

# ASTATINE FINAL PROJECT

Diabetes Indicators Classification Model

This project is supervised by:











## **TEAM 7 - ORION**

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+ DESCRIPTIVE PURPOSE







### DESCRIPTIVE AND PURPOSE



**ASTATINE** is a data science project to detect prediabetes and diabetes conditions based on Behavioral Risk Factor Surveillance System (BRFSS) indicators. This project uses **diabetes \_ binary \_ health \_ indicators \_ BRFSS2015.csv** is a clean dataset of **253,680 survey responses** to the CDC's BRFSS2015. The target variable Diabetes \_ binary **has 2 classes**. 0 is for no diabetes, and 1 is for prediabetes or diabetes. This dataset has **21 feature variables** and is **not balanced**. This dataset is

https://www.kaggle.com/datasets/alexteboul/diabetes-health-indicators-dataset?resource=download&select=diabetes\_binary\_health\_indicators\_BRFSS2015.csv

Before developing a **classification model**, **Exploratory Data Analysis (EDA)** and **Data Preprocessing** are first carried out. The EDA stage is aimed at identifying patterns, finding anomalies, testing hypotheses, and checking assumptions. Data Preprocessing is carried out to eliminate several problems that can interfere with data processing, such as data that is not normally distributed and data imbalance.

The prediction models developed in this project are:









# 02

# BASIC EXPLORATION

Check Data Distributions, The Outlier, Duplicated Data



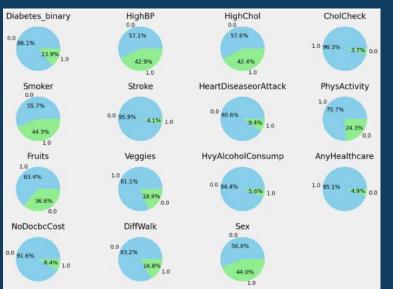


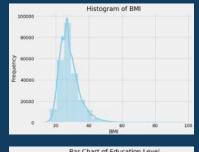


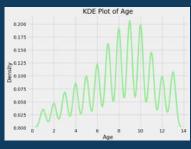


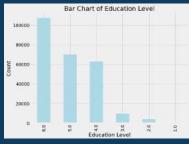


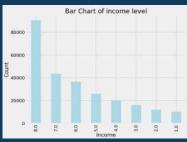
### **Check Data Distributions**











Shapiro-Wilk Test for BMI: Test Statistic: 0.8717145323753357 p-value: 0.0 Sample does not look Gaussian (reject H0)

Shapiro-Wilk Test for Income: Test Statistic: 0.8491994738578796 p-value: 0.0 Sample does not look Gaussian (reject H0) **Normality Test**: In the Shapiro-Wilk test for BMI and Income, the obtained p-value of 0.0 suggests strong evidence to reject the null hypothesis. This indicates that the **BMI** and **Income data** is **not normally distributed**.





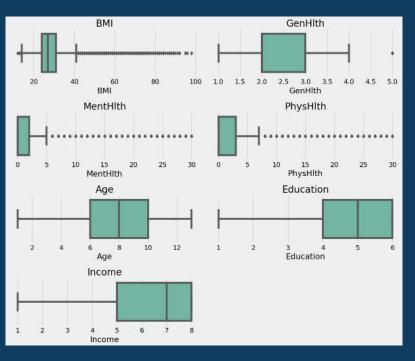








### **Check The Outliers**



There's outlier in column BMI, GenHlth, MenHlth, PhysHlth, but all columns will transpose to categorical value.















# Check and Drop Duplicated Data

# Transform The Data Into Integer

There were 24,206 duplicate rows in the DataFrame, but after performing the duplicate removal operation, there were no more duplicate rows, resulting in the total number of rows decreasing to 229,474 from the initial 253,680. This step is crucial for data cleaning and ensuring the integrity of the data used in analysis.

<cla< th=""><th>ss 'pandas.core.frame.</th><th>DataFrame'&gt;</th><th></th></cla<>	ss 'pandas.core.frame.	DataFrame'>	
Inde	x: 229474 entries, 0 t	0 253679	
Data	columns (total 22 col	umns):	
#	Column		Dtype
0	Diabetes_binary	229474 non-null	int64
1	HighBP	229474 non-null	int64
2	HighChol	229474 non-null	int64
3	CholCheck	229474 non-null	int64
4	BMI	229474 non-null	int64
5	Smoker	229474 non-null	int64
6	Stroke	229474 non-null	int64
7	HeartDiseaseorAttack	229474 non-null	int64
8	PhysActivity	229474 non-null	int64
9	Fruits	229474 non-null	int64
10	Veggies	229474 non-null	int64
11	HvyAlcoholConsump	229474 non-null	int64
12	AnyHealthcare	229474 non-null	int64
13	NoDocbcCost	229474 non-null	int64
14	GenHlth	229474 non-null	int64
15	MentHlth	229474 non-null	int64
16	PhysHlth	229474 non-null	int64
17	DiffWalk	229474 non-null	int64
18	Sex	229474 non-null	int64
19	Age	229474 non-null	int64
20	Education	229474 non-null	int64
21	Income	229474 non-null	int64
dtyp	es: int64(22)		
memo	rv usage: 40.3 MB		

As a result, all columns in the DataFrame now have an integer data type, with no missing values.











