classsifier_parameter

September 1, 2025

1 Analysis and Evaluation of Classification Models

This notebook aims to explore and compare the performance of different machine learning models for a classification problem. The main objectives are:

1. **Evaluate baseline models:** Analyze the performance of classifiers such as **Logistic Regression**, **Random Forest**, and **XGBoost** using the entire feature set.
2. **Perform feature selection:** Identify and use the 10 most relevant features to retrain the models, with the goal of improving efficiency and performance.
3. **Optimize parameters:** Find the best hyperparameters for each model using optimization techniques.
4. **Build and evaluate an ensemble:** Combine the optimized models into a **VotingClassifier** to leverage the collective strength of different algorithms and achieve more robust results.

Each section of the notebook is dedicated to a specific model, with charts and reports that document the different evaluation phases.

1.1 1) Setup and initialization

[1]:
```
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
%load_ext autoreload
%autoreload 2

from embeddings import EmbeddingBuilder
import os
import ipynbname
from scipy.stats import randint

from retrieval import ImageRetrieval
from sklearn.ensemble import VotingClassifier
from classifier import Classifier
import file_manager
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier
from scipy.stats import uniform
```

```
project_dir = f"{os.getcwd().
 ↪split('SIDS_revelation_project')[0]}SIDS_revelation_project/"
image_dataset_path = f"{project_dir}datasets/onback_onstomach_v3"
model_path = f"{project_dir}/models/4.weights/best.pt"
```

[3]:
```
emb_builder = EmbeddingBuilder(model_path, image_dataset_path, "load")
embeddings = emb_builder.embedding_all_features_norm()
```

```
Extracting dataset info from .coco.json
file:--------------------------------------------
Dataset contains 4158 valid samples, and labels are {'baby_on_back': 1,
'baby_on_stomach': 2}
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Loading features from
.csv------------------------------------------------------------
Features loaded succesfully, in particular there are 4158 files in the dataset
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Embedding builder initialized
successfully----------------------------------------------------
Face detection model: 4 (YOLOv8)
Dataset: /Users/lorenzodimaio/Download/SIDS_revelation_project/datasets/onback_o
nstomach_v3
Dataset dimension: 4158
Dataset labels: {'baby_safe': 0, 'baby_unsafe': 1}
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Creation of all features
embedding----------------------------------------------------
Features: ['flag_eye1', 'flag_eye2', 'flag_nose', 'flag_mouth', 'x_eye1',
'y_eye1', 'x_eye2', 'y_eye2', 'x_nose', 'y_nose', 'x_mouth', 'y_mouth',
'x_eye1_norm', 'y_eye1_norm', 'x_eye2_norm', 'y_eye2_norm', 'x_nose_norm',
'y_nose_norm', 'x_mouth_norm', 'y_mouth_norm', 'eye_distance',
'eye_distance_norm', 'face_vertical_length', 'face_vertical_length_norm',
'face_angle_vertical', 'face_angle_horizontal', 'symmetry_diff', 'head_ration']
FINISHED: 4158 embedding created
```

