), Dense Neural Network (DNN), Gradient Boosting Trees, Hard Voting (an ensemble method), Long Short-Term Memory (LSTM), and Random Forest.

3.1 Logistic Regression

Logistic Regression is a simple yet interpretable model. It demonstrates moderate performance in capturing the unique risk factors associated with AKI in patients with diabetes. In the first experiment, it achieves a recall of 0.52 for class 0 and 0.55 for class 1, with an accuracy of 0.53 and an ROC AUC score of 0.5352. In the second and third experiments, the model's performance improves slightly in terms of recall and accuracy, indicating that it might benefit from more data or tuning. However, the ROC AUC score remains relatively low, suggesting that the model may not effectively discriminate between the two classes. While it provides a preliminary understanding of the relationship, its ROC AUC score suggests that more complex models may be needed to fully comprehend this complex interaction.

3.2 Support Vector Classification (Linear Kernel)

Support Vector Classification with a linear kernel shows mixed performance, reflecting the intricacies of the relationship between diabetes and AKI. In the first experiment, it has a relatively low recall for class 0 (0.45) and class 1 (0.59). The accuracy and ROC AUC score are also moderate. In the second experiment, the model's recall for class 1 improves, but it still struggles with class 0, and the ROC AUC score increases. In the third experiment, there is a significant drop in class 1 recall and a slight improvement in class 0 recall, which results in a low ROC AUC score. While it demonstrates potential, there is room for improvement to better understand this complex interaction.

Model	Classify	Recall 0	Recall 1	Accuracy	ROC AUC Score
Logistic Regression	1	0.52	0.55	0.53	0.5352
	2	0.57	0.6	0.58	0.5831
	3	0.58	0.62	0.58	0.5967
Support Vector Classification	1	0.45	0.59	0.48	0.5184
(Linear Kernel)	2	0.55	0.67	0.57	0.6088
	3	0.58	0.42	0.57	0.5021
Dense Neural Network (DNN)	1	0.61	0.45	0.57	0.5315
	2	0.72	0.45	0.66	0.5830
	3	0.57	0.44	0.56	0.5047
Gradient Boosting Trees	1	0.44	0.61	0.49	0.5269
	2	0.56	0.55	0.56	0.5587
	3	0.62	0.41	0.61	0.5127
Voting (Hard)	1	0.50	0.58	0.52	0.5423
	2	0.57	0.63	0.59	0.6034
	3	0.53	0.44	0.52	0.4846
Long Short-Term Memory (LSTM)	1	0.49	0.56	0.52	0.5332
	2	0.58	0.61	0.60	0.6231
	3	0.52	0.62	0.57	0.6084
Random Forest	1	0.48	0.58	0.50	0.5319
	2	0.53	0.62	0.55	0.5734
	3	0.61	0.38	0.60	0.4954