# EDA EXPLORATORY DATA ANALYSIS

Univariate & Bivariate Analysis





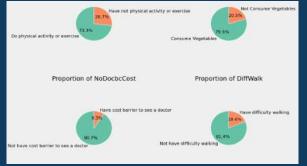


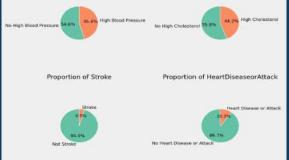


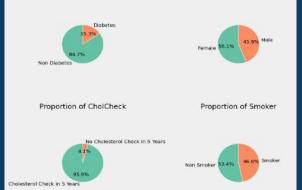
### Binary Variables Proportion +













individuals percentage smoke/have high blood pressure/high cholesterol is above 40%, whereas the lowest percentage is for individuals who have had a stroke or have not had their cholesterol checked in the last 5 years, which is below 5%.



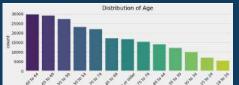




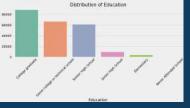


### Categorical Variables Proportion +

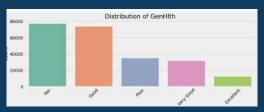




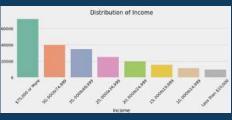
The majority of individuals fall within the age range of 55-64 years, while the least percentage is found in the age range of 18-44 years.



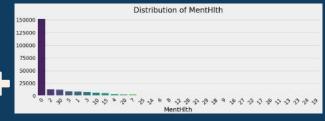
The highest frequency of education level is observed in "college student", followed by "some college or technical school", while the lowest frequency is found in "never attended school".



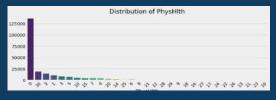
The distribution of general health is highest in the "fair" category. followed by "good".



The **highest** frequency of income level is in the category "\$75,000 or More", while the lowest frequency is in the category "Less than".



The highest distribution of mental health is observed at the value of followed by 2 and 30.



The highest distribution of physical health is observed at the value of 0, followed by 30, 2, 1 etc.









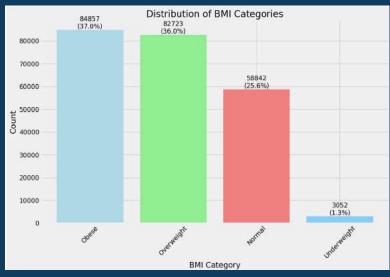




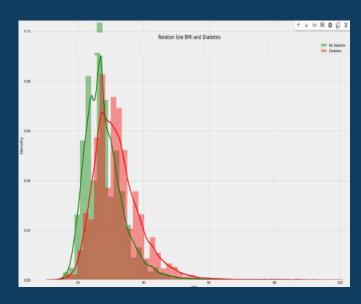
### Numerical Variables Proportion +



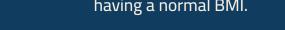




The majority of individuals in this dataset experience overweight to obesity, with only 25.6% having a normal BMI.



There is a significant relationship between BMI and diabetes.





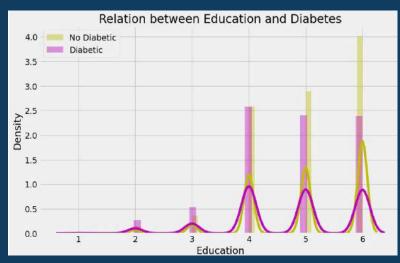




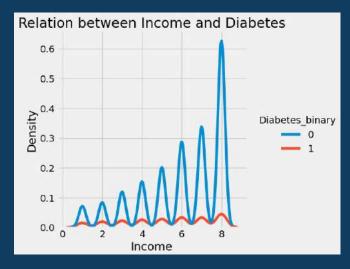
#### **Heart Disease** Correlation Factor 🛨







Most people have a high level of education, and those with higher levels of education tend to experience better overall health.



As the age increases, the chances of diabetes also commonly increases.







