2024 Data Structures

Using Three Tree-Based Ensemble Models to Assess the Risk of Myocardial Infarction

세가지 트리 기반 앙상블 모델을 활용한 심근경색 위험도 측정

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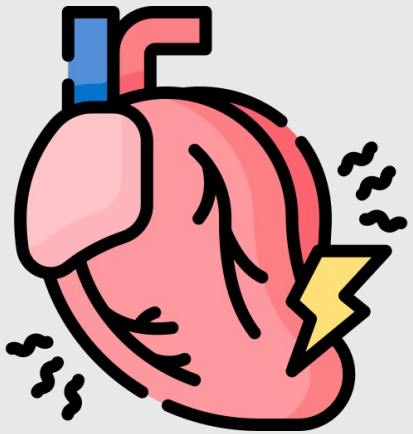

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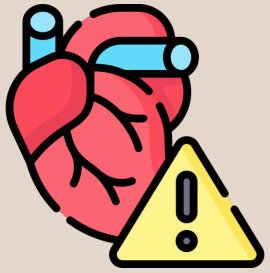
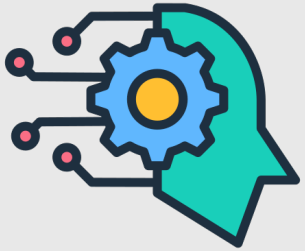
Introduction / 주제 설명



Myocardial Infarction (심근경색)
= Sudden & Life-threatening Disease
-> What if we could easily and frequently check its risk ?



Using tree-based AI Models
to predict simplified myocardial infarction (심근경색)

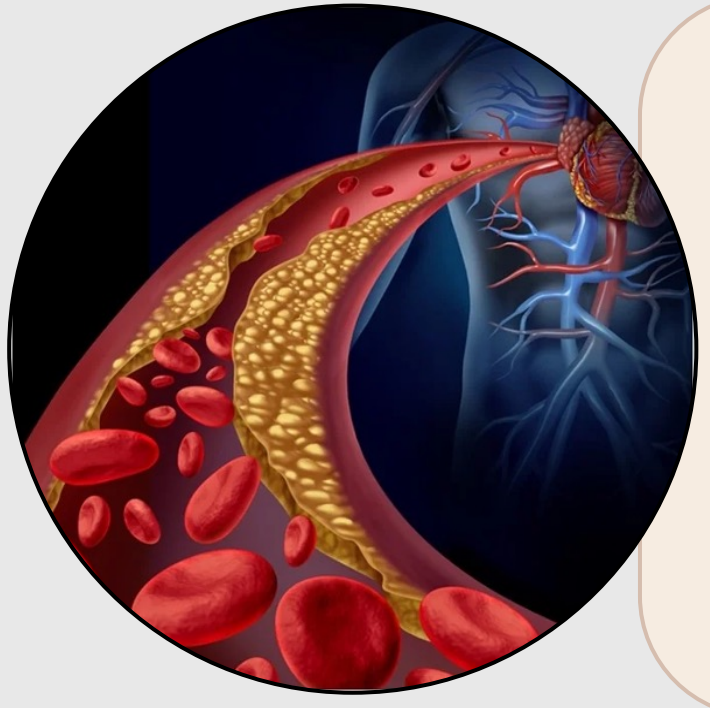
Introduction / 주제 설명

Daily medical check & Manage everyday lifestyle

Effects :
Make Body Healthier
& Protect us from Myocardial Infarction !!

Motivation / 동기

The Danger of Disease : Myocardial Infarction (심근경색)



Sudden chest pain without early symptoms
Clotted blood blocks blood vessels
33% death rate upon arrival at the hospital
5-10% survival rate with immediate medical care

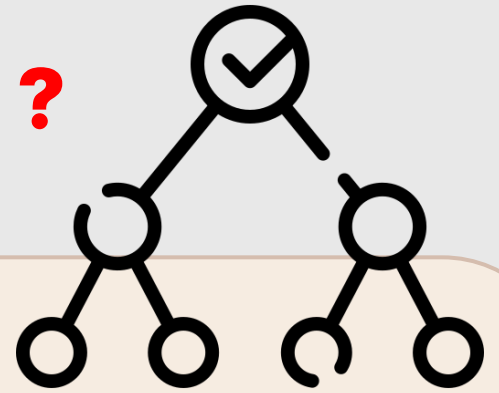
Primary factors : Cholesterol, Blood Pressure, Age

[Picture Reference]

[서울대학병원 N 의학정보]

Motivation / 동기

Q. Why did we choose tree-based models ?

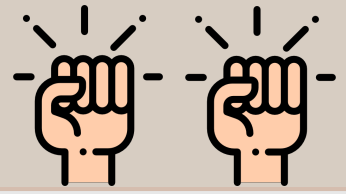


A.

- **Designate various decision criteria to each node**
- **Direction from parent node to child node**
  -> Easy to understand decision making process
- **Searching is fast in trees (Time complexity : O(log n))**
- **High classification accuracy and easy data visualization**

Role / 역할 분담

Together



**Searching topic, Data Discovery,
Model Reviews, Conclusion, Developments**

Jiyoung

Data Download & Bringing SAS data
Data Preprocessing (Data Scaling, Feature Selection)
Methods : Decision Tree, XGBoosting
Source Making : Motivation, Decision Tree, Gradient Boosting, XGBoosting

Kaeun

PI, Data Preprocessing (Data Sampling, Data Cleaning)
Methods : Random Forest / Gradient Boosting
**Primarily Making Slides : Role, Data Information, Data Preprocessing,
Ensemble Learning, Random Forest, Before Application**

Data Information / 데이터 정보

[국민건강영양조사]

국민건강영양조사 원시자료 2019 – 2021 (제 8기) 기본 DB

Contents : 검진조사, 건강설문조사, 영양조사

2019 : 8110 Data / 912 Variables

2020 : 7359 Data / 859 Variables

2021 : 7090 Data / 864 Variables

Columns = 행(세로) = Variables = Features

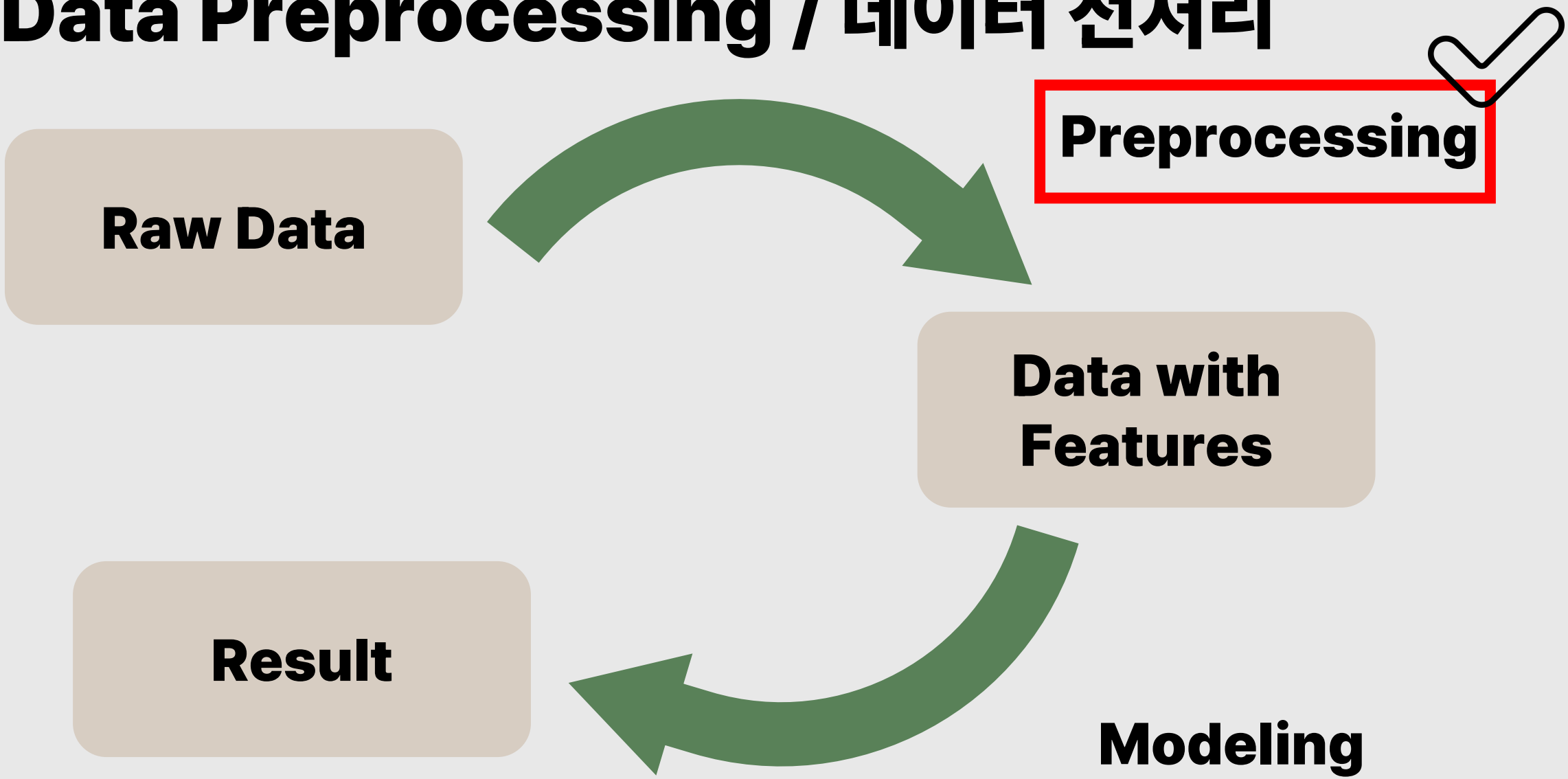
```
hn21_s.head()
```

	sex	age	DI1_dg	DI2_dg	DE1_dg	DI3_dg	DF2_dg	DI1_pr	DI2_pr	DE1_pr	...	HE_HLfh1	HE_HLfh2	HE_IHDfh1	HE_IHDfh2	HE_STRfh1	HE_STRfh2	HE_DMfh1	HE_DMfh2
0	1.0	61.0	1.0	0.0	0.0	0.0	1.0	1.0	8.0	8.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	1.0	57.0	1.0	0.0	0.0	0.0	0.0	1.0	8.0	8.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	2.0	39.0	0.0	0.0	0.0	0.0	0.0	8.0	8.0	8.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
3	2.0	19.0	0.0	0.0	0.0	0.0	0.0	8.0	8.0	8.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	1.0	70.0	0.0	0.0	0.0	0.0	0.0	8.0	8.0	8.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 33 columns

Rows = 열(가로) = Data = Observations = Samples

Data Preprocessing / 데이터 전처리



Data Preprocessing / 데이터 전처리

1. Data Cleaning :
Missing Values(NULL) + Uninformative values(모름/무응답)
We Discarded rows with missing and uninformative values.

2. Data Scaling : Standardization
(Rescaling different variables to a consistent range)
Rescaling each variable average 0, variance 1.

We used StandardScaler() provided by Scikit-learn.

Data Preprocessing / 데이터 전처리

3. Feature Selection : Selecting important variables

Raw(Original) Data :
Include many variables (both informative, uninformative)
-> Need to reduce variables for model training !!

