# Mini Project - Data Mining

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Berikut ini merupakan update template laporan Mini Project kuliah Penggalian Data.

Nilai Total: 120 poin

Tahap 0 (poin: 25): Business Objective/tujuan

Poin:

• Klasifikasi Churn

• Sumber : Kaggle Dataset

- Churn customer perusahaan telekomunikasi
- Pola perilaku pelanggan terhadap potensi churn
- Churn (Yes & No)

# Tahap 1 (poin: 25): Original Data

- Urgensi: Churn pelanggan merupakan masalah signifikan bagi perusahaan telekomunikasi karena kehilangan pelanggan berdampak langsung pada pendapatan. Analisis data churn dapat mengungkap pola perilaku pelanggan yang berisiko churn, memungkinkan perusahaan merancang strategi mitigasi yang efektif.
- Data:
  - Sumber Data: https://www.kaggle.com/datasets/blastchar/telco-customer-churn
  - Cara mendapatkan data: Data di download dari kaggle
  - o Jumlah instance: Terdapat 7043 instances
  - Atribut: Customer ID, gender, SeniorCitizen, Partner, Dependents, tenure,
     PhoneService, MultipleLines, InternetService, OnlineSecurity, OnlineBackup,

DeviceProtection, TechSupport, StreamingTV, StreamingMovies, Contract, PaperlessBilling, PaymentMethod, MonthlyCharges, TotalCharges, Churn.

o Atribut dapat dilihat pada Tabel 1

Tabel 1: Deskripsi Atribut.

Atribut	Tipe Data	Deskripsi
CustomerID	Object	ID unik untuk setiap pelanggan.
Gender	Object	Jenis kelamin pelanggan (Male/Female).
Senior Citizen	Integer	Apakah pelanggan merupakan warga lanjut usia (0/1).
Partner	Object	Apakah pelanggan memiliki pasangan (Yes/No).
Dependents	Object	Apakah pelanggan memiliki tanggungan anak/keluarga (Yes/No).
Tenure	Integer	Lama berlangganan (Bulan).
Phone Service	Object	Apakah pelanggan berlangganan layanan telepon rumah (Yes/No).
Multiple Lines	Object	Apakah pelanggan memiliki lebih dari satu jalur telepon (Yes/No/No phone service).
Internet Service	Object	Jenis layanan internet yang digunakan pelanggan (DSL/Fiber optic/No).
Online Security	Object	Apakah pelanggan memiliki fitur keamanan online (Yes/No/No internet service).
Online Backup	Object	Apakah pelanggan menggunakan layanan pencadangan online (Yes/No/No internet service).
Device Protection	Object	Apakah pelanggan memiliki perlindungan perangkat (Yes/No/No internet service).

Tech Support	Object	Apakah pelanggan mendapatkan layanan dukungan teknis (Yes/No/No internet service).
Streaming TV	Object	Apakah pelanggan memiliki layanan streaming TV (Yes/No/No internet service).
Streaming Movies	Object	Apakah pelanggan memiliki layanan streaming film (Yes/No/No internet service).
Contract	Object	Jenis kontrak langganan pelanggan (Month-to-month/One year/Two year).
Paperless Billing	Object	Apakah pelanggan menggunakan tagihan digital (Yes/No).
Payment Method	Object	Metode pembayaran yang digunakan pelanggan (Electronic check/Mailed check/Bank transfer/ Credit card).
Monthly Charges	Object	Jumlah biaya langganan bulanan yang harus dibayar pelanggan.
Total Charges	Object	Total biaya yang telah dibayarkan pelanggan selama berlangganan.
Churn	Object	Status apakah pelanggan berhenti berlangganan atau tidak (Yes/No).

- Data mining task yang akan digunakan:
   Klasifikasi (classification) digunakan untuk memprediksi apakah pelanggan akan churn (Yes) atau tidak (No), sebuah masalah klasifikasi biner.
- Sumber data (sertakan link).