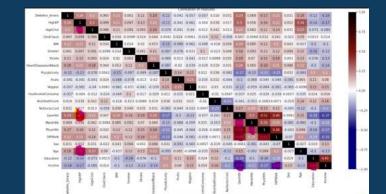


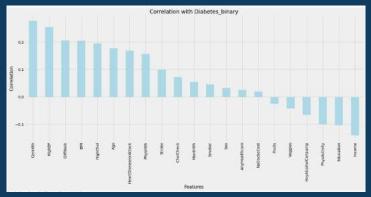




#### Feature Selection







Correlation values with Diabetes binary (sorted): GenH1th HighBP 0.254319 DiffMalk 0.205302 0.205086 HighCho] 0.194944 0.177263 HeartDiseaseorAttack 0.168213 PhysH1th 0.156211 Stroke 0.099193 CholCheck 0.072523 MentH1th 0.054153 Smoker 0.045504 Sex 0.032724 Anyttea1thcare 0.025331 NoDocheCost 0.020048 Fruits -0.024905 -0.001730 Veggles. HvyAlcoholConsump -0.065950 PhysActivity -0.100404 Education -0.19268G -0.140659 dtype: float64

Strong Correlation: GenHlth, HighBP, DiffWalk, BMI
Moderate Corellation with positive relation: HighChol, Age,
HeartDiseaseorAttack, PhysHlth, Stroke, CholCheck, MentHlth
Moderate Corellation with negative relation: Income, Education, PhysActivity,
HvyAlcoholConsump

Weak Correlation: Smoker, Sex, AnyHealthcare, NoDocbcCost, Fruits, Veggies











# Bivariate + Analysis



# VIF and ANOVA Test



In the result, the "const" variable has the highest VIF value, indicating high multicollinearity with other variables in the dataset. However, most other variables have VIF values close to 1, indicating low multicollinearity.

Nevertheless, the "GenHIth" variable stands out with a relatively high VIF value of 1.741, suggesting multicollinearity with other variables.

const	109.425291
Diabetes_binary	1.182154
HighBP	1.315161
HighCho1	1.166374
Cho1Check	1.035970
BMI	1.141796
Smoker	1.076125
Stroke	1.077944
HeartDiseaseorAttack	1.170400
PhysActivity	1.130550
Fruits	1.097950
Veggies	1.098136
HvyAlcoholConsump	1.027834
AnyHealthcare	1.109935
NoDocbcCost	1.135686
GenH1th	1.741508
MentH1th	1.221789
PhysHlth	1.594308
DiffWalk	1.513943
Sex	1.076736
Age	1.359039
Education	1.272148
Income	1.431806
dtype: float64	

	0	1	2	3	4	5	6	7	8	9
0	1	1	40	0	5	15	1	9	4	3
1	0	0	25	0	3	0	0	7	6	1
2	1	1	28	0	5	30	1	9	4	8

After conducting the **ANOVA test**, the **top 10 features** were selected from the data for further modeling. The selected feature matrix has dimensions of **229,474 rows** (samples) and **10 columns** (selected features).















# Chi Square Test +





	Feature	Score
15	PhysHith	97988.761672
3	BMI	15507.736174
14	MentHith	11419.584750
18	Age	8539.906340
0	HighBP	8098.548237
16	DifftValk	7875.496177
13	GenHith	7671.732832
6	HeartDiseaseorAttack	5822.145697
1	HighChol	4869.312739
20	Income	3377.099257
5	Stroke	2156.678382
10	HvyAlcoholConsump	937.401148
7	PhysActivity	617.563886
19	Education	479.112939
4	Smoker	253.826098
17	Sex	137.837135
12	NoDocbcCost	83.662830
9	Veggies	82.098846
8	Fruits	54.688897
2	CholCheck	48.904140
11	AnyHealthcare	7 949731

	columns (total 17 col		D4
#	COTOMIU	Non-Null Count	Dtype
0		229474 non-null	
1	HighBP	229474 non-null	070000000
2	HighChol	229474 non-nu11	int64
3	BMI	229474 non-nu11	int64
4	Smoker	229474 non-null	int6/
5	Stroke	229474 non-null	int64
6	HeartDiseaseorAttack	229474 non-null	int64
7	PhysActivity	229474 non-nu11	int64
8	HvyAlcoholConsump	229474 non-null	int64
9	GenH1th	229474 non-null	int64
10	MentH1th	229474 non-null	int64
11	PhysH1th	229474 non-nu11	int64
12	DiffWalk	229474 non-null	int64
13	5ex	229474 non-null	int64
14	Age	229474 non-null	int64
15	Education	229474 non-nu11	int64
16	Income	229474 non-null	int6/