Criteria we used in selecting important variables :

원시자료이용지침서 (국민건강영양조사)
Medical Information about Myocardial Infarction(심근경색)

[Medical Information Reference1] [Medical Information Reference2]

Data Preprocessing / 데이터 전처리

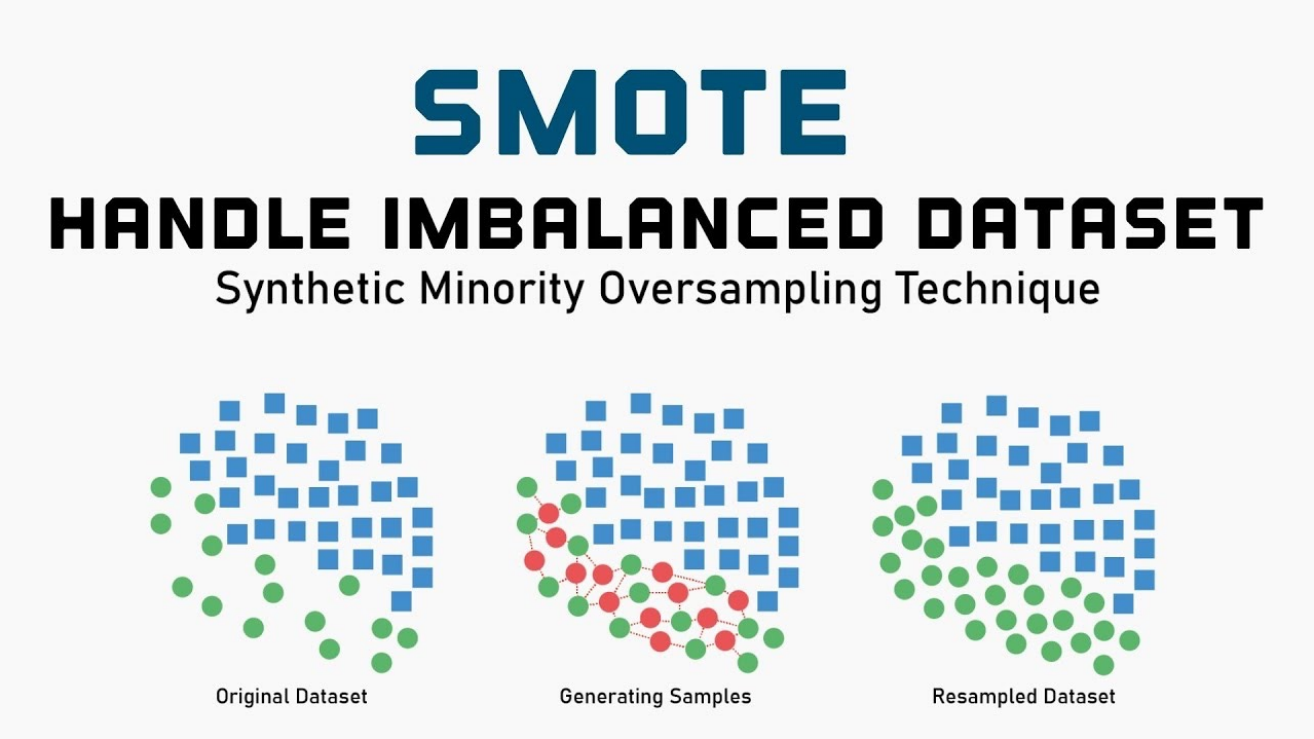
4. Data Sampling : Oversampling – SMOTE

	14215	54	348
Classes of Y(심근경색) :	NA(0)	SAFE(1)	DANGER(2)

We observed **Class Imbalance** in the dataset.
Class imbalance : Observations are **unevenly** distributed.
-> This may cause bias during model training.
-> Need to increase sample data in **minority** classes !!

Data Preprocessing / 데이터 전처리

4. Data Sampling : Oversampling
SMOTE (Synthetic Minority Oversampling Technique)



[Picture Reference]

In Our Data

Before : 0 1 2

14215 54 348

After : 0 1 2

14215 14215 14215

Data Preprocessing / 데이터 전처리

Introduction of Major Variables:

Total : 32 Variables

X (Independent Variables)

'age'	연령	Numerical
'DI1_pr'	고혈압 현재 유병여부	Categorical
'DE1_pr'	당뇨병 현재 유병여부	Categorical
'HE_glu'	공복혈당	Numerical
'HE_chol'	총콜레스테롤	Numerical
'HE_sbp'	수축기 혈압	Numerical
'HE_dbp'	이완기 혈압	Numerical

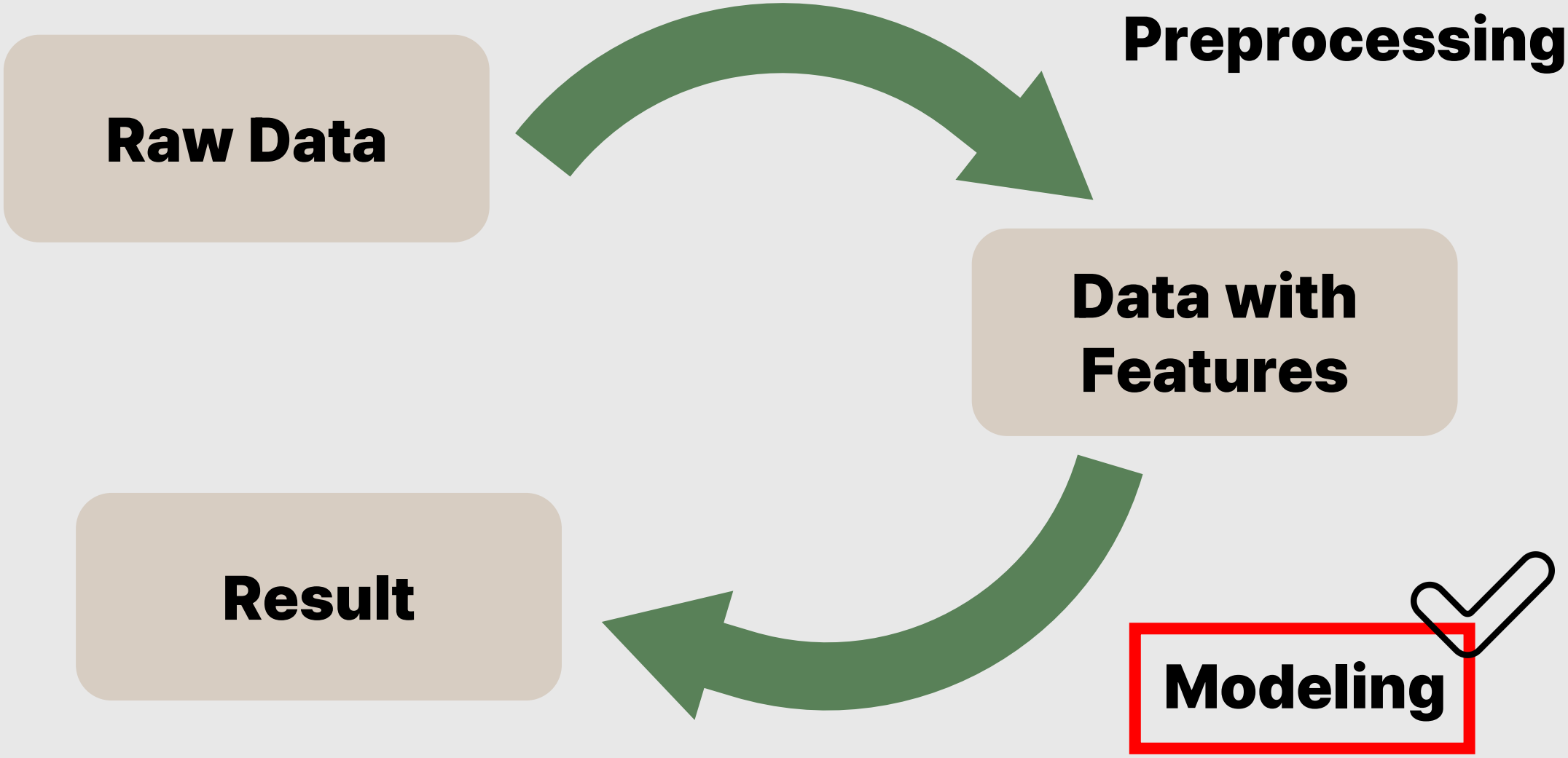
Data Information / 데이터 정보

Introduction of Major Variables:

Y (Dependent Variable)

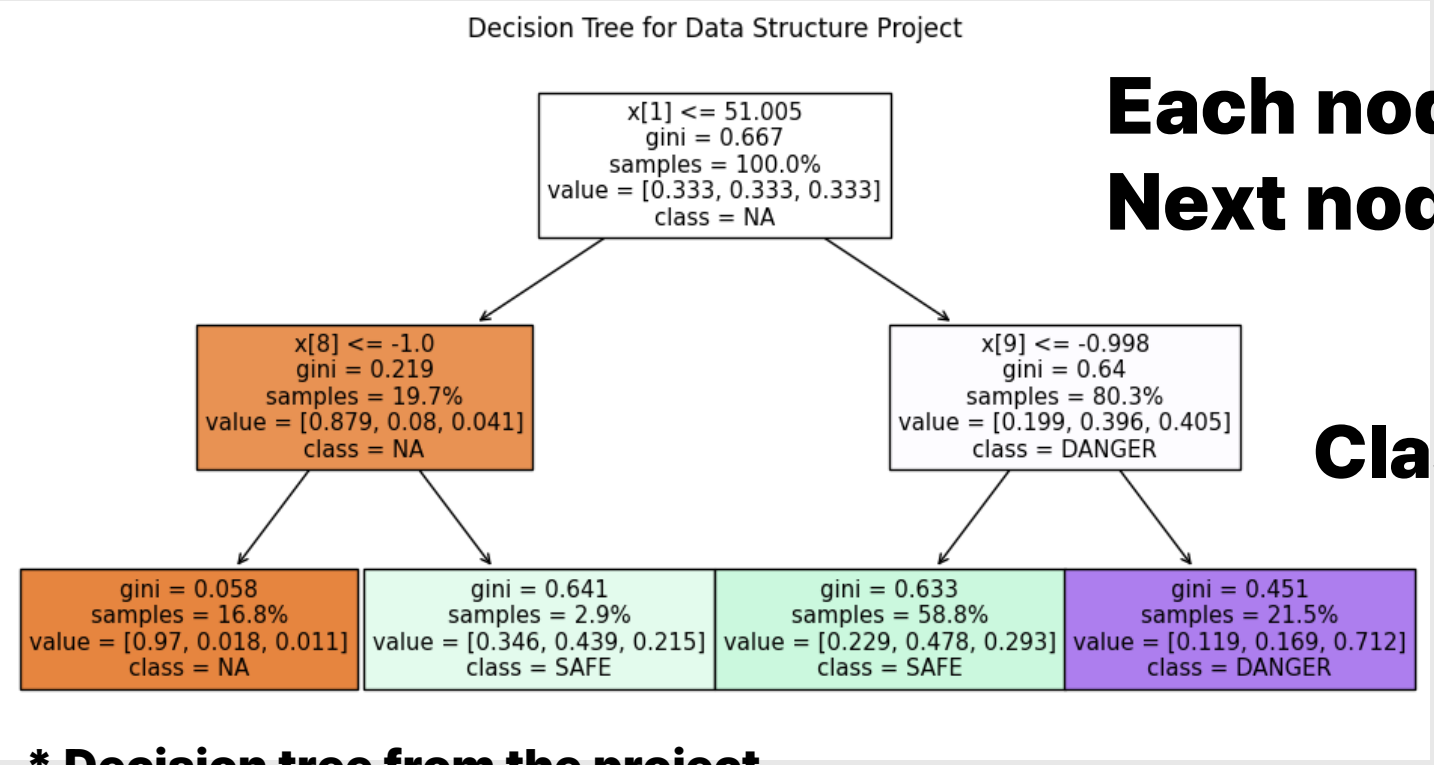
'DI4_pr'	심근경색 또는 협심증 현재 유병여부	Categorical