[4]:
```
clf = Classifier(embeddings, emb_builder.y, emb_builder.classes_bs)
```

2 2) Logistic Regression

[5]:
```python
lr_1, results_lr_1 = clf.logistic_regression(verbose=True)
```

```
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--------------------------------------FIRST
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/opt/anaconda3/envs/yolov8_env/lib/python3.10/multiprocessing/queues.py:122:
UserWarning: pkg_resources is deprecated as an API. See
https://setuptools.pypa.io/en/latest/pkg_resources.html. The pkg_resources
package is slated for removal as early as 2025-11-30. Refrain from using this
package or pin to Setuptools<81.
  return _ForkingPickler.loads(res)
/opt/anaconda3/envs/yolov8_env/lib/python3.10/multiprocessing/queues.py:122:
UserWarning: pkg_resources is deprecated as an API. See
https://setuptools.pypa.io/en/latest/pkg_resources.html. The pkg_resources
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UserWarning: pkg_resources is deprecated as an API. See
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package is slated for removal as early as 2025-11-30. Refrain from using this
package or pin to Setuptools<81.
  return _ForkingPickler.loads(res)
/opt/anaconda3/envs/yolov8_env/lib/python3.10/multiprocessing/queues.py:122:
```

```
UserWarning: pkg_resources is deprecated as an API. See
https://setuptools.pypa.io/en/latest/pkg_resources.html. The pkg_resources
package is slated for removal as early as 2025-11-30. Refrain from using this
package or pin to Setuptools<81.