Table 3: Model Performance Comparison

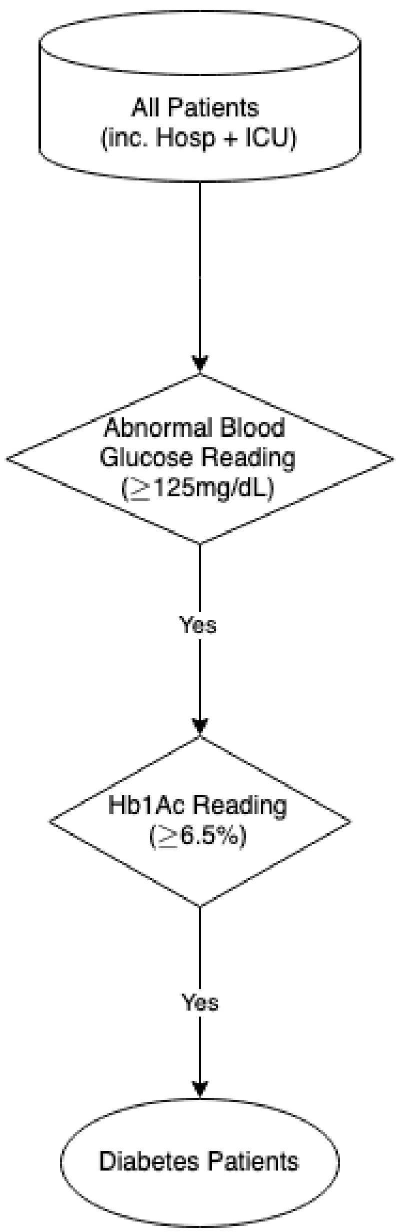

Figure 1: Diabetes case algorithm to filter MIMIC-IC patient cohort

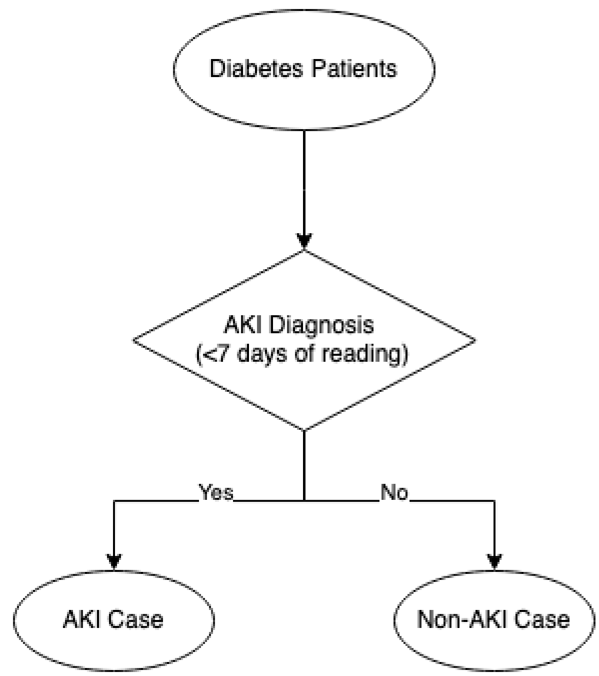

Figure 2: Acute Kidney Injury (AKI) case algorithm to filter through diabetes patient cohort

3.3 Dense Neural Network (DNN)

Dense Neural Network (DNN) exhibits potential in capturing the intricacies of AKI risk in diabetes. In the second experiment, it achieves the highest accuracy of all models (0.66) and a respectable ROC AUC score of 0.5830. However, its recall for class 1 is relatively low, indicating room for improvement. Fine-tuning the DNN architecture and training parameters could lead to better results. Experiment 3 shows that the model's performance can be sensitive to changes in data or hyperparameters, as it experiences a drop in accuracy and ROC AUC score.

3.4 Gradient Boosting Trees

Gradient Boosting Trees consistently provide competitive performance, making them a suitable choice for understanding the unique risk factors associated with AKI in diabetic patients. It demonstrate robust performance with consistent recall values for class 0 and class 1 across the experiments. The ROC AUC scores are relatively competitive, with the highest being 0.5587 in experiment 2. This model showcases stability and resilience, making it a reliable choice for binary classification tasks.

3.5 Hard Voting

Hard Voting combines the predictions of Logistic Regression, Support Vector Classification, and Gradient Boosting Trees. Experiment 2 shows the highest accuracy among all models, but it is not significantly better than Gradient Boosting Trees alone. The ROC AUC scores remain competitive. However, the ensemble does not provide a substantial advantage over individual models. The Hard Voting ensemble method demonstrates a modest improvement over individual models, but it may not fully capture the unique risk factors associated with AKI in diabetic patients. Further exploration of specialized ensemble strategies is warranted.

3.6 Long Short-Term Memory (LSTM)

LSTM, a recurrent neural network, demonstrates strong performance with the highest ROC AUC score of 0.6231 in the second experiment. It also exhibits good recall for class 1, indicating its capability to capture temporal dependencies in the data. This makes LSTM a promising choice for sequence-based binary classification tasks. Its competitive performance underscores its potential for further investigation.