Methods / 방법론


Raw Data
Preprocessing
Data with Features
Modeling
Result

Methods / 방법론 – Decision Tree

Separates Data according to specific criteria(questions)
Similar to human's decision-making process

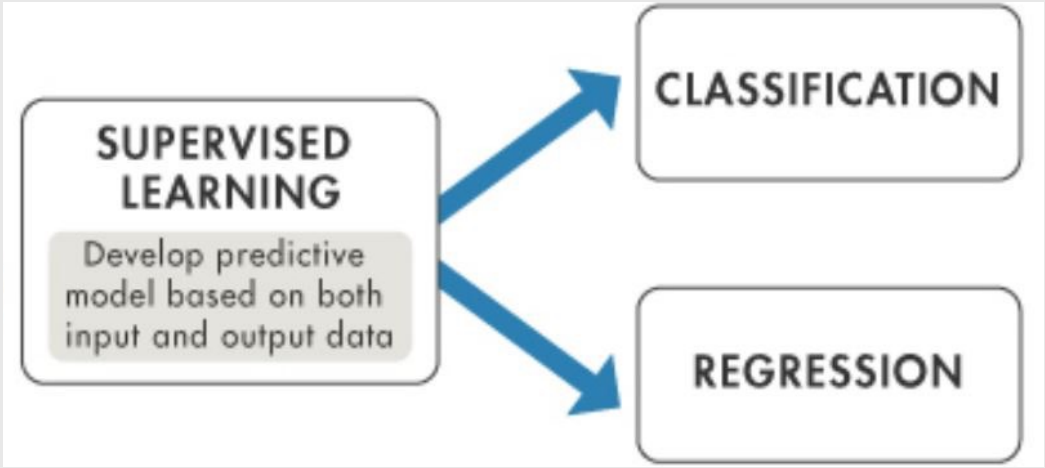


Each node contain split criterion
Next node is decided through it

Class = [NA, SAFE, DANGER]

*** Decision tree from the project**

Methods / 방법론 – Decision Tree



Decision Tree

- **Supervised Learning Method**

Supervised Learning :
Learning method including both X and Y Variables
Classification :
Predicting categorical output on given data
Regression :
Predicting numerical output on given data

[Picture Reference]

Methods / 방법론 – Decision Tree

Pros

Simple and effective for classifying
: especially decision for medical field
White-box model : easy to interpret for human

Cons

Easy to be overfitted
(next page)

Methods / 방법론 – Decision Tree

Overfitting : Model is too precisely trained on given data, which may result in bad prediction to new data.

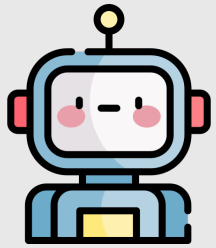
Common problem in decision trees (too much classified)

Solution : Ensemble Models ! (training multiple decision trees)

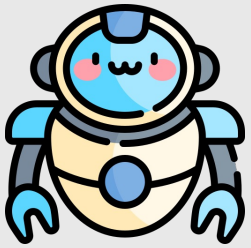
Methods / 방법론 – Ensemble Learning

Ensemble

“ A group of Weak Learners can come together to form a Strong Learner ”

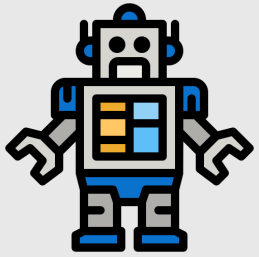


Weak Learner 1

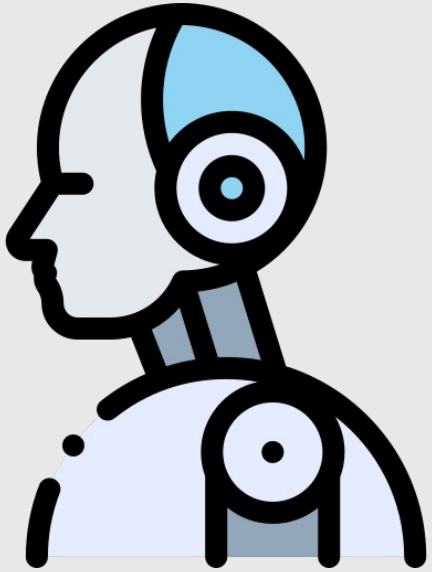


Weak Learner 2

Weak Learner 3



Weak Learner 4



Strong Learner

Methods / 방법론 – Ensemble Learning

Ensemble

Create multiple classifiers
+ Combine their predictions
=> a more Accurate Final Prediction

Bagging — **Boosting** — **Stacking**

Random Forest

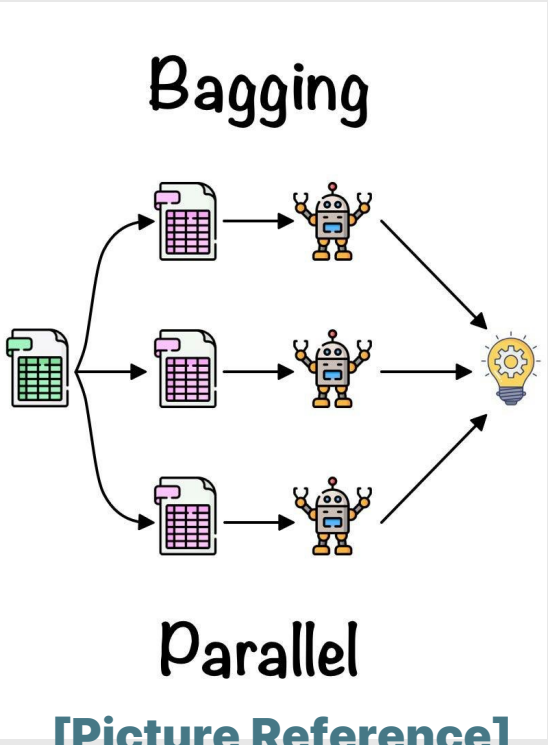
Gradient Boosting
XGBoosting

Methods / 방법론 – Ensemble Learning

Bagging

Bootstrap Aggregating = Bagging
Aggregate the bootstrap sampling !

- **Bootstrap Sampling** :
  Random Sampling with Replacement
- **Train individual models on each dataset**
- **Aggregation** :
  - **Classification : Majority Voting**
  - **Regression : Average of Outputs**



[Picture Reference]

Related Model : Random Forest

Methods / 방법론 – Ensemble Learning

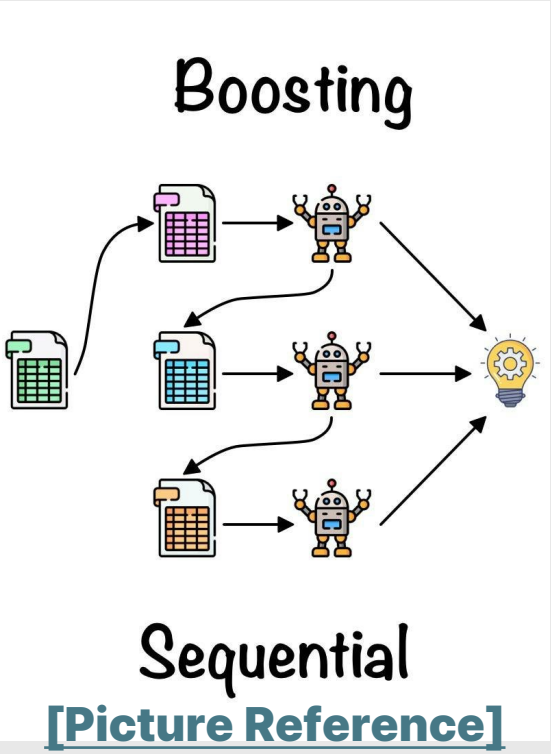
Boosting

Iterative Learning

Update the models by focusing on the errors of previous iterations

- **Increase the weight of misclassified data**
- **Focus more on difficult cases**
- **Combine these weak learners linearly**

Related Model :
Gradient Boosting, XGBoosting



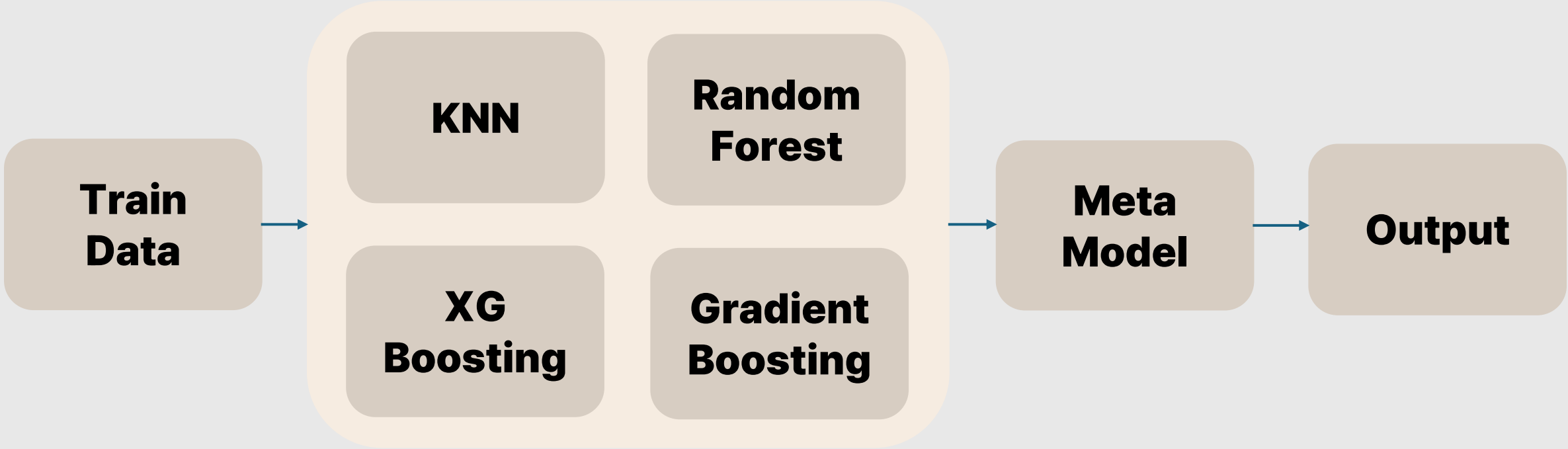
[Picture Reference]

Methods / 방법론 – Ensemble Learning

Stacking

Meta Learning

Combining predictions from Multiple Models (meta-model)



Methods / 방법론 – Ensemble Learning

Pros

Accuracy and Stability
Reduced overfitting problem
: Often vulnerable in decision tree algorithm

Cons

Interpretability
: Hard to interpret the decision-making of models
Computational Complexity