Kaggle:https://www.kaggle.com/datasets/blastchar/telco-customer-churn

Drive: https://drive.google.com/drive/folders/1t3NOAZhU4MGkWKnA8b\_7EHCOT8Y6 IW4D?usp=sharing

# ■ Sampel data dapat dilihat pada Tabel 2

Tabel 2: Sampel data churn telco customer.

Customer ID	Gender	Senior Citizen	Dependents	Phone Service	Multiple Lines	Online Backup	Device Protection	Streamig Movies	Total Charges
7590-VHVEG	Female	0	No	No	No phone service	Yes	No	No	29,85
5575-GNVDE	Male	0	No	Yes	No	No	Yes	No	1889,5
3668-QPYBK	Male	0	No	Yes	No	Yes	No	No	108,15
7795-CFOCW	Male	0	No	No	No phone service	No	Yes	No	1840,75
9237-HQITU	Female	0	No	Yes	No	No	No	No	151,65
9305-CDSKC	Female	0	No	Yes	Yes	No	Yes	Yes	820,5
1452-KIOVK	Male	0	Yes	Yes	Yes	Yes	No	No	1949,4
6713-OKOM C	Female	0	No	No	No phone service	No	No	No	301,9
7892-POOKP	Female	0	No	Yes	Yes	No	Yes	Yes	3046,05
6388-TABGU	Male	0	Yes	Yes	No	Yes	No	No	3487,95

Tenure	Contract	Payment Method	Monthly Charges	Internet Service	Online Security	Tech Support	Streaming TV	Paperless Billing	Partner	Churn
1	Month-to-month	Electronic check	29,85	DSL	No	No	No	Yes	Yes	No
34	One year	Mailed check	56,95	DSL	Yes	No	No	No	No	No
2	Month-to-month	Mailed check	53,85	DSL	Yes	No	No	Yes	No	Yes
45	One year	Bank transfer (automatic)	42,3	DSL	Yes	Yes	No	No	No	No
2	Month-to-month	Electronic check	70,7	Fiber optic	No	No	No	Yes	No	Yes
8	Month-to-month	Electronic check	99,65	Fiber optic	No	No	Yes	Yes	No	Yes
22	Month-to-month	Credit card (automatic)	89,1	Fiber optic	No	No	Yes	Yes	No	No
10	Month-to-month	Mailed check	29,75	DSL	Yes	No	No	No	No	No
28	Month-to-month	Electronic check	104,8	Fiber	No	Yes	Yes	Yes	Yes	Yes

				optic						
62	One year	Bank transfer (automatic)	56,15	DSL	Yes	No	No	No	No	No

o Task: klasifikasi churn dengan label Yes & No

## **Tahap 2 (poin: 10)**: Target Data (Optional)

• Poin ini digunakan ketika tidak semua atribut (pada data yang dipilih) digunakan.

### Poin:

- Atribut yang digunakan = Senior Citizen, Partner, Dependents, tenure, Online Security, Online Backup, Device Protection, Tech Support, Contract, Paperless Billing, Total Charges.
- Atribut yang tidak digunakan = Customer ID, Gender, Phone Service, Multiple Lines, Streamig Movies, Payment Method, Monthly Charges, Internet Service, Streaming TV.
- Alasan/justifikasi penggunaanya
  - o **Fitur customerID** dihapus karena berisi pengenal unik untuk setiap pelanggan, yang tidak memberikan informasi bermakna untuk analisis prediktif atau pemodelan machine learning.
  - o **Fitur** (Gender, Phone Service, Multiple Lines, Streaming Movies, Payment Method, Monthly Charges, Internet Service, Streaming TV.) tidak digunakan karena memiliki korelasi yang rendah terhadap churn.
  - o **Fitur** (Senior Citizen, Partner, Dependents, tenure, Online Security, Online Backup, Device Protection, Tech Support, Contract, Paperless Billing, Total Charges.) dipilih karena memiliki korelasi yang baik terhadap churn untuk mendapatkan pola perilaku customer.
  - o **Churn** merupakan target label yang menentukan apakah customer tersebut churn/tidak churn.
- Contoh dapat dilihat pada Tabel 3:

Tabel 3: Sampel target data telco customer.

