

Predicting Diabetes
Status Using
Biomedical and
Demographic Data

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Project Background

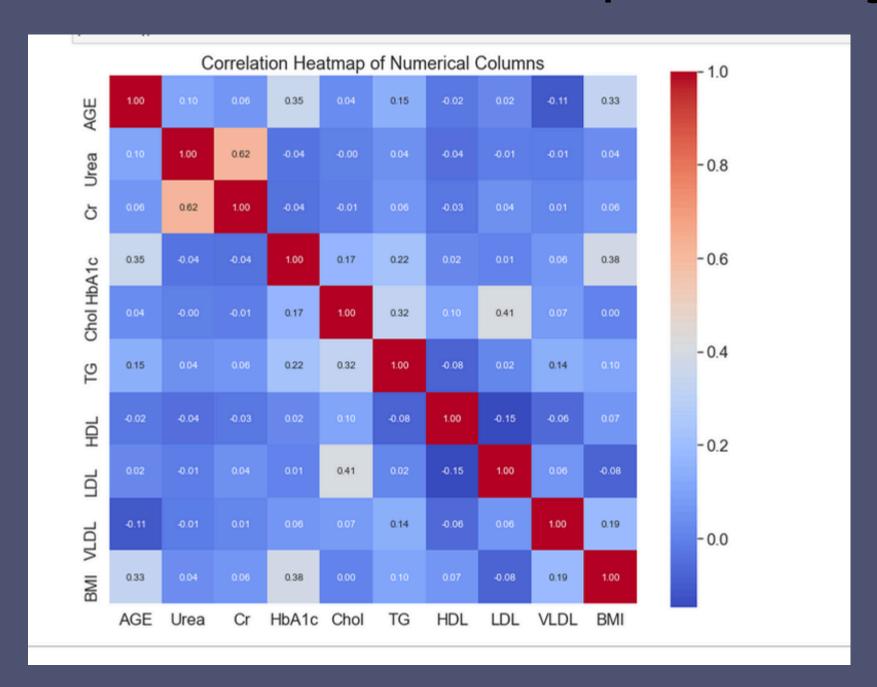
The Challenge

Diabetes is a rising global health concern. Early detection is crucial but limited by accessibility and cost of traditional diagnostic methods.

Our Solution

Use existing patient data (e.g., cholesterol, HbA1c, age, BMI) to automatically predict diabetes status using machine learning.

Exploratory Insights

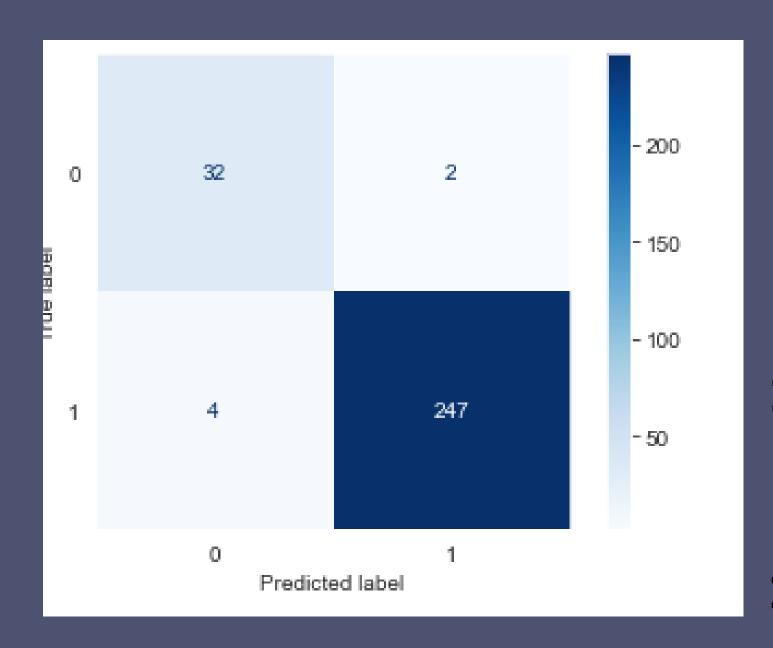


Urea and Creatinine (Cr) → 0.62

Both are indicators of kidney function and often rise together in diabetic nephropathy.