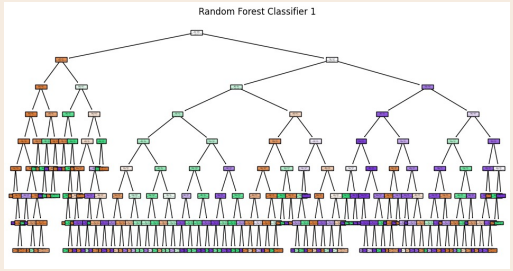
Methods / 방법론 – Random Forest

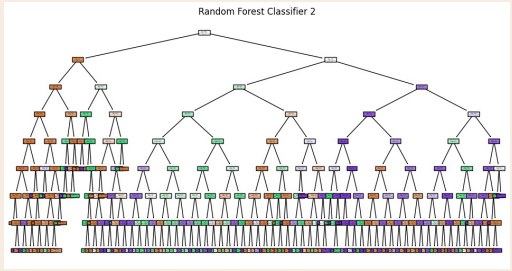
Ensemble - Bagging

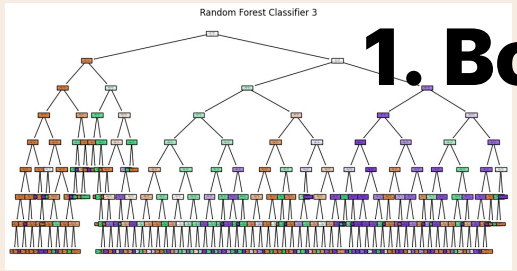
Random Data Sampling + Multiple Decision Trees
=> " Random Forest "

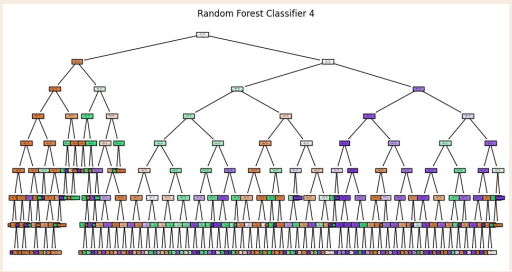
1. **Create Random Samples - Bootstrap Sampling**
2. **Train multiple decision trees**
3. **Aggregate them in a single model**
4. **Predict the output**

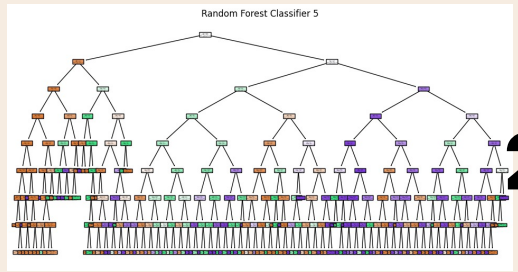
Methods / 방법론 – Random Forest











1. Bootstrap sampling

2. Multiple Decision Trees

***Trees from the project**

3. Aggregating

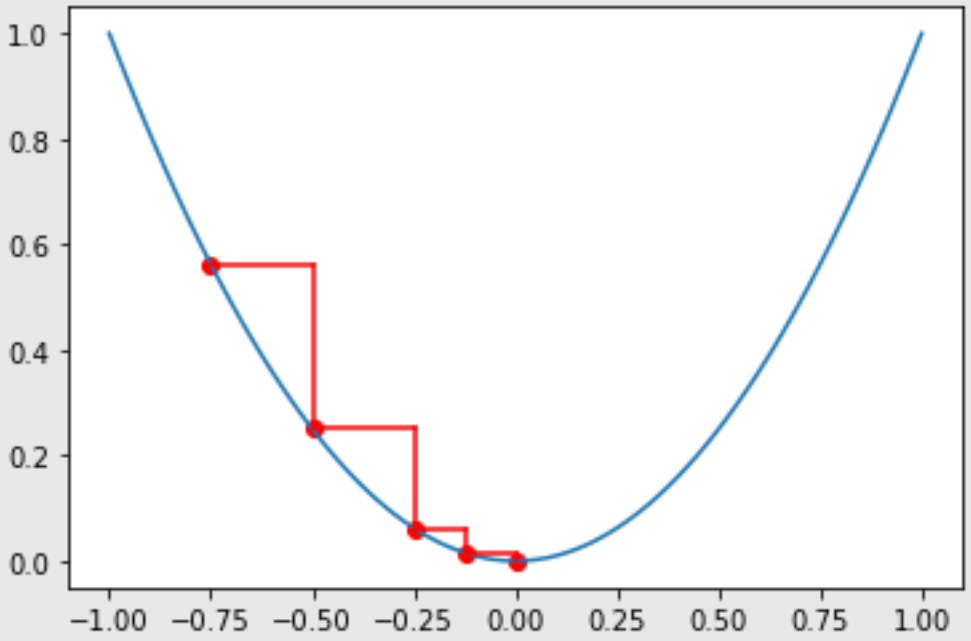
4. Prediction Output

Methods / 방법론 – Gradient Boosting

Ensemble – Boosting

Use gradient descent sequentially for enhancing previous model

- **Gradient Descent : Moving towards smaller gradients to locate the point with the minimum gradient**

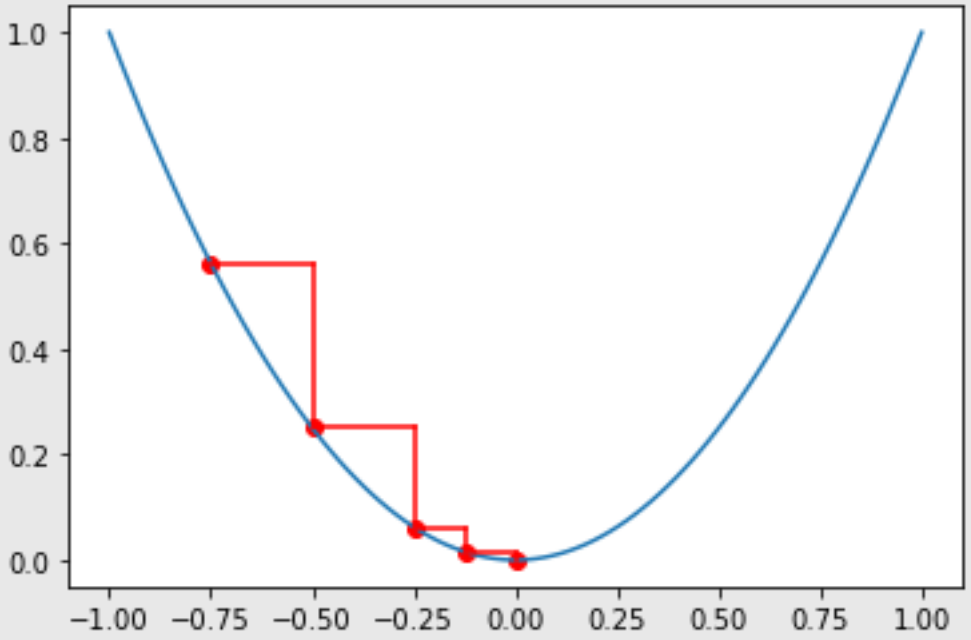


[Picture Reference]

Methods / 방법론 – Gradient Boosting

- **Cost Function: Function that shows how well the model predicted**

Keep updates errors through gradient descent by reducing the value of cost function

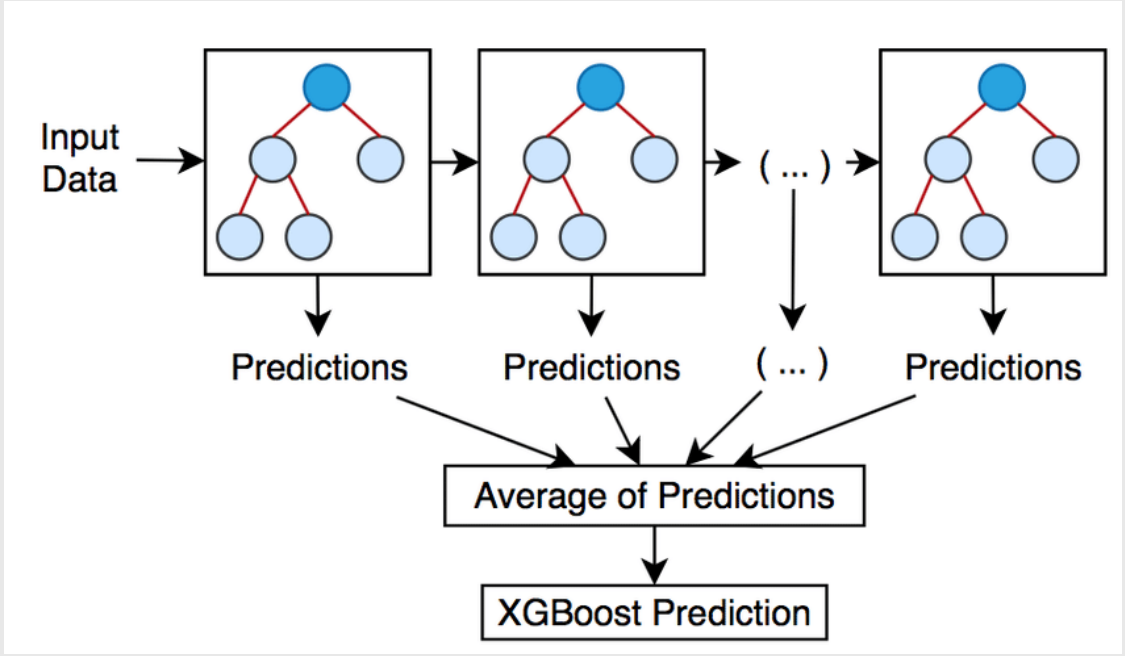


[Picture Reference]

Methods / 방법론 – XGBoosting

Ensemble – Boosting

Like gradient boosting
- Less overfitted, and thus
- Better precision



[Picture Reference]

Thanks to Regularization
Regularization
: Adjust the importance of each factor to enhance fitness

Before Application : Modeling

Using Scikit-learn (Python Programming Library)

Common Modeling Structure :

```
model = DecisionTreeClassifier() -> 모델 선언
model.fit(train_x, train_y) -> 모델 훈련
model.predict(test_x) -> 모델 예측
```

Split data into train and test -> Train the data with model -> Use this model to predict y variables of test dataset

Before Application : Modeling

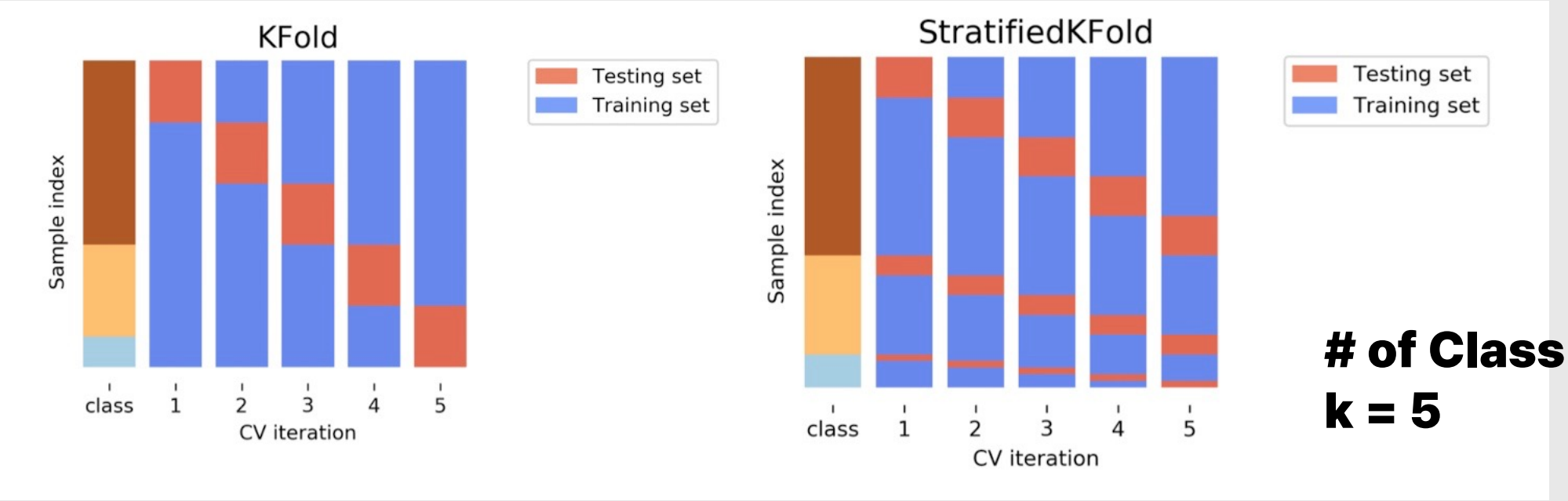
Using Scikit-learn (Python Programming Library)

Classifiers we used in Scikit-learn:

DecisionTreeClassifier()
RandomForestClassifier()
GradientBoostingClassifier()
XGBClassifier()

Those are the classifiers to build each predictive models.