Senior Citizen	Partner	Dependents	Tenure	Online Security	Online Backup	Device Protection	Tech Support	Contract	Paperless Billing	Total Charges	Churn
0	Yes	No	1	No	Yes	No	No	Month-to -month	Yes	29,85	No
0	No	No	34	Yes	No	Yes	No	One year	No	1889,5	No
0	No	No	2	Yes	Yes	No	No	Month-to -month	Yes	108,15	Yes
0	No	No	45	Yes	No	Yes	Yes	One year	No	1840,75	No
0	No	No	2	No	No	No	No	Month-to -month	Yes	151,65	Yes
0	No	No	8	No	No	Yes	No	Month-to -month	Yes	820,5	Yes

0	No	Yes	22	No	Yes	No	No	Month-to -month	Yes	1949,4	No
0	No	No	10	Yes	No	No	No	Month-to -month	No	301,9	No
0	Yes	No	28	No	No	Yes	Yes	Month-to -month	Yes	3046,05	Yes
0	No	Yes	62	Yes	Yes	No	No	Month-to -month	No	3487,95	No

Tahap 3-4 (poin: 25): Data Pre-processing & Transformation

## **Pre-processing:**

- 1. Data cleaning
  - a. Membersihkan dan mengonversi kolom
  - b. Mengisi nilai hilang
- 2. Data reduction
  - a. Drop kolom yang tidak digunakan

# **Hasil Data Pre-processing:**

Tabel 4: Sampel data setelah pre-processing.

Senior Citizen	Partner	Dependents	Tenure	Online Security	Online Backup	Device Protection	Tech Support	Contract	Paperless Billing	Total Charges
0	Yes	No	1	No	Yes	No	No	Month-to- month	Yes	29,85
0	No	No	34	Yes	No	Yes	No	One year	No	1889,5
0	No	No	2	Yes	Yes	No	No	Month-to- month	Yes	108,15
0	No	No	45	Yes	No	Yes	Yes	One year	No	1840,75
0	No	No	2	No	No	No	No	Month-to- month	Yes	151,65
0	No	No	8	No	No	Yes	No	Month-to- month	Yes	820,5
0	No	Yes	22	No	Yes	No	No	Month-to- month	Yes	1949,4
0	No	No	10	Yes	No	No	No	Month-to- month	No	301,9

0	Yes	No	28	No	No	Yes	Yes	Month-to- month	Yes	3046,05
0	No	Yes	62	Yes	Yes	No	No	Month-to- month	No	3487,95

# **Transformation:**

- 1. Encode categorical data
  - a. Label encoder
- 2. Data discretization
  - a. Binning
- 3. Data normalization
  - a. Minmax scaling

## **Hasil Data Transformation:**

Tabel 5: Sampel data setelah transformation.

						l data sete	1				
Senior Citizen	Partne	Dependents	Tenure	Online Security	Online Backup	Device Protectio n	Tech Support	Contract	Paperless Billing	Total Charges	Tenure Group
0	1	0	0.0138	0	1	0	0	0	1	0.0012	2
0	0	0	0.4722	1	0	1	0	1	0	0.2158	1
0	0	0	0.0277	1	1	0	0	0	1	0.0103	2
0	0	0	625	1	0	1	1	1	0	0.2102	1
0	0	0	0.0277	0	0	0	0	0	1	0.0153	2
0	0	0	0.1111	0	0	1	0	0	1	0.0925	2
0	0	1	0.3055	0	1	0	0	0	1	0.2227	1
0	0	0	0.1388	1	0	0	0	0	0	0.0326	2
0	1	0	0.3888	0	0	1	1	0	1	0.3493	1
0	0	1	0.8611	1	1	0	0	1	0	0.4003	0

# Tahap 5 (poin: 25): Data Mining

### • Klasifikasi:

## o Algoritma yang digunakan:

- Decision Tree
- Naive Bayes

## o Eksperimen:

- > Random Forest
  - Train-test split: 80:20 (stratified).
  - Feature selection: Non Selection Feature, Chi2 & SFS
  - Data Augmentation: SMOTE.
- ➤ Naive Bayes
  - Train-test split: 80:20 (stratified).
  - Feature selection: Non Selection Feature, Chi2 & SFS
  - Data Augmentation: SMOTE.