	count	mean	std	min	25%	56%	75%	BEEK
Diabetes_binary	229474.0	0.152945	0.359936	0.0	0.0	0.0	0.0	1.0
HighBP	229474.0	0.454343	0.497912	0.0	0.0	0.0	1.0	1.0
HighChol	229474.0	0.441640	0,496584	0.0	0.0	0.0	1.0	1.0
вмі	229474.0	28.687507	6.789204	12.0	24.0	27.0	32.0	98.0
Smoker	229474.0	0.465800	0,498830	0.0	0.0	0.0	1.0	1.0
Stroke	229474.0	0.044816	0.206899	0.0	0.0	0.0	0.0	1.0
HeartDiseaseorAttack	229474.0	0.103336	0.304398	0.0	0.0	0.0	0.0	1.0
PhysActivity	229474.0	0.733042	0.442371	0.0	0.0	1.0	1.0	1.0
HvyAlcoholConsump	229474.0	0.060791	0.238947	0.0	0.0	0.0	0.0	1.0
GenHith	229474.0	2.601820	1.064962	1.0	2.0	3.0	3.0	5.0
MentHith	229474.0	3.509866	7.717643	0.0	0.0	0.0	2.0	30.0
PhysHith	229474.0	4.681219	9.050877	0.0	0.0	0.0	4.0	30.0
DiffWalk	229474.0	0.185751	0.388906	0.0	0.0	0.0	0.0	1.0
Sex	229474.0	0.439087	0.496277	0.0	0.0	0.0	1.0	1.0
Age	229474.0	8.085068	3.094451	1.0	6.0	8.0	10.0	13.0
Education	229474.0	4.979741	0.992989	1.0	4.0	5.0	6.0	6.0
Income	229474.0	5.888615	2.092888	1.0	4.0	6.0	8.0	8.0

The top 10 best features selected from the data based on the chi-square test. These features are chosen for their ability to predict the target variable effectively. After feature selection, several columns are removed from the original dataset, namely ["Fruits", "Veggies", "NoDocbcCost", "CholCheck", "AnyHealthcare"]. Following this removal, information and descriptive statistics about the remaining data are displayed, providing insights into the data types, non-null counts, and summary statistics.













# DATA PRE-PROCESSING

Operational Variable & Treatment for Imbalance Data and Data Scaling









### **OPERATIONAL VARIABLE**

	HighBP	HighChol	ВИІ	Smoker	Stroke	HeartDiseaseorAttack	PhysActivity	HvyAlcoholConsump	GenH1th	MentH1th	PhysH1th	DiffWalk	Sex	Age	Education	Income
0	1	1	40	1	0	0	0	0	5	18	15	1	0	9	4	3
1	0	0	25	1	0	0	1	0	3	0	0	0	0	7	6	1
2	1	1	28	0	0	0	0	0	5	30	30	1	0	9	4	8
3	1	0	27	0	0	0	3	0	2	0	0	0	0	11	3	6
4	1	1	24	0	0	0	1	0	2	3	0	0	0	11	5	4
	400		66	m	m	564	55	iii.	, iii			166	ió	360	(60.0)	00
253675	1	1	45	0	0	0	0	0	3	0	5	0	1	5	6	7
253676	1	1	18	0	0	0	0	0	4	0	0	1	0	11	2	4
253677	0	0	28	0	0	0	1	0	1	0	0	0	0	2	5	2
253678	1	0	23	0	0	0	0	0	3	0	0	0	1	7	5	1
253679	1	1	25	0	0	1	1	0	2	0	0	0	0	9	6	2
229474 n	ows × 16	columns														

In this section, the **independent variables X** are separated by removing the "**Diabetes\_binary**" column from the DataFrame df. The dependent variable Y is then defined as the "**Diabetes\_binary**" column from the same DataFrame. Finally, the independent variables X are displayed. This process essentially separates the predictor variables from the target variable for further analysis.











# TREATMENT OF IMBALANCE DATA AND DATA SCALING

#### Y.value counts()

Diabetes\_binary

194377

1 35097

Name: count, dtype: int64

#### y\_sm.value\_counts()

Diabetes binary

0 350971 35097

Name: count, dtype: int64

y\_sm.shape , x\_sm.shape

((70194,), (70194, 16))

#### In this section:

- Frequency of each class in the target variable Y is counted.
- 2. NearMiss resampling technique is initialized with version 1 and 10 nearest neighbors.
- Resampling is applied to the feature matrix X and the target variable Y, resulting in resampled feature matrix x\_sm and resampled target variable y\_sm.
- 4. The shapes of the resampled matrices are printed, indicating the number of samples generated.
- 5. Counts of each class in the resampled target variable y\_sm are displayed, showing balanced distribution.
- 6. Data is split into training and testing sets with a test size of 0.3 and using random state 37