Before Application : Stratified k-fold



# of Class : 3
k = 5

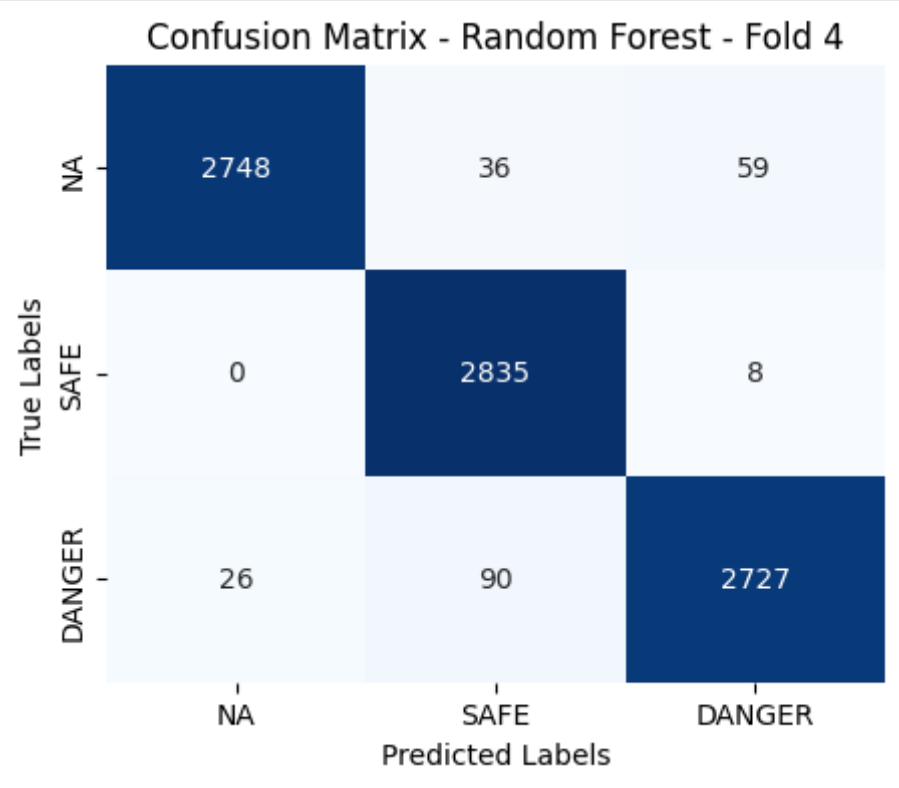
[Picture Reference]

k-fold : Simply divides data into number of folds of equal size
But ! All data may not be evenly distributed across each fold
Stratified k-fold : Divides data evenly across classes

Before Application : Metrics

F1-score : Harmonic mean of Precision and Recall

Confusion matrix : Tool for evaluating classification models using actual and predicted classes matching



Precision :

Actual [Class] out of Model Predicted [Class]

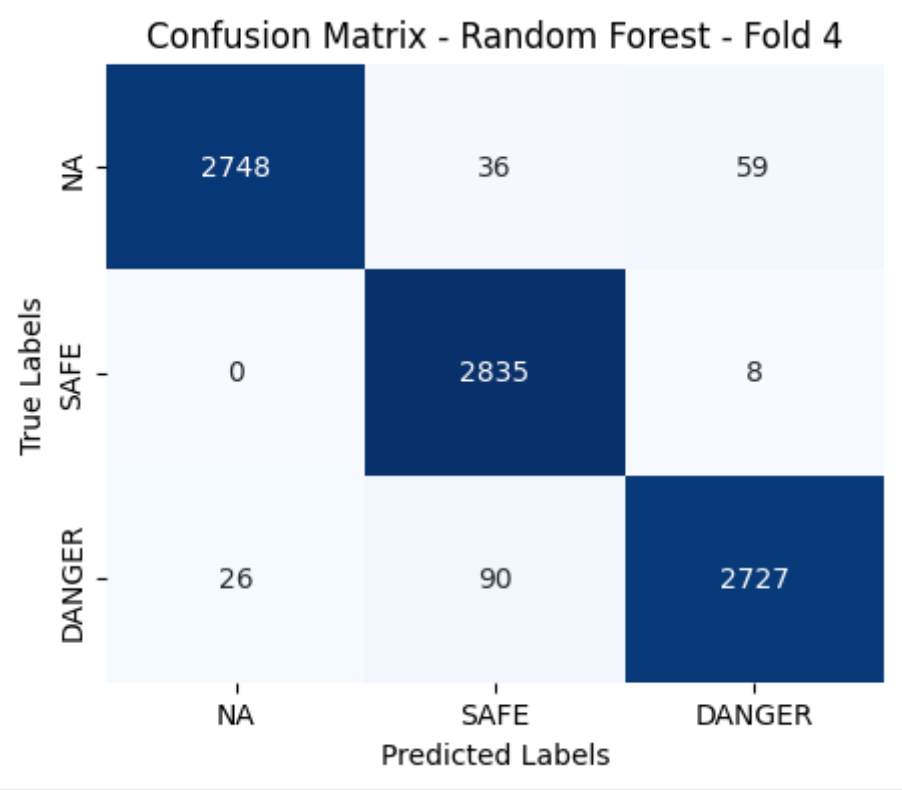
Precision of Class [Danger] : 2727 / (2727+8+59) = 0.976

***Confusion matrix from the project**

Before Application : Metrics

Recall : Model Predicted as [Class] out of Actual [Class]

Accuracy : Predicted Correctly out of Total



Recall of Class [Danger] : 2727 / (26+90+2727) = 0.959

Accuracy : (2748+2835+2727) / 8529 = 0.974

***Confusion matrix from the project**

Application / 적용 – Decision Tree

```python
k_fold = StratifiedKFold(n_splits=5)  # k = 5

dt_f1_scores = []
accuracies = []
precisions = []
recalls = []

for fold, (train_idx, test_idx) in enumerate(k_fold.split(X_train_over, y_train_over), 1):
    train_x, train_y = X_train_over[train_idx], y_train_over[train_idx]
    test_x, test_y = X_train_over[test_idx], y_train_over[test_idx]

    dt = DecisionTreeClassifier()
    dt.fit(train_x, train_y)
    pred_y = dt.predict(test_x)
```

Stratified k-fold

Modeling

```python
# Confusion Matrix 시각화
plt.figure(figsize=(5, 4))
sns.heatmap(confusion_matrix(test_y, pred_y), annot=True, cmap='Reds', fmt='d', cbar=False,
            xticklabels=['NA', 'SAFE', 'DANGER'], yticklabels=['NA', 'SAFE', 'DANGER'])
plt.title(f"Confusion Matrix - Decision Tree - Fold {fold}")
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

Confusion Matrix

Application / 적용 – Decision Tree

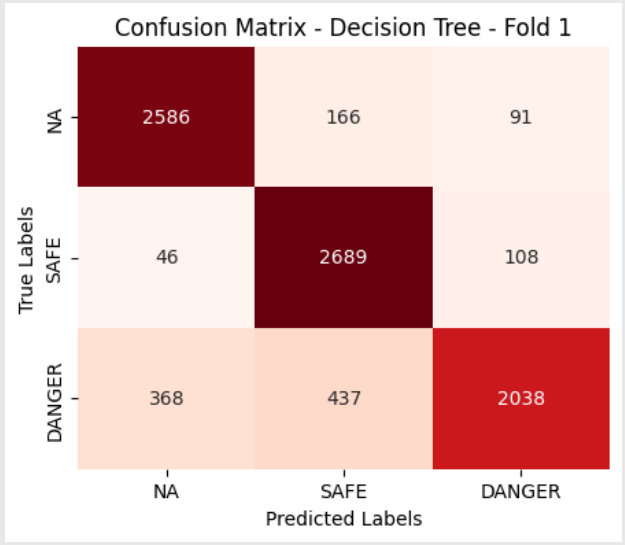
```
    # 각 fold에서 f1-score를 출력
    print(f"Fold {fold}:")
    print(f"  F1-score: {dt_f1:.4f}")
    print(f"  Accuracy: {accuracy:.4f}")
    print(f"  Precision:")
    for j in range(len(precision)):
        print(f"    Class {j}: {precision[j]:.4f}")
    print(f"  Recall:")
    for j in range(len(recall)):
        print(f"    Class {j}: {recall[j]:.4f}")
    print()
```

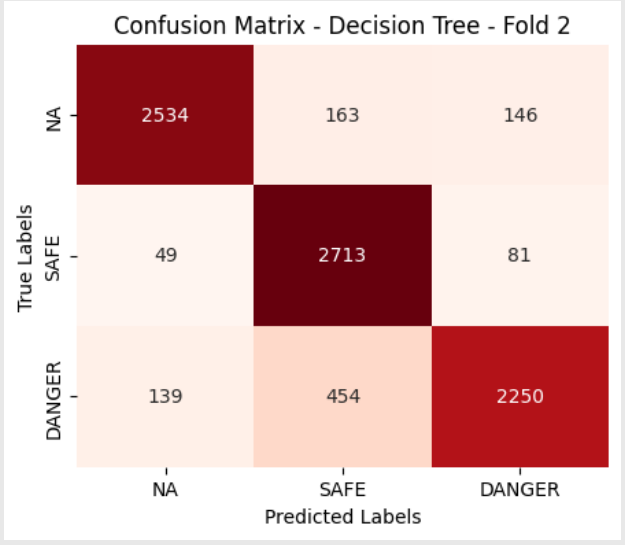
Printing Metrics for each fold

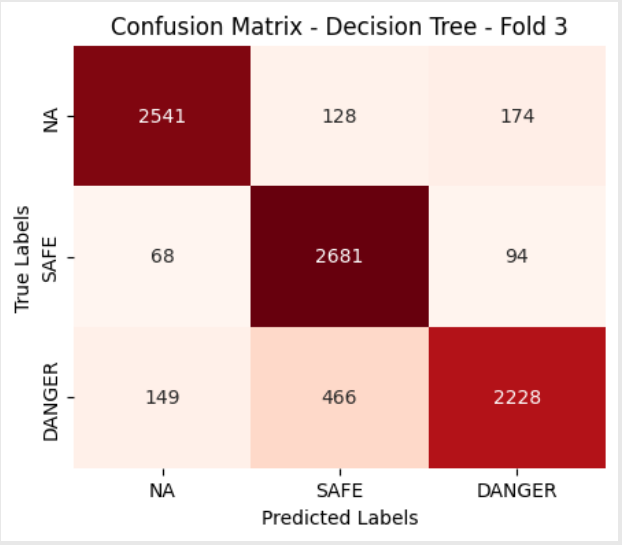
```
# 평균 f1-score, accuracy, precision, recall 계산 및 출력
avg_f1 = np.mean(dt_f1_scores)
avg_accuracy = np.mean(accuracies, axis=0)
avg_precision = np.mean(precisions, axis=0)
avg_recall = np.mean(recalls, axis=0)