### o Evaluasi Model:

### > Decision Tree dan Non Selection Feature

Tabel 6: Classification Report Decision Tree Non Selection Feature.

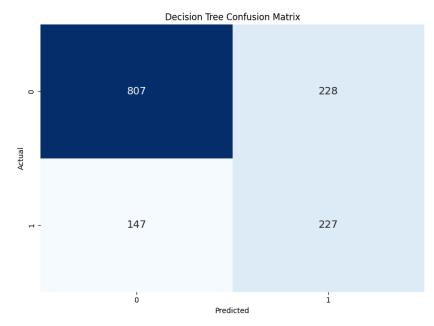
	Precision	Recall	F1-Score	Support
0	0.85	0.78	0.81	1035
1	0.50	0.61	0.55	374
accuracy			0.73	1409
macro avg	0.67	0.69	0.68	1409
weighted avg	0.75	0.73	0.74	1409

Tabel 7: Hasil ROC AUC, Train, Test, Gap Accuracy.

The er /: Trush Tre e Tre e, Trush, Test, cup Tre unue).							
Train Accuracy	0.9042						
Test Accuracy	0.7339						
Accuracy Gap	0.1704						

ROC AUC	0.7449
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## • Confusion Matrix



Gambar 1. Confusion Matrix - Decision Tree

- Decision Tree Visualization
  - i. Decision Tree Depth: 26
  - ii. Link untuk gambar lebih jelas:
    - DT\_NonFeatureSelection\_visualization.png
  - iii. Visualization:



Gambar 2. Visualisasi Decision Tree

# ➤ Naive Bayes dan Non Selection Feature

Tabel 8: Classification Report Naive Bayes Non Selection Feature.

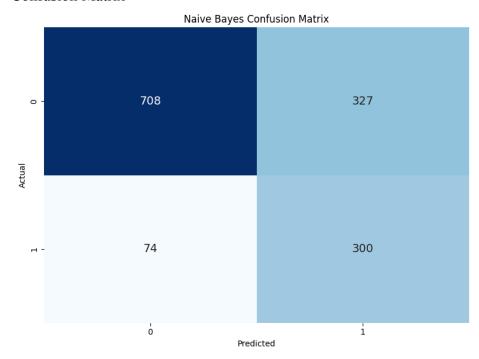
	Precision	Recall	F1-Score	Support
0	0.91	0.68	0.78	1035
1	0.48	0.80	0.60	374
accuracy			0.72	1409

macro avg	0.69	0.74	0.69	1409
weighted avg	0.79	0.72	0.73	1409

Tabel 9: Hasil ROC AUC, Train, Test, Gap Accuracy.

Train Accuracy	0.7596
Test Accuracy	0.7154
Accuracy Gap	0.0442
ROC AUC	0.8166

## Confusion Matrix



Gambar 3. Confusion Matrix - Naive Bayes

## > Decision Tree dan Chi2

Tabel 10: Classification Report Decision Tree dan Chi2.

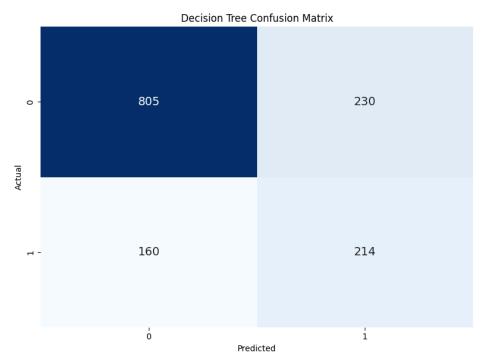
	Precision	Recall	F1-Score	Support
0	0.83	0.78	0.81	1035

1	0.48	0.57	0.52	374
accuracy			0.72	1409
macro avg	0.66	0.67	0.66	1409
weighted avg	0.74	0.72	0.73	1409

Tabel 11: Hasil ROC AUC, Train, Test, Gap Accuracy.