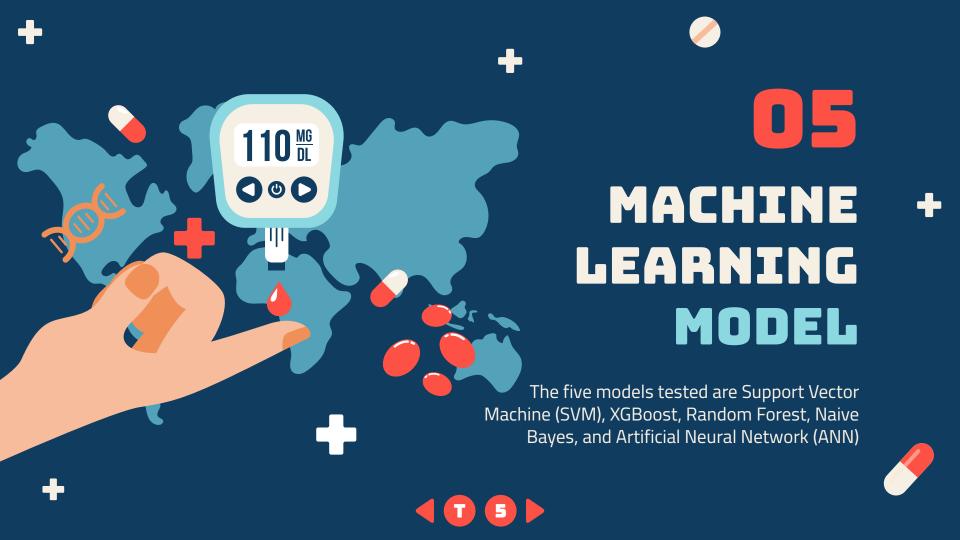
scalar = StandardScaler()
X\_train = scalar.fit\_transform(X\_train)
X\_test = scalar.fit\_transform(X\_test)

In this process, the features in the training set (X\_train) are standardized using StandardScaler, which calculates the mean and standard deviation of each feature and scales them accordingly. The same scaling parameters are then applied to standardize the testing set (X\_test) to maintain consistency in feature scaling between the training and testing data.











# SVM



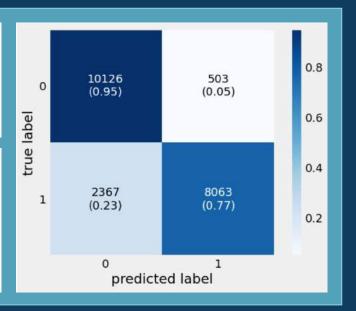
SVM Evaluation

Training set score: 0.8646

Test set score: 0.8637

Mean Squared Error: 0.1362837741583171

	precision	recall	f1-score	support
0	0.81	0.95	0.88	10629
1	0.94	0.77	0.85	10430
accuracy			0.86	21059
macro avg	0.88	0.86	0.86	21059
weighted avg	0.88	0.86	0.86	21059













# XGBOOST



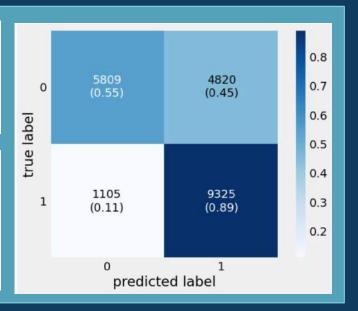
XGBoost Evaluation

Training set score: 0.8725

Test set score: 0.7186

Mean Squared Error: 0.28135239090175224

	precision	recall	f1-score	support
0	0.84	0.55	0.66	10629
1	0.66	0.89	0.76	10430
accuracy			0.72	21059
macro avg	0.75	0.72	0.71	21059
weighted avg	0.75	0.72	0.71	21059













### **RANDOM FOREST EVALUATION** -

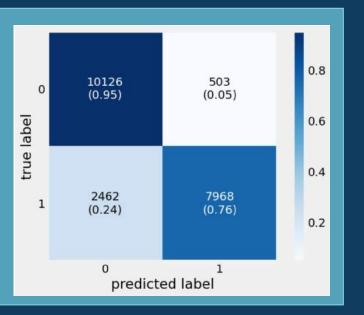
Random Forest Evaluation

Training set score: 0.8689

Test set score: 0.8592

Mean Squared Error : 0.1407949095398642

	precision	recall	f1-score	support
0	0.80	0.95	0.87	10629
1	0.94	0.76	0.84	10430
accuracy			0.86	21059
macro avg	0.87	0.86	0.86	21059
weighted avg	0.87	0.86	0.86	21059