  return _ForkingPickler.loads(res)
/opt/anaconda3/envs/yolov8_env/lib/python3.10/multiprocessing/queues.py:122:
UserWarning: pkg_resources is deprecated as an API. See
https://setuptools.pypa.io/en/latest/pkg_resources.html. The pkg_resources
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/opt/anaconda3/envs/yolov8_env/lib/python3.10/multiprocessing/queues.py:122:
UserWarning: pkg_resources is deprecated as an API. See
https://setuptools.pypa.io/en/latest/pkg_resources.html. The pkg_resources
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/opt/anaconda3/envs/yolov8_env/lib/python3.10/multiprocessing/queues.py:122:
UserWarning: pkg_resources is deprecated as an API. See
https://setuptools.pypa.io/en/latest/pkg_resources.html. The pkg_resources
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/opt/anaconda3/envs/yolov8_env/lib/python3.10/multiprocessing/queues.py:122:
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https://setuptools.pypa.io/en/latest/pkg_resources.html. The pkg_resources
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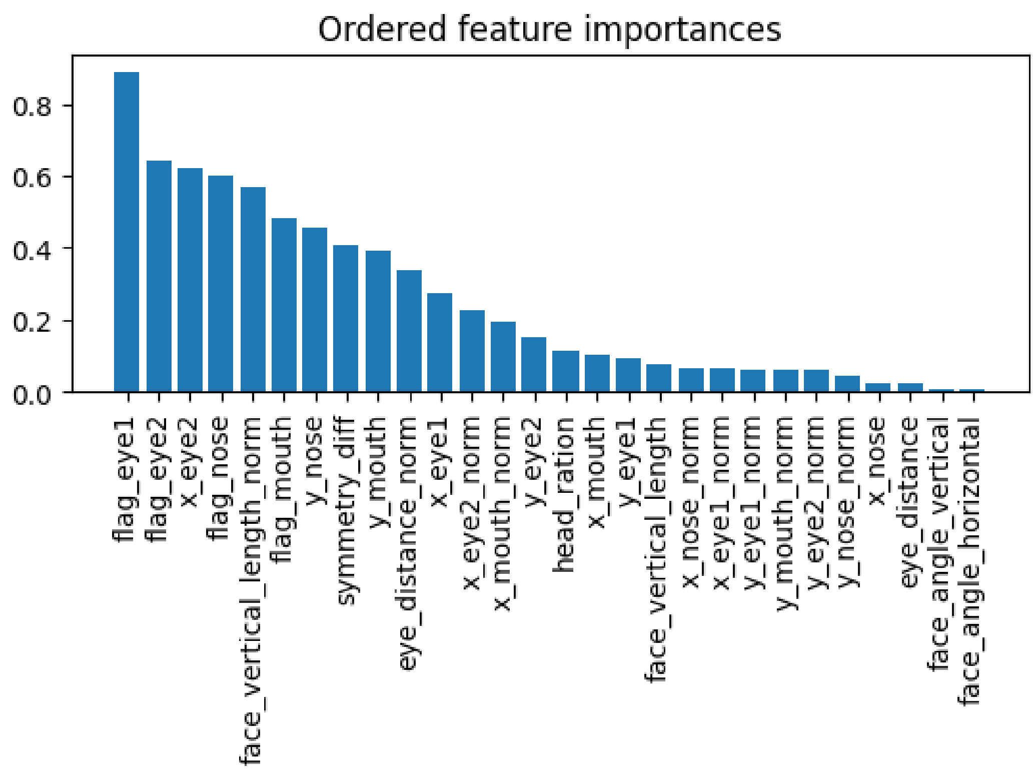
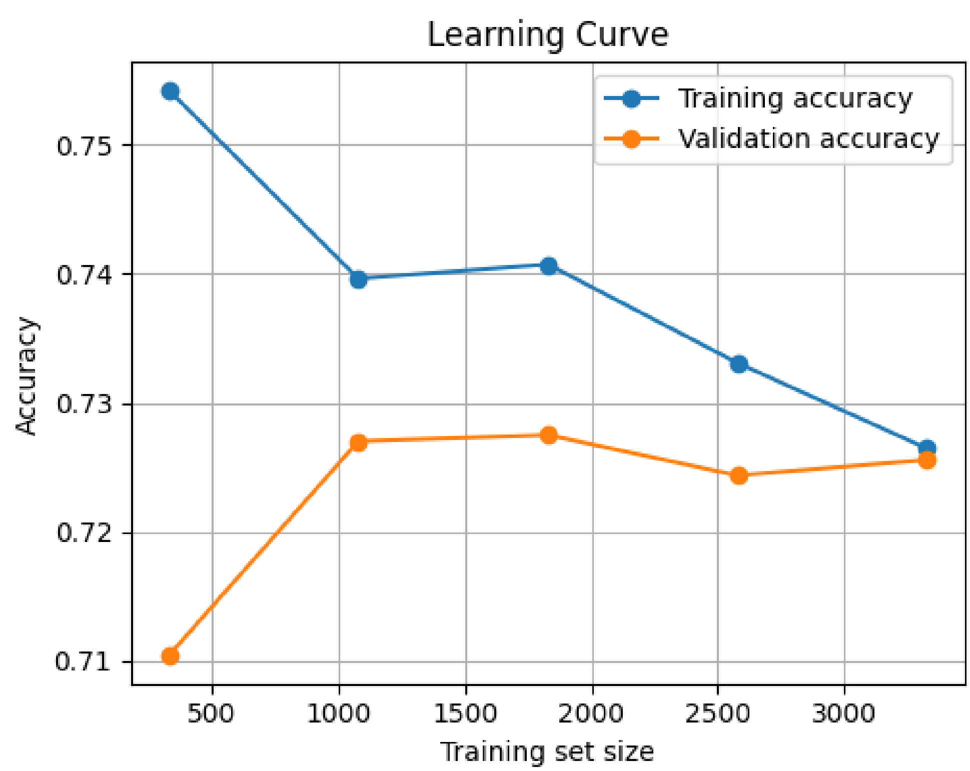
/opt/anaconda3/envs/yolov8_env/lib/python3.10/multiprocessing/queues.py:122:
UserWarning: pkg_resources is deprecated as an API. See
https://setuptools.pypa.io/en/latest/pkg_resources.html. The pkg_resources
package is slated for removal as early as 2025-11-30. Refrain from using this
package or pin to Setuptools<81.
  return _ForkingPickler.loads(res)
```