print("Decision Tree")
print(f"  Average F1-score: {avg_f1:.4f}")
print(f"  Average Accuracy: {avg_accuracy:.4f}")
print("  Average Precision:")
for j in range(len(avg_precision)):
    print(f"    Class {j}: {avg_precision[j]:.4f}")
print("  Average Recall:")
for j in range(len(avg_recall)):
    print(f"    Class {j}: {avg_recall[j]:.4f}")
```

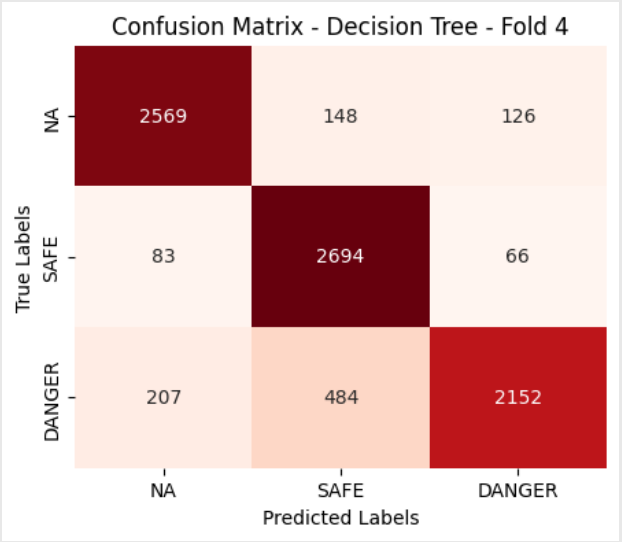
Printing Average of Metrics across folds

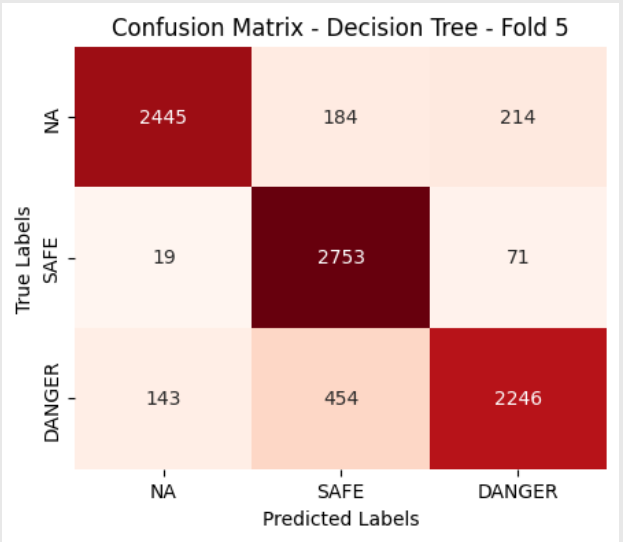
Application / 적용 – Decision Tree







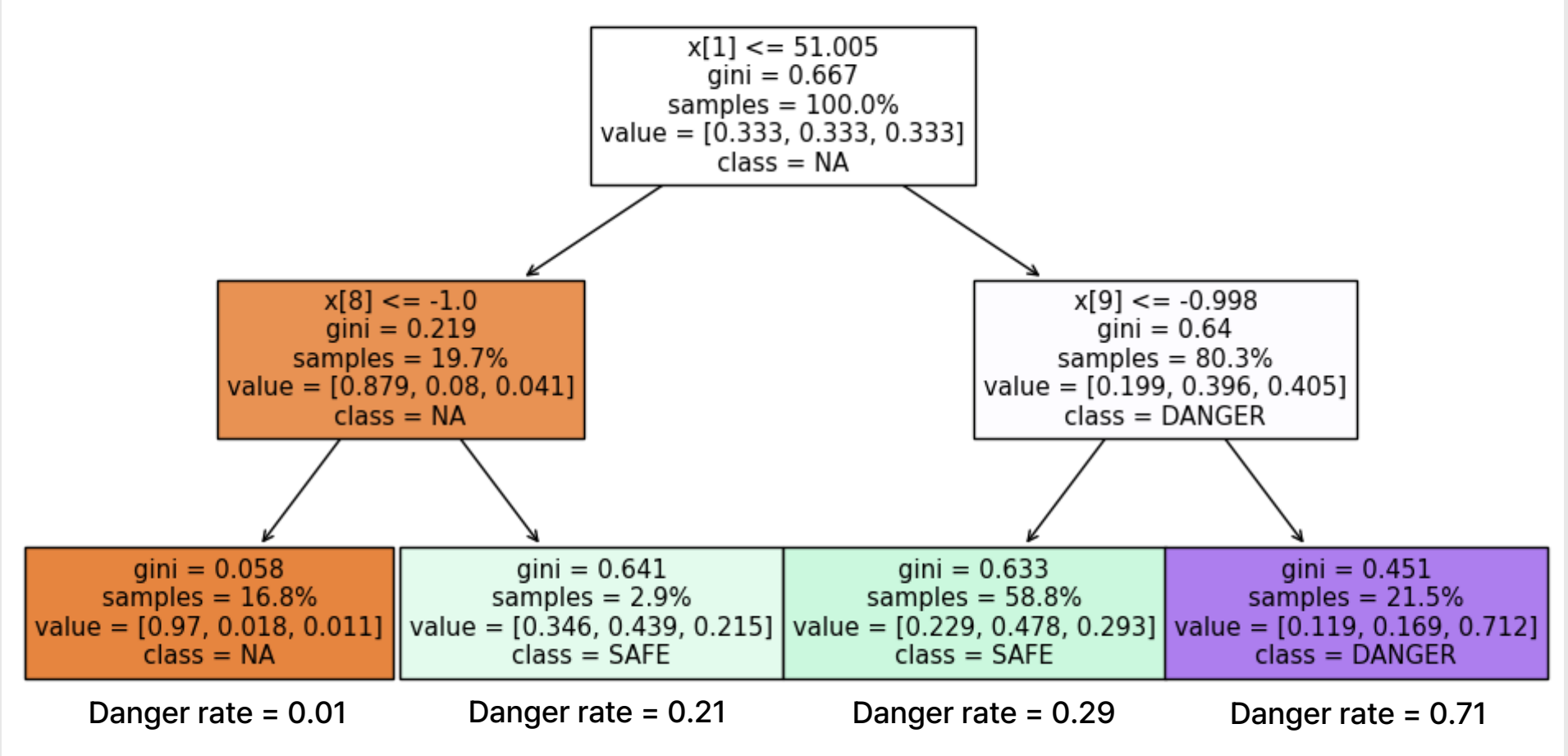





```
Decision Tree
  Average F1-score: 0.8704
  Average Accuracy: 0.8704
  Average Precision:
    Class 0: 0.9101
    Class 1: 0.8144
    Class 2: 0.9035
  Average Recall:
    Class 0: 0.8917
    Class 1: 0.9518
    Class 2: 0.7678
```

Application / 적용 – Decision Tree

Calculating Danger rate when depth = 2 (for visual clarity)



Application / 적용 – Random Forest

```
k_fold = StratifiedKFold(n_splits=5) # k = 5

rf_f1_scores = []
rf_accuracies = []
rf_precisions = []
rf_recalls = []

for fold, (train_idx, test_idx) in enumerate(k_fold.split(X_train_over, y_train_over), 1):
    print(f'Fold {fold}:')

    x_train, y_train = X_train_over[train_idx], y_train_over[train_idx]
    x_test, y_test = X_train_over[test_idx], y_train_over[test_idx]

    scaler = StandardScaler()
    x_train = scaler.fit_transform(x_train)
    x_test = scaler.transform(x_test)

    # Random Forest Classifier
    rf = RandomForestClassifier()
    rf.fit(x_train, y_train)
    y_pred_rf = rf.predict(x_test)
```

Stratified k-fold

Modeling

```
# Confusion Matrix 시각화
plt.figure(figsize=(5, 4))
sns.heatmap(confusion_matrix(y_test, y_pred_rf), annot=True, cmap='Blues', fmt='d', cbar=False,
            xticklabels=['NA', 'SAFE', 'DANGER'], yticklabels=['NA', 'SAFE', 'DANGER'])
plt.title(f"Confusion Matrix - Random Forest - Fold {fold}")
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

Confusion Matrix

Application / 적용 – Random Forest

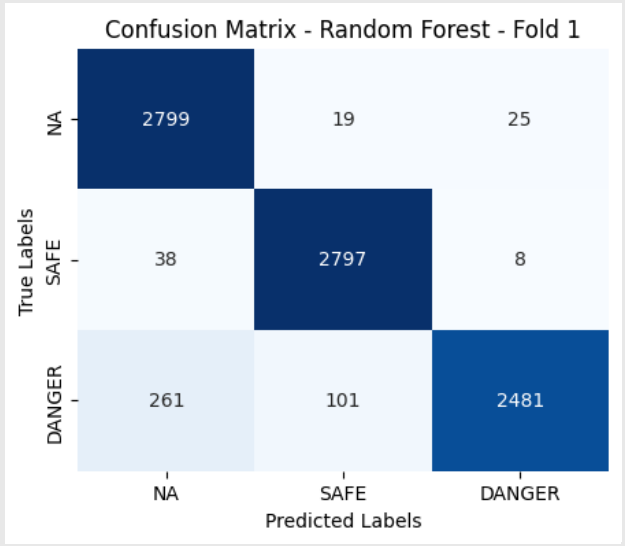
```
# 각 fold에서 f1-score를 출력
print(f"Fold {fold}:")
print(f"  F1-score: {rf_f1:.4f}")
print(f"  Accuracy: {rf_accuracy:.4f}")
print(f"  Precision:")
for j in range(len(rf_precision)):
    print(f"    Class {j}: {rf_precision[j]:.4f}")
print(f"  Recall:")
for j in range(len(rf_recall)):
    print(f"    Class {j}: {rf_recall[j]:.4f}")
print()
```

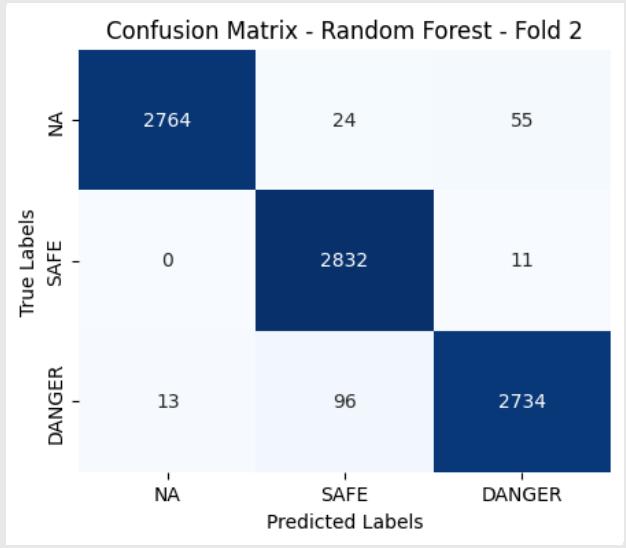
Printing Metrics for each fold

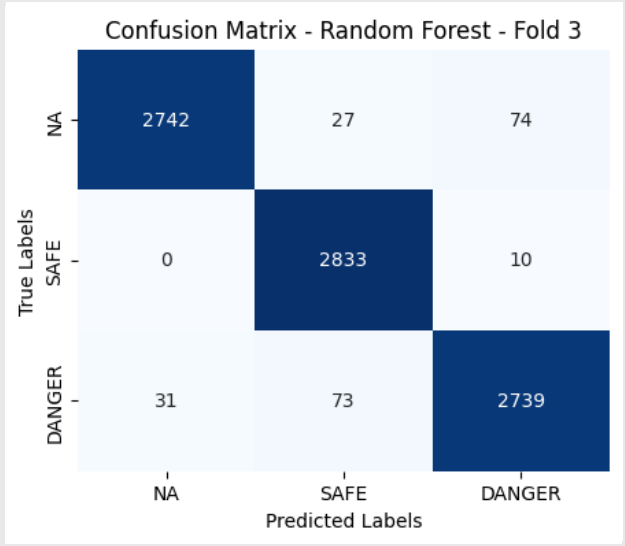
```
# 평균 F1-score, Accuracy, Precision, Recall 계산 및 출력
rf_avg_f1 = np.mean(rf_f1_scores)
rf_avg_accuracy = np.mean(rf_accuracies)
rf_avg_precision = np.mean(rf_precisions, axis=0)
rf_avg_recall = np.mean(rf_recalls, axis=0)

# 결과 출력
print("Random Forest:")
print(f"  Average F1-score: {rf_avg_f1:.4f}")
print(f"  Average Accuracy: {rf_avg_accuracy:.4f}")
print("  Average Precision:")
for j in range(len(rf_avg_precision)):
    print(f"    Class {j}: {rf_avg_precision[j]:.4f}")
print("  Average Recall:")
for j in range(len(rf_avg_recall)):
    print(f"    Class {j}: {rf_avg_recall[j]:.4f}")
print()
```