# NAIVE BAYES



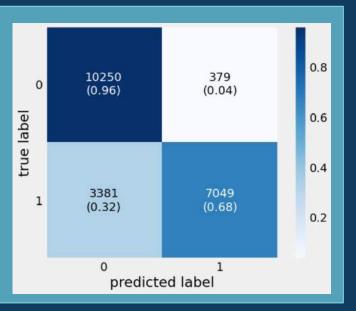
Naive Bayes Evaluation

Training set score: 0.8203

Test set score: 0.8215

Mean Squared Error: 0.178545989838074

	precision	recall	f1-score	support
0	0.75	0.96	0.85	10629
1	0.95	0.68	0.79	10430
accuracy			0.82	21059
macro avg	0.85	0.82	0.82	21059
weighted avg	0.85	0.82	0.82	21059













# ANN



ANN Evaluation

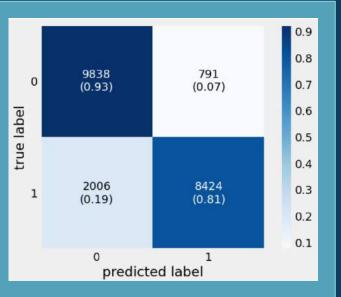
Training set accuracy: 0.8737

Test set accuracy: 0.8672

**659/659 1s** 1ms/step

Mean Squared Error: 0.1328

	precision	recall	f1-score	support
Ø	0.83	0.93	0.88	10629
1	0.91	0.81	0.86	10430
accuracy			0.87	21059
macro avg	0.87	0.87	0.87	21059
weighted avg	0.87	0.87	0.87	21059











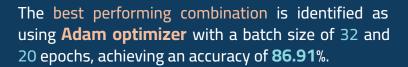


# **TUNING BEST MODEL (ANN)**



```
Best: 0.869095 using {'batch size': 32, 'epochs': 20, 'optimizer': 'adam'
0.864414 (0.001805) with: {'batch size': 16, 'epochs': 5, 'optimizer': 'adam'}
         (0.002918) with: {'batch size': 16, 'epochs': 5, 'optimizer': 'rmsprop'
         (0.002072) with: {'batch_size': 16, 'epochs': 10, 'optimizer': 'adam']
0.866714 (0.002635) with: {'batch_size': 16, 'epochs': 15,
         (0.002567) with: {'batch size': 16,
                                             'epochs': 15, 'optimizer': 'rmsprop'
0.867630 (0.001034) with: {'batch size': 16.
                                             'epochs': 20.
0.866083 (0.001016) with: {'batch_size': 16, 'epochs': 20,
0.864191 (0.002736) with: {'batch_size': 32,
0.865554 (0.002384) with: {'batch size': 32, 'epochs': 5,
                          {'batch_size': 32, 'epochs': 10,
0.867121 (0.003037) with: {'batch size': 32, 'epochs': 10, 'optimizer': 'rmsprop'
0.867976 (0.001830) with: {'batch_size': 32, 'epochs': 15, 'optimizer':
                          {'batch_size': 32,
                                            'epochs': 15, 'optimizer': 'rmsprop'
                          {'batch size': 32, 'epochs': 20, 'optimizer': 'adam'
                          {'batch_size': 32, 'epochs': 20, 'optimizer': 'rmsprop'}
0.863458 (0.001802) with: {'batch_size': 64,
0.861545 (0.003583) with: {'batch size': 64,
                                             'epochs': 5,
0.867447 (0.001233) with: {'batch_size': 64, 'epochs': 10, 'optimizer': 'adam'
0.866368 (0.002242) with: {'batch size': 64, 'epochs': 10,
0.868017 (0.001457) with: {'batch size': 64, 'epochs': 15,
                          {'batch_size': 64, 'epochs': 20,
                          {'batch size': 64, 'epochs': 20,
0.861789 (0.002680) with: {'batch size': 128, 'epochs': 5,
                          {'batch_size': 128, 'epochs': 5, 'optimizer': 'rmsprop'
0.866165 (0.002797) with: {'batch size': 128,
                          {'batch_size': 128,
                          {'batch_size': 128,
                                               'epochs': 15.
0.867549 (0.001570) with: {'batch_size': 128,
                                              'epochs': 15,
                          {'batch size': 128,
                                              'epochs': 20,
0.866816 (0.001847) with: {'batch size': 128, 'epochs': 20, 'optimizer': 'rmsprop
```

In this section, a grid search cross-validation is performed to optimize the hyperparameters of an Artificial Neural Network (ANN) model. The hyperparameters tested include different optimizers (Adam and RMSprop), batch sizes (16, 32, 64, and 128), and numbers of epochs (5, 10, 15, and 20).