	, , , 1
Train Accuracy	0.8962
Test Accuracy	0.7232
Accuracy Gap	0.1730
ROC AUC	0.7287

## Confusion Matrix



Gambar 4. Confusion Matrix - Decision Tree dan Chi2.

- Decision Tree Visualization
  - i. Decision Tree Depth: 22
  - ii. Link untuk gambar lebih jelas:
    - DT\_Chi2\_visualization.png

# iii. Visualization:



Gambar 5. Visualisasi Decision Tree dan Chi2.

# ➤ Naive Bayes dan Chi2

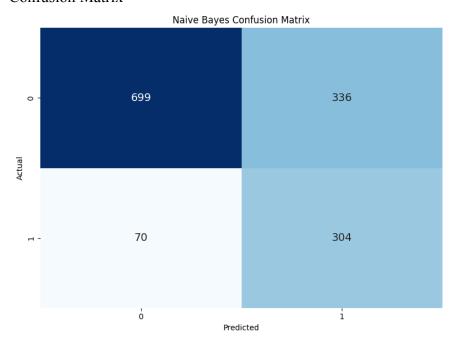
Tabel 12: Classification Naive Bayes dan Chi2.

	Precision	Recall	F1-Score	Support
0	0.91	0.68	0.77	1035
1	0.47	0.81	0.60	374
accuracy			0.71	1409
macro avg	0.69	0.74	0.69	1409
weighted avg	0.79	0.71	0.73	1409

Tabel 13: Hasil ROC AUC, Train, Test, Gap Accuracy.

	, , , 1
Train Accuracy	0.7550
Test Accuracy	0.7119
Accuracy Gap	0.0432
ROC AUC	0.8191

# Confusion Matrix



Gambar 6. Confusion Matrix - Naive Bayes dan Chi2.

# > Decision Tree dan SFS

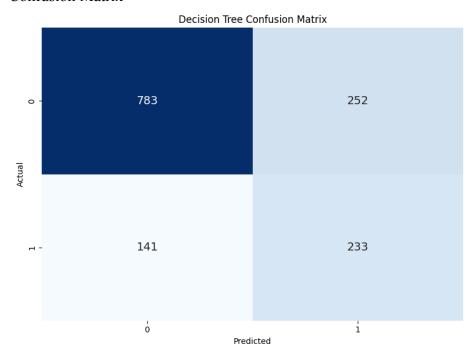
Tabel 14: Classification Decision Tree dan SFS.

	Precision	Recall	F1-Score	Support
0	0.85	0.76	0.80	1035
1	0.48	0.62	0.54	374
accuracy			0.72	1409
macro avg	0.66	0.69	0.67	1409
weighted avg	0.75	0.72	0.73	1409

Tabel 15: Hasil ROC AUC, Train, Test, Gap Accuracy.

Train Accuracy	0.8769
Test Accuracy	0.7211
Accuracy Gap	0.1558
ROC AUC	0.7533

### Confusion Matrix



Gambar 7. Confusion Matrix - Decision Tree dan SFS.

- Decision Tree Visualization
  - i. Decision Tree Depth: 25
  - ii. Link untuk gambar lebih jelas:
    - DT\_SFS\_visualization.png
  - iii. Visualization:



Gambar 8. Visualisasi Decision Tree dan SFS.

## > Naive Bayes dan SFS

Tabel 16: Classification Naive Bayes dan SFS.