Ordered feature importances
0.0
0.2
0.4
0.6
0.8
flag_eye1
flag_eye2
x_eye2
flag_nose
face_vertical_length_norm
flag_mouth
y_nose
symmetry_diff
y_mouth
eye_distance_norm
x_eye1
x_eye2_norm
x_mouth_norm
y_eye2
head_ration
x_mouth
y_eye1
face_vertical_length
x_nose_norm
x_eye1_norm
y_eye1_norm
y_mouth_norm
y_eye2_norm
y_nose_norm
x_nose
eye_distance
face_angle_vertical
face_angle_horizontal


Learning Curve
Training accuracy
Validation accuracy
Accuracy
0.71
0.72
0.73
0.74
0.75
500
1000
1500
2000
2500
3000
Training set size

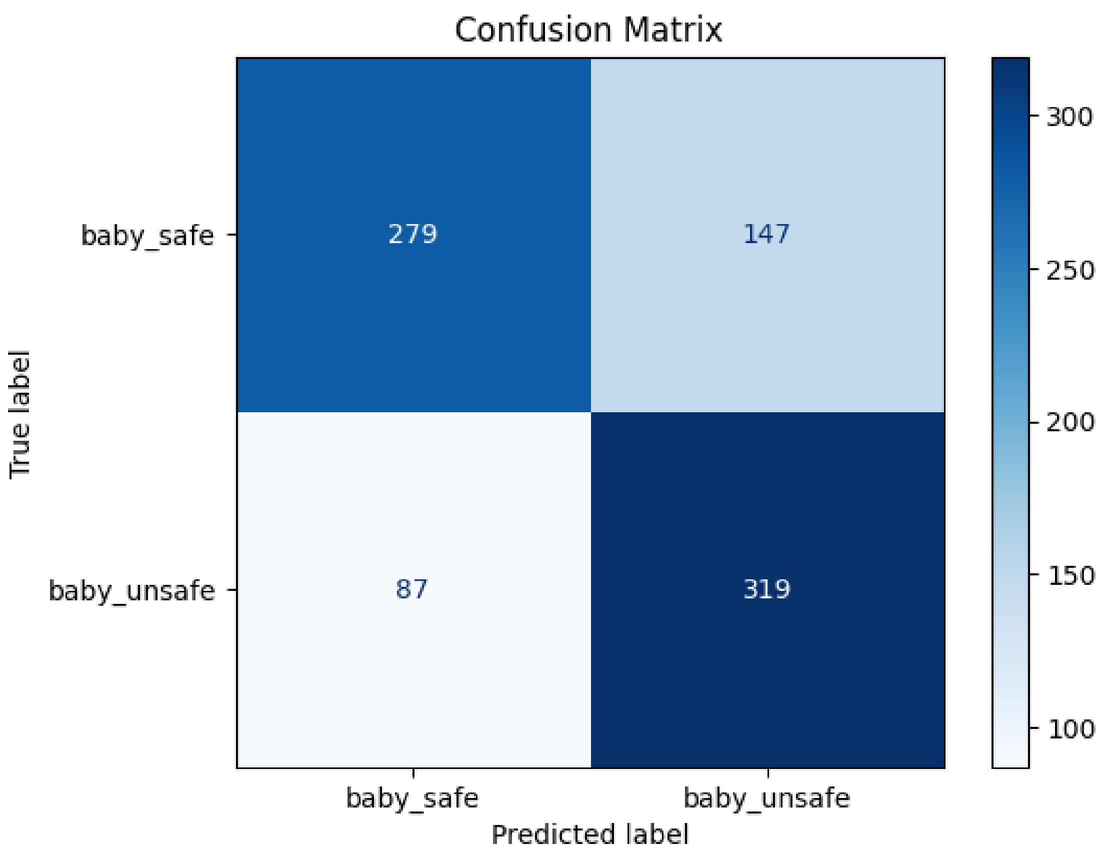
```
Dataset labels:----------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report-------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.76      0.65      0.70       426
 baby_unsafe       0.68      0.79      0.73       406

    accuracy                           0.72       832
   macro avg       0.72      0.72      0.72       832
weighted avg       0.72      0.72      0.72       832

Confusion matrix---------------------------------------
```