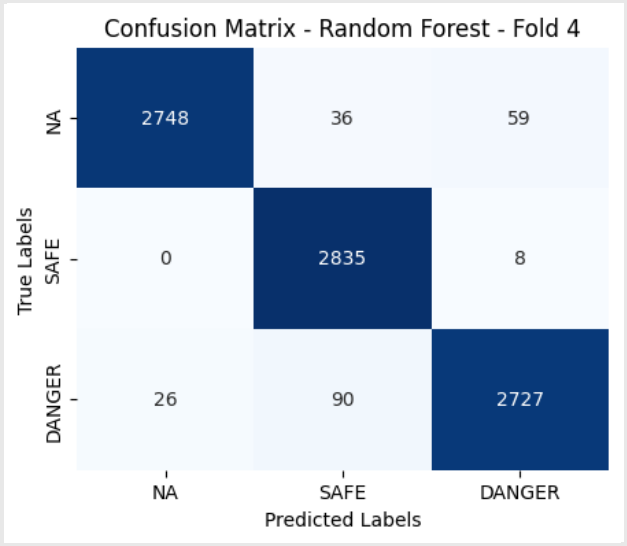
Printing Average of Metrics across folds

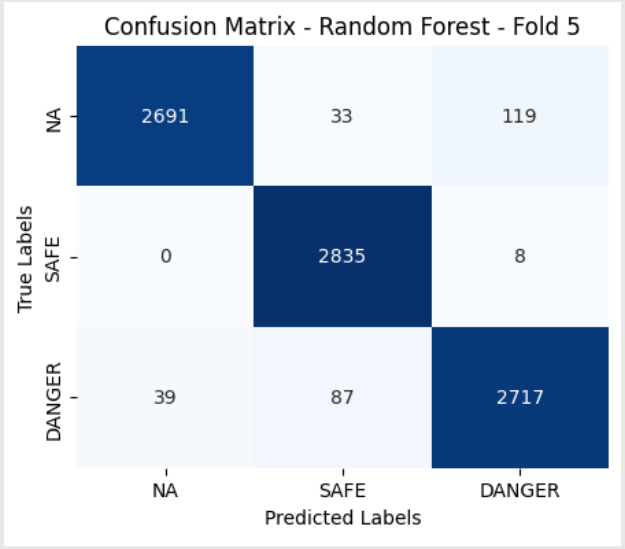
Application / 적용 – Random Forest












```
Random Forest:
  Average F1-score: 0.9679
  Average Accuracy: 0.9679
  Average Precision:
    Class 0: 0.9728
    Class 1: 0.9602
    Class 2: 0.9730
  Average Recall:
    Class 0: 0.9669
    Class 1: 0.9942
    Class 2: 0.9425
```

Application / 적용 – Gradient Boosting

```
k_fold = StratifiedKFold(n_splits=5) # k = 5
```

Stratified k-fold

```
gb_f1_scores = []
gb_accuracies = []
gb_precisions = []
gb_recalls = []

for fold, (train_idx, test_idx) in enumerate(k_fold.split(X_train_over, y_train_over), 1):
    print(f'Fold {fold}:')

    x_train, y_train = X_train_over[train_idx], y_train_over[train_idx]
    x_test, y_test = X_train_over[test_idx], y_train_over[test_idx]

    scaler = StandardScaler()
    x_train = scaler.fit_transform(x_train)
    x_test = scaler.transform(x_test)

    # Gradient Boosting Classifier
    gb = GradientBoostingClassifier()
    gb.fit(x_train, y_train)
    y_pred_gb = gb.predict(x_test)
```

Modeling

```
# Confusion Matrix 시각화
plt.figure(figsize=(5, 4))
sns.heatmap(confusion_matrix(y_test, y_pred_gb), annot=True, cmap='Greens', fmt='d', cbar=False,
            xticklabels=['NA', 'SAFE', 'DANGER'], yticklabels=['NA', 'SAFE', 'DANGER'])
plt.title(f"Confusion Matrix - Gradient Boosting - Fold {fold}")
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

Confusion Matrix

Application / 적용 – Gradient Boosting

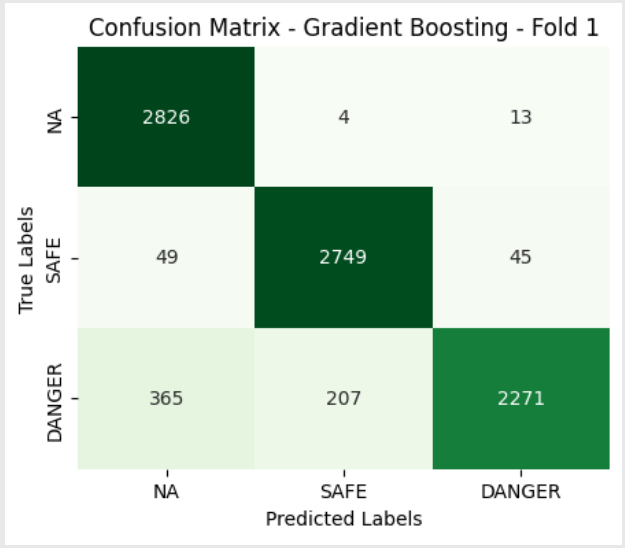
```
    # 각 fold에서 f1-score를 출력
    print(f"Fold {fold}:")
    print(f"  F1-score: {gb_f1:.4f}")
    print(f"  Accuracy: {gb_accuracy:.4f}")
    print(f"  Precision:")
    for j in range(len(gb_precision)):
        print(f"    Class {j}: {gb_precision[j]:.4f}")
    print(f"  Recall:")
    for j in range(len(gb_recall)):
        print(f"    Class {j}: {gb_recall[j]:.4f}")
    print()
```

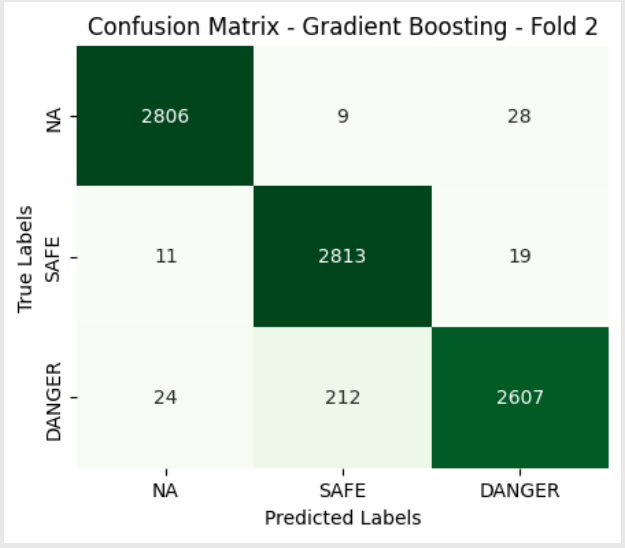
Printing Metrics for each fold

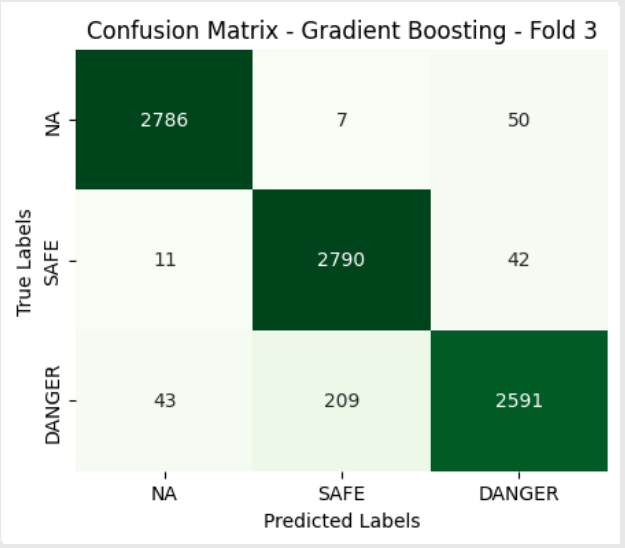
```
# 평균 F1-score, Accuracy, Precision, Recall 계산 및 출력

gb_avg_f1 = np.mean(gb_f1_scores)
gb_avg_accuracy = np.mean(gb_accuracies)
gb_avg_precision = np.mean(gb_precisions, axis=0)
gb_avg_recall = np.mean(gb_recalls, axis=0)

# 결과 출력
print("Gradient Boosting:")
print(f"  Average F1-score: {gb_avg_f1:.4f}")
print(f"  Average Accuracy: {gb_avg_accuracy:.4f}")
print("  Average Precision:")
for j in range(len(gb_avg_precision)):
    print(f"    Class {j}: {gb_avg_precision[j]:.4f}")
print("  Average Recall:")
for j in range(len(gb_avg_recall)):
    print(f"    Class {j}: {gb_avg_recall[j]:.4f}")
print()
```

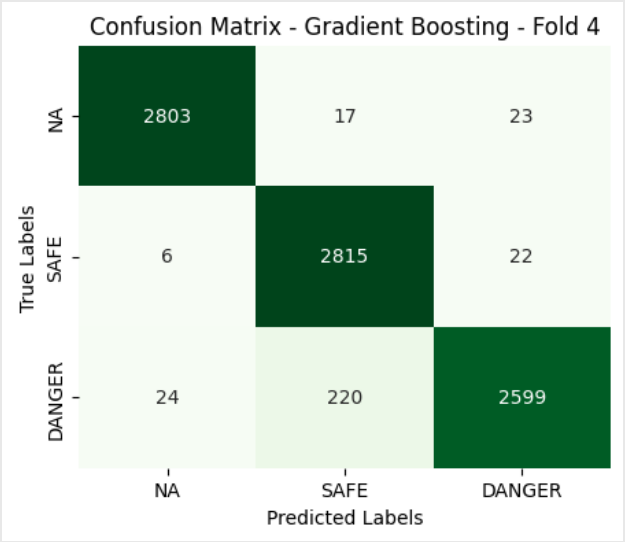
Printing Average of Metrics across folds

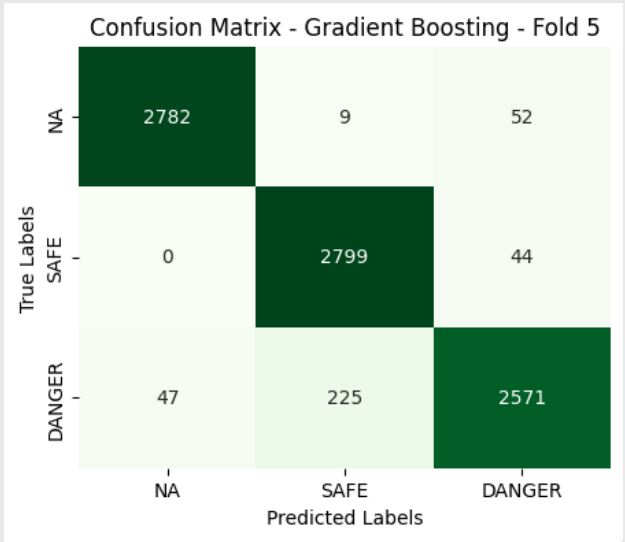
Application / 적용 – Gradient Boosting