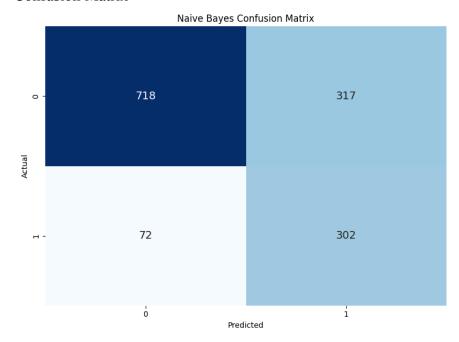
	Precision	Recall	F1-Score	Support
0	0.91	0.69	0.79	1035
1	0.49	0.81	0.61	374
accuracy			0.72	1409

macro avg	0.70	0.75	0.70	1409
weighted avg	0.80	0.72	0.74	1409

Tabel 17: Hasil ROC AUC, Train, Test, Gap Accuracy.

Train Accuracy	0.7502
Test Accuracy	0.7239
Accuracy Gap	0.0263
ROC AUC	0.8260

# • Confusion Matrix



Gambar 9. Confusion Matrix - Naive Bayes dan SFS.

# • Perbandingan:

Tabel 18: Perbandingan setiap model pada setiap seleksi fitur.

	Non Seleksi Fitur							
Model	Target Class	Precision	Recall	F1-Score	Accuracy			
Decision	Not Churn	0.85	0.78	0.81	0.72			
Tree	Churn	0.50	0.61	0.55	0.73			
Naive Bayes	Not Churn	0.91	0.68	0.78	0.72			
	Churn	0.48	0.80	0.60	0.72			
		Seleksi Fit	tur (Chi2)					
Model	Target Class	Precision	Recall	F1-Score	Accuracy			
Decision	Not Churn	0.83	0.78	0.81	0.72			
Tree	Churn	0.48	0.57	0.52				
Naive Bayes	Not Churn	0.91	0.68	0.77	0.71			
	Churn	0.47	0.81	0.60				
		Seleksi Fitur (	SFS forward)					
Model	Target Class	Precision	Recall	F1-Score	Accuracy			
Decision	Not Churn	0.85	0.76	0.80	0.72			
Tree	Churn	0.48	0.62	0.54	0.72			
Naive Bayes	Not Churn	0.91	0.69	0.79	0.72			
	Churn	0.49	0.81	0.61	0.72			

# Tahap 6 (poin: 20): Knowledge Interpretation

- Menggunakan Explainable AI (LIME) untuk Interpretasi Hasil dan Error Analysis
- Error Analysis :

Tabel 19. Error Analysis

Model	Feature Selection	Categories	Number of Wrongly Predicted as	Number of Misclassified	Sample Instances	Cause of Error
Decision Tree	Non Feature Selection	Not Churn	Churn (228)	228	id: 1175 {gender (0), SeniorCitizen (0), Partner (0), Dependents (0), Tenure (0.180556), PhoneService (1),}	Model memberikan bobot tinggi pada tenure <= 0.07 (0.200504), yang mengindikasikan tenure rendah cenderung diprediksi Churn. Data menunjukkan tenure = 0.181, yang sesuai dengan bobot ini, namun seharusnya tidak cukup untuk mengklasifikasikan sebagai Churn.
		Churn	Not Churn (147)	147	id: 5183 {gender (0), SeniorCitizen (1), Partner (1), Dependents (1), Tenure (0.472222), PhoneService (1),}	Model memberikan bobot tinggi pada Contract <= 0.00 (0.385282), yang menunjukkan kontrak bulanan cenderung diprediksi sebagai Not Churn. Namun, data menunjukkan Contract = 0 dan tenure = 0.472, yang seharusnya