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```

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---------------------------------TOP 10 FEATURES
ANALYSIS---------------------------------
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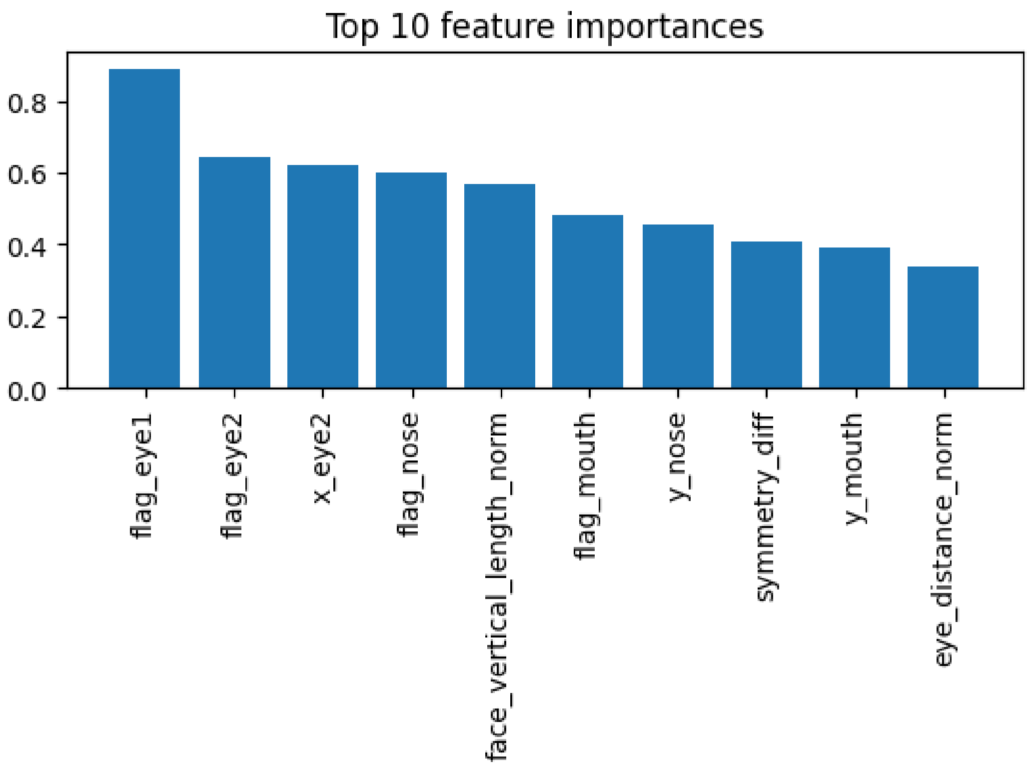
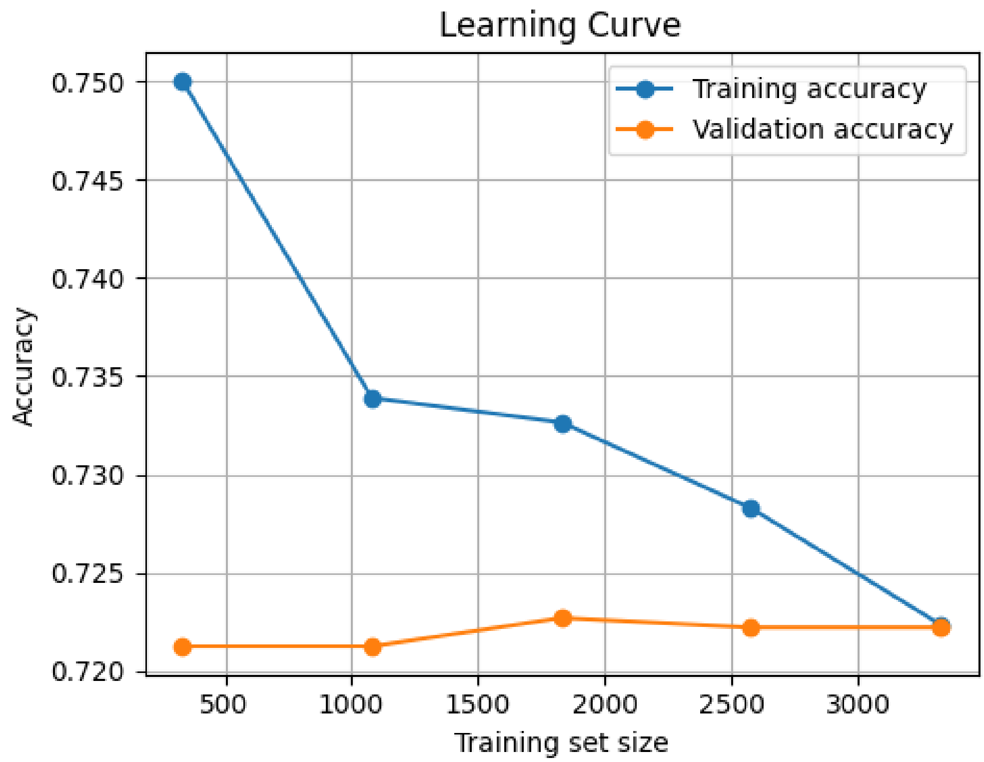
```





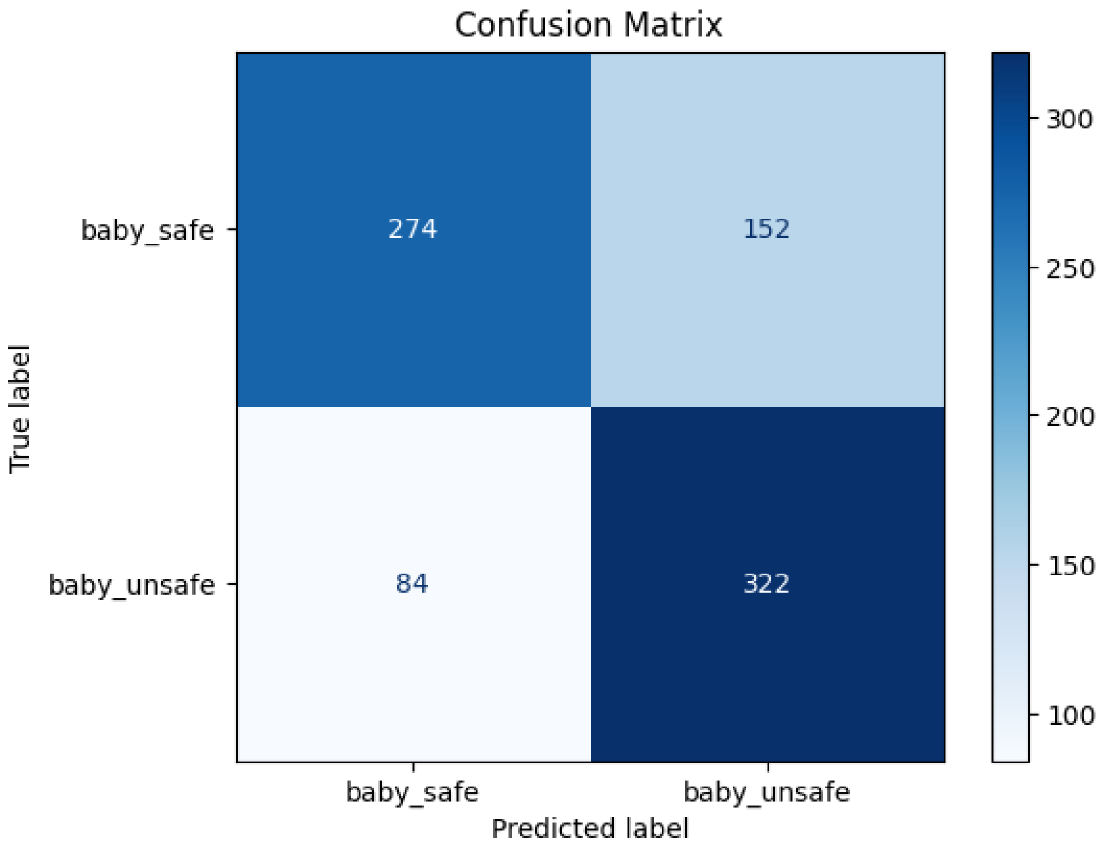