HbA1c and BMI → 0.38
Suggests individuals with higher BMI tend to have higher long-term blood sugar levels.

confusion matrix



- >The model is highly effective at identifying diabetic patients (only 4 missed cases).
- >It also avoids over-diagnosing (only 2 false positives).
- >This makes it very suitable for clinical decision support where missing a case is costly.

Decision Tree Classifier

The model achieved an accuracy of 97.2%, correctly identifying most patients.

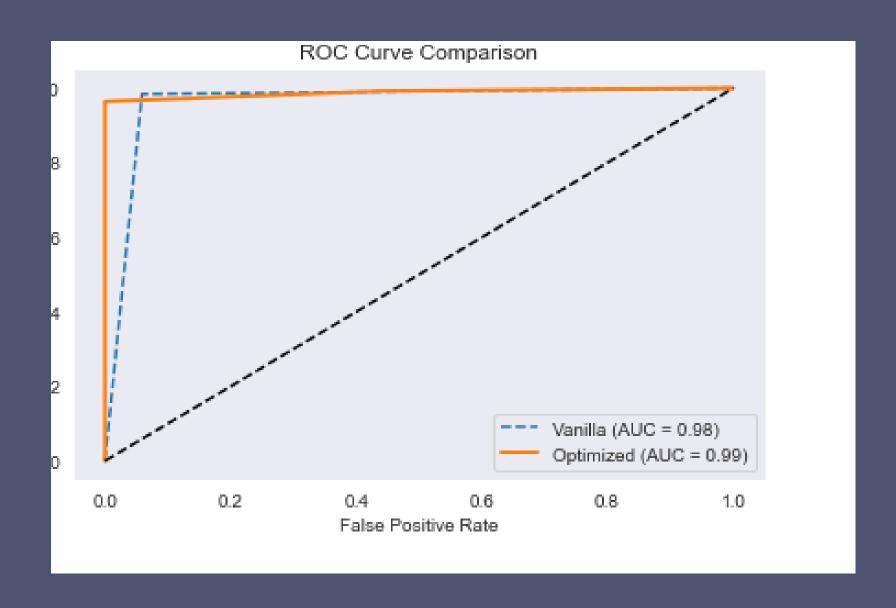
It showed very high precision (99.2%), meaning almost no false diabetes predictions.

Recall was also strong at 98.4%, capturing nearly all actual diabetic cases.

The F1-score of 98.8% confirms excellent balance between precision and recall

```
HbA1c <= -1.06
                                                       gini = 0.5
                                                    samples = 1186
                                                   value = [593, 593]
                                                       class = 0
                                        BMI <= -1.036
                                                                    gini = 0.0
                                        gini = 0.116
                                                                  samples = 554
                                       samples = 632
                                                                  value = [0, 554]
                                       value = [593, 39]
                                                                    class = 1
                                          class = 0
                          Chol <= 0.073
                                                       gini = 0.0
                            gini = 0.06
                                                     samples = 20
                          samples = 612
                                                     value = [0, 20]
class = 1
                         value = [593, 19]
                             class = 0
                                         TG <= -0.29
               gini = 0.0
                                         gini = 0.372
             samples = 535
                                        samples = 77
            value = [535, 0]
                                       value = [58, 19]
               class = 0
                                          class = 0
                         VLDL <= -0.165
                                                       gini = 0.0
                           gini = 0.094
                                                      samples = 16
                           samples = 61
                                                     value = [0, 16]
                          value = [58, 3]
                                                       class = 1
                             class = 0
            HbA1c <= -1.681
                                          gini = 0.0
              gini = 0.033
                                         samples = 2
             samples = 59
                                         value = [0, 2]
             value = [58, 1]
class = 0
                                          class = 1
  gini = 0.0
                            gini = 0.0
                           samples = 58
 samples = 1
                          value = [58, 0]
 value = [0, 1]
  class = 1
                             class = 0
n: 6
```

leaves: 7



ROC Curve & AUC

AUC Score: was at 0.99 -model is extremely good at distinguishing diabetic vs. nondiabetic.

Key Takeaways

- > High potential to detect diabetes using readily available data
 - > Decision Tree performed well and is easy to interpret
- > Logistic Regression offers simplicity and robustness

Recommendations

> Deploy model as a diagnostic support tool in clinics

> Train health workers to use it during patient intake

> Conduct follow-up studies to expand dataset and improve accuracy