						mengindikasikan stabilitas pelanggan.
	Chi2	Not Churn	Churn (230)	230	id: 560 {Contract (1), OnlineSecurity (0), TechSupport (2), Tenure (0.777778), Tenure_Group (0), }	Contract = 0 sesuai bobot Contract <= 0.00 (0.343616), mendukung Not Churn, meskipun tenure = 0.0417 (sesuai tenure <= 0.08 0.19098) dan TechSupport = 0 (bobot 0.064356) seharusnya mendukung Churn.
	CIIIZ	Churn	Not Churn (160)	160	id: 5547 {Contract (0), OnlineSecurity (0), TechSupport (0), Tenure (0.041667), Tenure_Group (2),}	tenure = 0.778 jauh di atas tenure <= 0.08 (0.19098), tapi TechSupport = 2 dan OnlineSecurity = 0 (bobot 0.0456801) serta PaymentMethod = 2 (bobot 0.0433989) mungkin mendorong prediksi Churn yang salah.
	SFS Forward	Not Churn	Churn (252)	252	id: 4817 {gender (0), SeniorCitizen (0), Partner (0), Dependents (0), Tenure (0.013889), PhoneService (1),}	tenure = 0.014 sesuai bobot tenure <= 0.07 (0.200504), mendukung Churn, meskipun TechSupport = 1 (bobot -0.0924175) dan OnlineSecurity = 1 seharusnya mengurangi

						prediksi Churn.
		Churn	Not Churn (141)	141	id: 3197 {gender (0), SeniorCitizen (0), Partner (1), Dependents (1), Tenure (0.305556), PhoneService (1),}	Contract = 1 tidak sesuai bobot Contract <= 0.00 (0.385282), tapi tenure = 0.306 (melebihi tenure <= 0.07 0.200504) dan Dependents = 1 mungkin memengaruhi prediksi Not Churn yang salah.
Naive Bayes	Non Feature Selection	Not Churn	Churn (327)	327	id: 3064 {gender (0), SeniorCitizen (0), Partner (0), Dependents (0), Tenure (0.291667), PhoneService (1),}	Contract = 0 sesuai bobot Contract <= 0.00 (0.555091) dan OnlineSecurity = 0 sesuai bobot OnlineSecurity <= 0.00 (0.152944) mendukung Churn, meskipun tenure = 0.236111 (bobot negatif -0.215473) seharusnya mengurangi prediksi Churn.
		Churn	Not Churn (74)	74	id: 2424 {gender (0), SeniorCitizen (0), Partner (0), Dependents (0), Tenure (0.791667), PhoneService (1),}	Contract = 0 sesuai bobot Contract <= 0.00 (0.555091) dan Dependents = 0 sesuai bobot Dependents <= 0.00 (0.305499) mendukung Not Churn, meskipun tenure = 0.791667 (bobot negatif -0.215473)

						seharusnya mendukung Churn.
Chi2	CI.:2	Not Churn	Churn (336)	336	id: 1992 {gender (0), SeniorCitizen (0), Partner (0), Dependents (0), Tenure (0.236111), }	Contract = 0 sesuai bobot Contract <= 0.00 (0.555091) dan OnlineSecurity = 0 (bobot 0.152944) mendukung Churn, meskipun tenure = 0.236111 (bobot -0.156885) seharusnya mengurangi prediksi Churn.
	Chi2	Churn	Not Churn (70)	70	id: 6853 {gender (0), SeniorCitizen (0), Partner (2), Dependents (0), Tenure (0.750000), }	Contract = 0 sesuai bobot Contract <= 0.00 (0.555091) dan Dependents = 0 (bobot 0.305499) mendukung Not Churn, meskipun OnlineSecurity = 0 (bobot 0.152944) seharusnya mendukung Churn.
	SFS Forward	Not Churn	Churn (317)	317	id: 6184 {gender (1), SeniorCitizen (0), Tenure (0.569444), PhoneService (1),}	Contract = 0 sesuai bobot Contract <= 0.00 (0.553236) dan TechSupport = 0 (bobot 0.161726), mendukung Churn, meskipun tenure = 0.569 (di luar tenure <= 0.08) seharusnya mengurangi prediksi Churn.

		Churn	Not Churn (72)	72	id: 110 {gender (1), SeniorCitizen (0), Tenure (0.763889), PhoneService (1),}	Contract = 0 sesuai bobot Contract <= 0.00 (0.553236), mendukung Not Churn, meskipun tenure = 0.764 (di luar bobot) dan TechSupport = 0 (bobot 0.161726) seharusnya mendukung Churn.
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# • Interpretasi Hasil dari Tabel Perbandingan setiap Model

- Model dengan Akurasi Tertinggi: Decision Tree + None Seleksi Fitur (0.73)
- Model dengan Akurasi Terendah: Naive Bayes + Seleksi Fitur (Chi2) (0.71)

## Tahap 7 (poin: 15): Reporting

Academic Poster.