```
Gradient Boosting:
  Average F1-score: 0.9522
  Average Accuracy: 0.9522
  Average Precision:
    Class 0: 0.9627
    Class 1: 0.9258
    Class 2: 0.9740
  Average Recall:
    Class 0: 0.9851
    Class 1: 0.9825
    Class 2: 0.8891
```

Application / 적용 –XGBoosting

```
k_fold = StratifiedKFold(n_splits=5) # k = 5

xgb_f1_scores = []
xgb_accuracies = []
xgb_precisions = []
xgb_recalls = []

for fold, (train_idx, test_idx) in enumerate(k_fold.split(X_train_over, y_train_over), 1):
    print(f'Fold {fold}:')

    x_train, y_train = X_train_over[train_idx], y_train_over[train_idx]
    x_test, y_test = X_train_over[test_idx], y_train_over[test_idx]

    scaler = StandardScaler()
    x_train = scaler.fit_transform(x_train)
    x_test = scaler.transform(x_test)

    # XGBoost Classifier
    xgb = XGBClassifier()
    xgb.fit(x_train, y_train)
    y_pred_xgb = xgb.predict(x_test)
```

Stratified k-fold

Modeling

```
# Confusion Matrix 시각화
plt.figure(figsize=(5, 4))
sns.heatmap(confusion_matrix(y_test, y_pred_xgb), annot=True, cmap='Reds', fmt='d', cbar=False,
            xticklabels=['NA', 'SAFE', 'DANGER'], yticklabels=['NA', 'SAFE', 'DANGER'])
plt.title(f"Confusion Matrix - XGBoost - Fold {fold}")
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

Confusion Matrix

Application / 적용 –XGBoosting

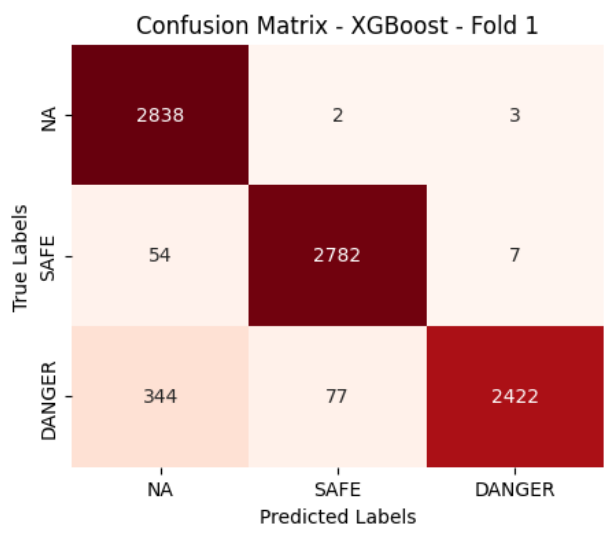
```
    # 각 fold에서 f1-score를 출력
    print(f"Fold {fold}:")
    print(f"  F1-score: {xgb_f1:.4f}")
    print(f"  Accuracy: {xgb_accuracy:.4f}")
    print(f"  Precision:")
    for j in range(len(xgb_precision)):
        print(f"    Class {j}: {xgb_precision[j]:.4f}")
    print(f"  Recall:")
    for j in range(len(xgb_recall)):
        print(f"    Class {j}: {xgb_recall[j]:.4f}")
    print()
```

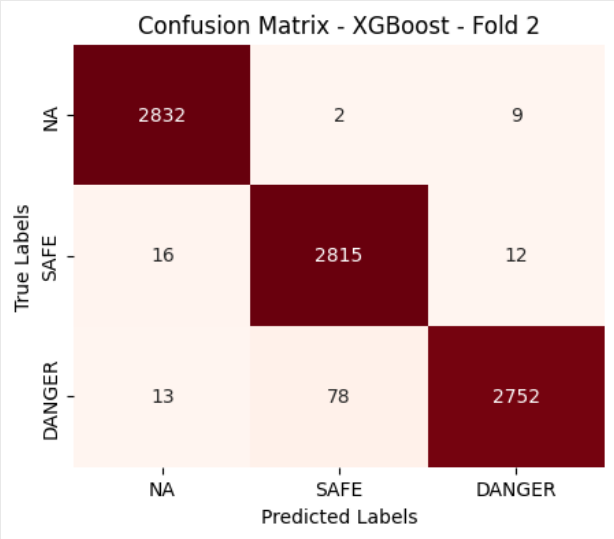
Printing Metrics for each fold

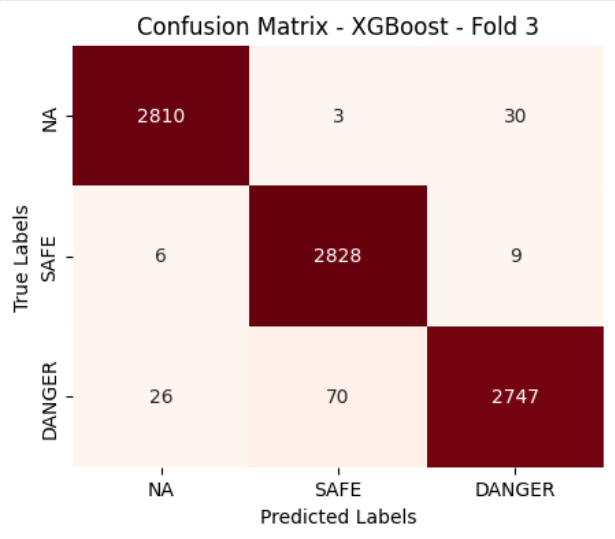
```
# 평균 F1-score, Accuracy, Precision, Recall 계산 및 출력
xgb_avg_f1 = np.mean(xgb_f1_scores)
xgb_avg_accuracy = np.mean(xgb_accuracies)
xgb_avg_precision = np.mean(xgb_precisions, axis=0)
xgb_avg_recall = np.mean(xgb_recalls, axis=0)

# 결과 출력
print("XGBoost:")
print(f"  Average F1-score: {xgb_avg_f1:.4f}")
print(f"  Average Accuracy: {xgb_avg_accuracy:.4f}")
print("  Average Precision:")
for j in range(len(xgb_avg_precision)):
    print(f"    Class {j}: {xgb_avg_precision[j]:.4f}")
print("  Average Recall:")
for j in range(len(xgb_avg_recall)):
    print(f"    Class {j}: {xgb_avg_recall[j]:.4f}")
print()
```

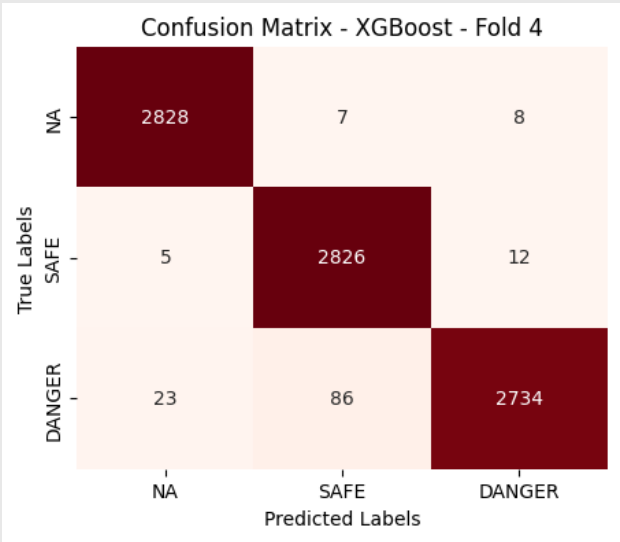
Printing Average of Metrics across folds

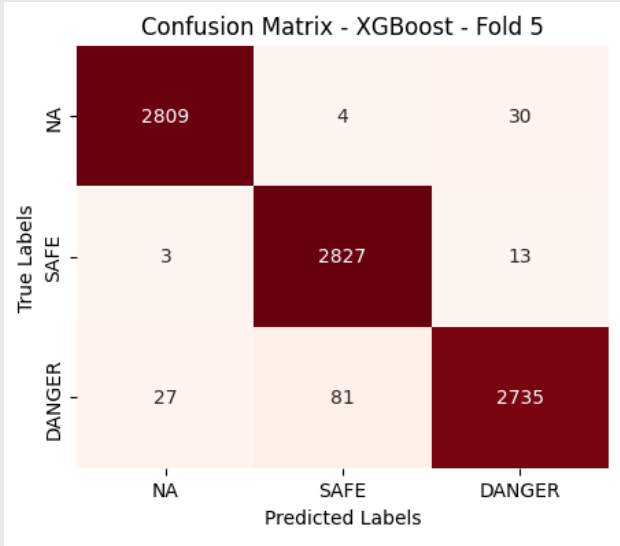
Application / 적용 –XGBoosting












```
XGBoost:
  Average F1-score: 0.9751
  Average Accuracy: 0.9751
  Average Precision:
    Class 0: 0.9670
    Class 1: 0.9717
    Class 2: 0.9903
  Average Recall:
    Class 0: 0.9931
    Class 1: 0.9904
    Class 2: 0.9420
```

Conclusion / 결론

1. Model Performance

Single Decision Tree << Ensemble Models

Comparing F1-score

Decision Tree	Random Forest	Gradient Boosting	XGBoosting
0.8704	0.9679	0.9522	0.9751

Gradient Boosting, XGBoosting took long time calculating

Conclusion / 결론

2. Further Idea Proposal

Our Goal :

- **Society More aware of the danger of Myocardial Infarction**
- **Manage Disease & Live Healthier**

How it works ? :

- **Users take blood and our system analyze it**
- **If the danger rate is high, it will be notified to the user**

Developments / 발전가능성

1. Using Various Hyperparameter :
   - To prevent overfitting
   - Advancing model usage

2. Evaluation Metrics were very high.
   - Need to check for overfitting

3. Hard to view danger rate in models
   - Considering Interpretability of ensemble tree-based models
   - Don’t know if the danger rate is calculated properly

References / 참고문헌

[Medical References]

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- 국민건강영양조사 제 8기 Raw Data, 이용지침서 (https://knhanes.kdca.go.kr/knhanes/main.do)
- Child's Heart Disease (https://m.post.naver.com/viewer/postView.nhn?volumeNo=15348174&memberNo=38360564)
- 서울아산병원; 혈색소 (https://www.amc.seoul.kr/asan/mobile/healthinfo/management/managementDetail.do?managementId=119)

References / 참고문헌

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[Model References – Decision Tree]

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