NAME: SNEHA K

MAIN PROJECT

POWER BI INSIGHTS

11. Healthcare Appointment No-Show Prediction

Objective: Predict whether patients will miss their appointments and optimize scheduling.

Tools: Python (Sklearn, Pandas), Power BI

Mini Guide:

Import and clean appointment data

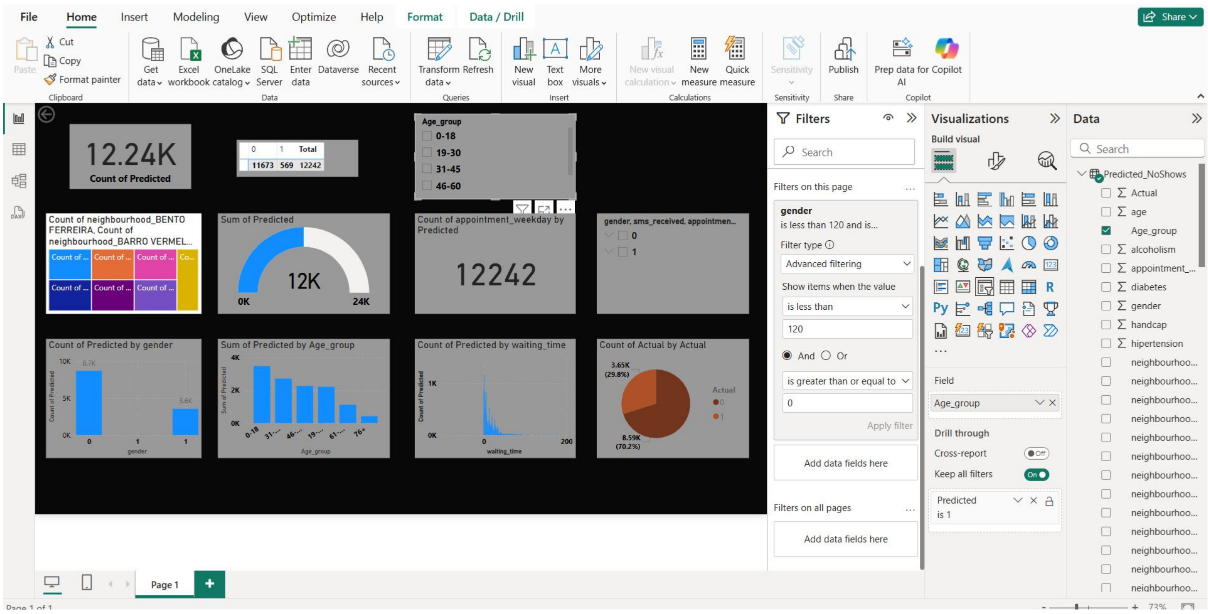
Train decision tree model to predict no-shows

Analyze trends like SMS reminders, age, weekday

Deliverables:

Prediction model

Power BI insight dashboard



1. KPI Card: "Count of Predicted" – 12.24K

- **What it shows:** Total number of appointment records your prediction model processed.
- **Interpretation:** Your model evaluated **12,242** appointment cases for predicting whether a patient would show up or not.

2. Matrix: Count by Actual vs Prediction (Top Center)

- **Values:**
  - **Predicted = 1 (No-Show)**: 569
  - **Predicted = 0 (Show)**: 11,673
  - **Total = 12,242**
- **Interpretation:**
  - Majority were predicted as **shows**.
  - **Only 4.6% (569/12,242)** were predicted as no-shows.

3. Slicer: Age Group

- Age groups include:
  - 0–18
  - 19–30
  - 31–45
  - 46–60
- **Purpose:** Filter the entire dashboard based on selected age group(s).
- **Interpretation Tip:** Enables demographic-specific analysis (e.g., which group misses appointments most).

4. Card: "Count of Appointment Weekday by Predicted" – 12,242

- **What it shows:** Total appointments predicted, possibly grouped by weekday (though not shown in this card).

- **Interpretation:** Again reinforces total prediction count. This card needs better labelling or breakdown for added insight.

5. Clustered Column Chart: Count by Neighbourhood

- **What it shows:** Number of predictions by patient neighbourhood.
- **Interpretation:**
    - Neighbourhoods like **BENTO FERREIRA**, **BARRO VERMELHO**, etc., have the highest predicted records.
    - This helps identify **location-based appointment behaviour**.

6. Gauge Chart: "Sum of Predicted" – 12K

- **What it shows:** Shows how many were predicted as total (but lacks clarity if 1s or 0s).
- **Interpretation:** Might be summarizing total "show" predictions or total prediction attempts. Could be labelled more clearly.

7. Clustered Column Chart: Predicted by Gender

- **What it shows:**
    - Gender 0 (Female): ~8.7K
    - Gender 1 (Male): ~3.6K
- **Interpretation:** More appointment predictions for **females**, indicating they visit healthcare services more or their data dominates.

8. Column Chart: Predicted by Age Group

- **What it shows:**
    - Highest predictions for **31–45**, followed by **46–60**.
    - Lower values for **0–18** and **76+**.
- **Interpretation:** Middle-aged patients are the **largest demographic** in this dataset and model focus.

9. Histogram: Count of Predicted by Waiting Time

- **What it shows:** Frequency of predictions vs waiting time.
- **Interpretation:**
    - Majority of patients have **very low waiting times**.

- Very few patients waited a long time, implying efficient scheduling or early dropout.

10. Pie Chart: Count of Actual by Actual

- **Actual = 0 (Show):** 8.59K → **70.2%**
- **Actual = 1 (No-Show):** 3.65K → **29.8%**

- **Interpretation:**
  - Around **3 out of 10 patients miss their appointments**.
  - Important insight for **hospital resource planning** and predictive modelling focus.

11. Filters

- **Gender Filter:** Applied for patients with gender codes less than 120 (a safeguard for dirty data).
- **Drill-through Field (prediction)** is active for deep dives.

Overall Insights

1. Most patients are middle-aged (31–60), female, and come from specific neighbourhoods.
2. Waiting time is short for most patients, possibly improving attendance.
3. No-show rate is 30%, which is a significant issue for healthcare efficiency.
4. Your model predicts mostly "shows," which might indicate bias or class imbalance.
5. Neighbourhood and age are potential predictors of attendance.

3. Optimal Recommendations:

- Overbooking Strategy: Slightly overbook time slots with historically high no-show likelihood (e.g., young patients, Monday mornings)
- SMS Reminder Optimization: Send reminders specifically to groups with mid-level no-show probability, where it's most effective
- Scheduling Adjustments: Avoid scheduling high-risk patients during peak no-show timeframes
- Priority Handling: Fast-track elderly or chronic patients to reduce cancellation risk
- Follow-Up System: Flag predicted no-shows for pre-appointment follow-ups