## **Telco Customer Churn Classification**

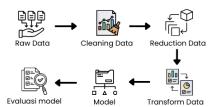
Nizam Avif Anhari, Al Fitra Nur Ramadhani

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#### **Overview**

- Churn pelanggan di telekomunikasi menggerus pendapatan berulang dan menaikkan biaya akuisisi. Penelitian ini memanfaatkan decision tree pada dataset untuk mengungkap faktor risiko churn, seperti durasi kontrak, biaya bulanan, dan ketersediaan layanan lain.
- Projek ini penting karena dengan mengenali faktor utama churn, perusahaan bisa menawarkan kontrak jangka panjang fleksibel dan layanan tambahan untuk mempertahankan pelanggan.

#### Methodology



- Preprocessing data dengan 4 tahapan
- o Data cleaning, menangani nilai NaN, dan lain lain
- Data reduction, menghapus fitur "Customer ID"
- Transformation, menggunkan label encoder, binning, minmax scaling.
- Feature Selection dengan chi2 dan SFS forward
- Evaluasi Model dengan XAI (LIME)
- Algoritma klasifikasi yang digunakan, yaitu:
  - Decision Tree
  - Naive Bayes

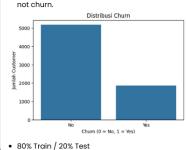
#### Discussion

- Performa Model: Model Decision Tree Non-Seleksi Fitur mencapai akurasi tertinggi (0.73), namun perbedaan akurasi antar model kecil, menunjukkan performa yang kompetitif.
- Analisis Kesalahan: Confusion Matrix menunjukkan kesalahan prediksi lebih tinggi pada kelas minoritas (churn = yes), dengan 228 data salah diklasifikasikan.
- Ketidakseimbangan Data: Dataset tidak seimbang (80% no churn, 20% churn), menyebabkan model cenderung bias ke kelas mayoritas.
- Keterbatasan Konteks: Fitur yang digunakan terbatas pada data pelanggan, kurang memperhitungkan faktor eksternal seperti kompetitor atau kepuasan layanan.

#### **Dataset**

#### Telco Customer Churn

- Dataset memiliki 7043 instance dengan 21 colom diantaranya yaitu, CustomerID, Gender, Monthly Charges, Total Charges.
- Target class terbagi menjadi 2 yaitu, churn dan not churn.



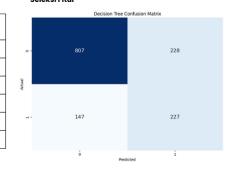
#### Results

#### • Decision Tree Classification Report

Accuracy
0.73
0.72
0.72
0.71
0.72
0.72

- Model Terbaik : Decission Tree Non Seleksi Fitur
- Model Terburuk : Naive Bayes + Seleksi Fitur Chi2

# Results & Discussion



Visualisasi Confusion Matrix Decission Tree Non

#### **Future**

- Uji model ensemble untuk meningkatkan akurasi dan mengurangi bias pada kelas minoritas.
- Pengembangan model dengan fitur tambahan, seperti data kepuasan pelanggan atau tren pasar.
- Pengujian model secara berkala untuk memprediksi churn dalam konteks yang lebih dinamis

#### Reference

#### Kaggle :

https://www.kaggle.com/datasets/blastchar/ telco-customer-churn

Gambar 5. Academic Poster

## → Link Poster:

https://www.canva.com/design/DAGnJ05Emwk/rU4MwQgv4BYEcCIb\_FXUKQ/view?utm\_content=DAGnJ05Emwk&utm\_campaign=designshare&utm\_medium=link2&utm\_source=uniquelinks&utlId=he2766b22a5

- Notebook (Google Colab.):
  Note Book Data Mining Kelompok 6.ipynb
- Dashboard