3.7 Random Forest

Random Forest models consistently deliver competitive and robust performance. Their proficiency in handling complex data relationships positions them as a promising choice for exploring specific risk factors related to AKI in diabetic patients. Across experiments, they maintain consistent performance with competitive recall values and ROC AUC scores. Their stability and reliability make them a suitable option for binary classification tasks.

4 Discussion

4.1 Implications

The use of machine learning models on electronic health records (EHRs) are rapidly gaining popularity within the medical context. It has allowed for more in-depth analysis such as ours to better understand intricate links between health conditions. Since EHR data is present longitudinally, this facilitates better understanding of a diseases' natural history as well as the 'real world' health response.[11]

Kidney disease is a complex medical condition that poses a challenge towards modern healthcare. It acts as an independent risk factor to all-cause mortality, especially within patients that suffer other co-morbidities such as diabetes. An observational cohort study[6] has shown that patients that suffer from diabetes have a 4.7 fold higher AKI rate, indicating the significantly risk that diabetes patients face. It is especially apparent when trying to distinguish the risk factor for AKI amongst those that also suffer from Chronic Kidney Disease (CKD).[8] In people with preserved renal function, rate of AKI is 4.9-fold higher in people with diabetes than in people without diabetes; whereas, in people with CKD, the rate of AKI for those in the diabetic group is two-fold higher than in patients without diabetes.

The above findings only speaks volumes regarding the need for further review of the current medical interventions in place. Our study, through the development of various classification models such as Random Forests, Logistic Regression and many others show the promise that some of these models could potentially be used as tools to aid medical practitioners in identifying patients in need of further medical assistance. However, it should be acknowledged that further medical intervention may not lead to improvements in medical outcomes as displayed in a study conducted in 2021[15] which found only modest improvements. This is largely attributed to the heterogeneous effect of alerts across hospitals and speaks volumes for the need for a more rigorous approach in evaluating the efficacy and safety of current and future health alert systems for AKI.[15]

Our research has shown the potential application for machine learning models to be used as a tool by medical practitioners to potentially improve patient outcomes by providing preemptive medical care amongst those that are identified to be prone to AKI incidents within a certain time period. However, there are limitations that should addressed in future analyses.

4.2 Limitations

There are a number of limitations to be acknowledged and should be addressed if further studies are done to extend the work that has been completed.

While the process of identifying diabetes patients uses a multitude of laboratory tests and medications to identify those that are diabetic, the identification of acute kidney injury episodes is limited to ICD diagnosis codes (namely *N179*). The ideal scenario would be to combine both ICD diagnosis along with medications and laboratory results to provide a comprehensive set of patients.

The study's scope might be limited by the inconsistent or incomplete use of Electronic Health Records (EHRs) across hospital settings. Variability in the quality, consistency, and accessibility of EHR data might affect the accuracy and depth of the patient information available. Incomplete or sparse EHR documentation within the MIMIC-IV dataset may have led to missing critical data that could influence the analysis and predictions, potentially impacting the overall model performance.

Addressing these limitations could potentially enhance the robustness and applicability of the findings, leading to a more comprehensive understanding of the relationship between AKI and diabetes, enabling more accurate risk prediction and informed clinical interventions.

5 Conclusion

In summary, we describe the development and validation of a number of machine learning techniques that could be potentially used to help identify the incidence of AKI within the next 7 days for a diabetic patient. We believe that some of these models, namely Hard Voting, Gradient Boosting Trees and Random Forests, to show promising results and should be the target of further research and implementation.

6 Appendix

- Link to GitHub repository
- Link to Google Colab

Note: The code within this repository was uploaded for the sole purpose of allowing teaching staff access. We did not use a GitHub repository over the course of this project and instead used Google Colab. The link to the Google Colab can be found above as well.

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7 Contributions

Note:

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Contributor Role	**Name**
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Funding Acquisition	n/a
Investigation	A.B, Z.D, V.L, A.S, R.Z
Methodology	A.B, Z.D, V.L, A.S, R.Z
Project Administration	Z.D, A.S,
Resources	Z.D
Software	A.B, R.Z
Supervision	n/a
Validation	A.B, Z.D, V.L, A.S, R.Z
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Table 4: Contributions