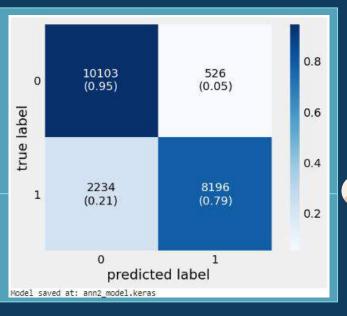
### +

# RUNNING TUNING MODEL ANN +

Epoch 1/10	
1536/1536	4s 2ms/step - accuracy: 0.8170 - loss: 0.3955 - val_accuracy: 0.8559 - val_loss: 0.3294
Epoch 2/10	
1536/1536	3s 2ms/step - accuracy: 0.8589 - loss: 0.3266 - val_accuracy: 0.8645 - val_loss: 0.3266
Epoch 3/10	
1536/1536	3s 2ms/step - accuracy: 0.8655 - loss: 0.3157 - val_accuracy: 0.8653 - val_loss: 0.3136
Epoch 4/10	
1536/1536	3s 2ms/step - accuracy: 0.8673 - loss: 0.3129 - val_accuracy: 0.8654 - val_loss: 0.3116
Epoch 5/10	
1536/1536	3s 2ms/step - accuracy: 0.8694 - loss: 0.3092 - val_accuracy: 0.8697 - val_loss: 0.3074
Epoch 6/10	
1536/1536	3s 2ms/step - accuracy: 0.8734 - loss: 0.3026 - val_accuracy: 0.8643 - val_loss: 0.3126
Epoch 7/10	
1536/1536	3s 2ms/step - accuracy: 0.8704 - loss: 0.3024 - val_accuracy: 0.8687 - val_loss: 0.3056
Epoch 8/10	
1536/1536	3s 2ms/step - accuracy: 0.8728 - loss: 0.3013 - val_accuracy: 0.8701 - val_loss: 0.3004
Epoch 9/10	
1536/1536	6s 2ms/step - accuracy: 0.8747 - loss: 0.2953 - val_accuracy: 0.8707 - val_loss: 0.3006
Epoch 10/10	
1536/1536	3s 2ms/step - accuracy: 0.8713 - loss: 0.2981 - val_accuracy: 0.8689 - val_loss: 0.3009

The Artificial Neural Network (ANN) model attained a training accuracy of 87.49% and a test accuracy of 86.89%, suggesting robust predictive capability. However, slight overfitting was observed as the training accuracy surpassed the test accuracy, indicating potential room for model refinement.

Training set ac Test set accura				
659/659			s/step	
Nean Squared Er	ror: 0.131	1		
Root Mean Squar	ed Error:	0.3620		
F	recision	recall	f1-score	support
0	0.82	0.95	0.88	10629
1	0.94	0.79	0.86	18438
accuracy			0.87	21059
macro avg	0.99	0.87	0.87	21059
weighted avg	0.88	9.87	0.87	21059







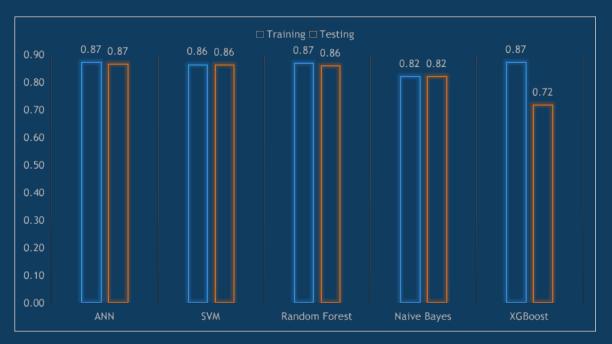




### +

## **ACCURACY MODEL**





The Artificial Neural Network (ANN) model attained a training accuracy of 87.49% and a test accuracy of 86.89%, suggesting robust predictive capability.

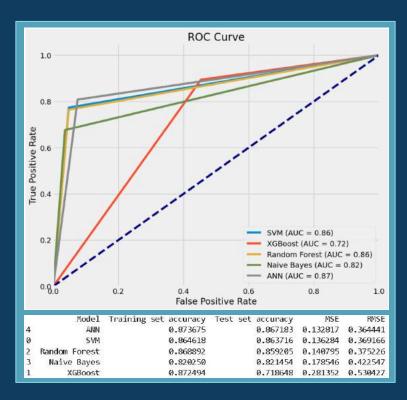








# + RUNNING TUNING MODEL ANN +



In summary, the SVM, Random Forest, and ANN models demonstrate relatively strong discriminatory abilities, as indicated by their higher AUC scores, while the XGBoost and Naive Bayes models also show reasonable performance, albeit with slightly lower AUC scores.







### +

## RUNNING TUNING MODEL ANN +

```
Enter value for HighBP (0 for No. 1 for Yes): 1
Enter value for HighChol (0 for No. 1 for Yes): 1
Enter value for BMI (Numeric value, based on formula): 25
Enter value for Smoker (0 for No, 1 for Yes): 1
Enter value for Stroke (0 for No, 1 for Yes): 1
Enter value for HeartDiseaseorAttack (0 for No. 1 for Yes): 1
Enter value for PhysActivity (0 for No. 1 for Yes): 0
Enter value for HvvAlcoholConsump (0 for No, 1 for Yes): 0
Enter value for Sex (0 for Female, 1 for Male): 1
Enter value for GenHlth (Range: 1-5): 3
Enter value for MentHlth (Numeric value between 0-30): 2
Enter value for PhysHlth (Numeric value between 0-30): 2
Enter value for DiffWalk (0 for No. 1 for Yes): 1
Enter value for Age (Range: 1-13): 4
Enter value for Education (Range: 1-6): 3
Enter value for Income (Range: 1-8): 3
                      — 0s 309ms/step
                      BMI Smoker Stroke HeartDiseaseorAttack PhysActivity HvyAlcoholConsump Sex GenHlth MentHlth PhysHlth DiffNalk Age Education Income
                 10 250
                                      1.0
                                                           1.0
                                                                         0.0
                                                                                            00 10
       10
                              1.0
                                                                                                                                      10 40
Based on our research model, it is predicted that you have a Prediabetes/Diabetes status. We recommend you see a doctor soon.
```

The code successfully allows for input of health feature values from users, then predicts the likelihood of prediabetes or diabetes based on a previously trained artificial neural network model. The prediction results are displayed to users along with a recommendation to consult a doctor if there is a risk of diabetes detected.









# **DEPLOYMENT MODEL**

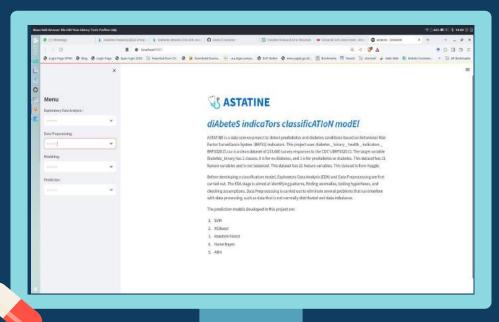
















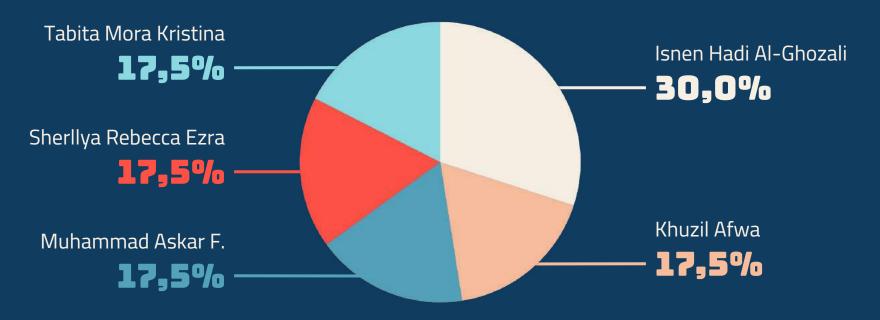




# +

# **CONTRIBUTION IN PERCENTAGES**











### +

# **JOB LIST**

Final Project							
	*	Keterangan	Kak Isnen	Kak Tabita	Kak Askar	Kak Afwa	Kak Ezra
	Google Colab	19/04/2024	Ì		1		1
	EDA	data info, data describe, missing value, visualisasi data		Х	X		
					II.		II.
	Data pre-processing	regularisasi data, oek outlier, distribusi data, data anomali, korelasi, feature selection		×	×		
	Deadline	15/04/2024		83	1	183	-
	Model training	ML Traditional :kNN, Decision Tree (C.45), Random Forest ML Deep Learning eksperimen untuk Boosting atau majority voting tambahkan algoritma Apriori untuk menunjukkan gejala/kondisi yg dapat menyebabkan diabetes	×			×	3
	Model evaluation	convution metric (recall, precision, accuracy, F-1 Score), ROC, AUC		8		8	×
	Streamlit				1		
	Modul Inisiasi		×	Х	1		ii e
	Modul EDA		×		X		j
	Modul Dara Prepocessing		X	-	ji	X	
	Deadline	24/04/2023			II .		1
	Modul Model Training		×		ĵ.		×
	Modul Evaluation Model		×		ĵ.		ĵ.
	Deadline	25/04/2023					
	Presentasi	Buat slide untuk project	X		X		3
	Deadline	28/04/2024	-				29







# THANK YOU - ORION TEAM