```
Dataset labels:---------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.77      0.64      0.70       426
 baby_unsafe       0.68      0.79      0.73       406

    accuracy                           0.72       832
   macro avg       0.72      0.72      0.72       832
weighted avg       0.72      0.72      0.72       832

Confusion matrix--------------------------------------
```



[6]:
```
from scipy.stats import loguniform
from sklearn.linear_model import LogisticRegression

param_grid = {
    'C': loguniform(0.001, 1000),
    'penalty': ['l1', 'l2', 'elasticnet'],
    'solver': ['liblinear', 'saga'],
    'l1_ratio': [0.1, 0.5, 0.9] # Usato solo con penalty='elasticnet'
}

best_params = clf.optimize_model(lr_1, param_grid,verbose=False)
lr_2 = LogisticRegression(**best_params)
results_lr_2 = clf.evaluation_pipeline(lr_2,verbose=True)
```

```
Start random search…

Random Search Results:
Best parameters found:  {'C': np.float64(530.0369711220895), 'l1_ratio': 0.1,
'penalty': 'l2', 'solver': 'liblinear'}
```

```
Best mean cross-validation accuracy:  0.7495472916525548
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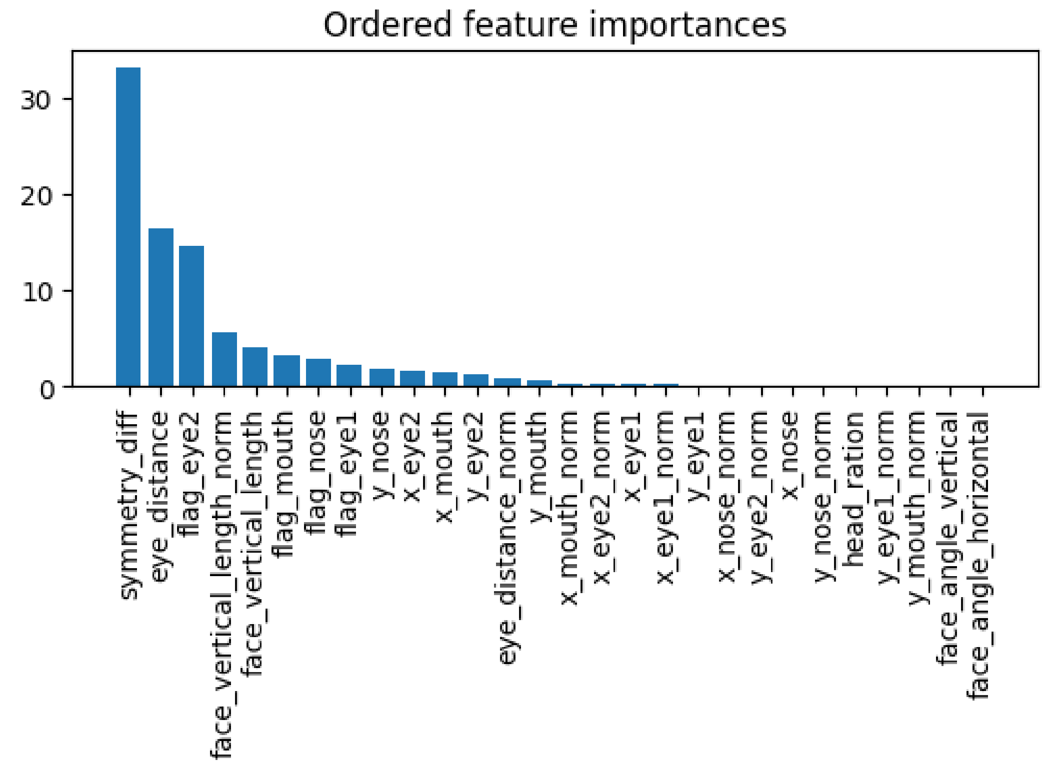
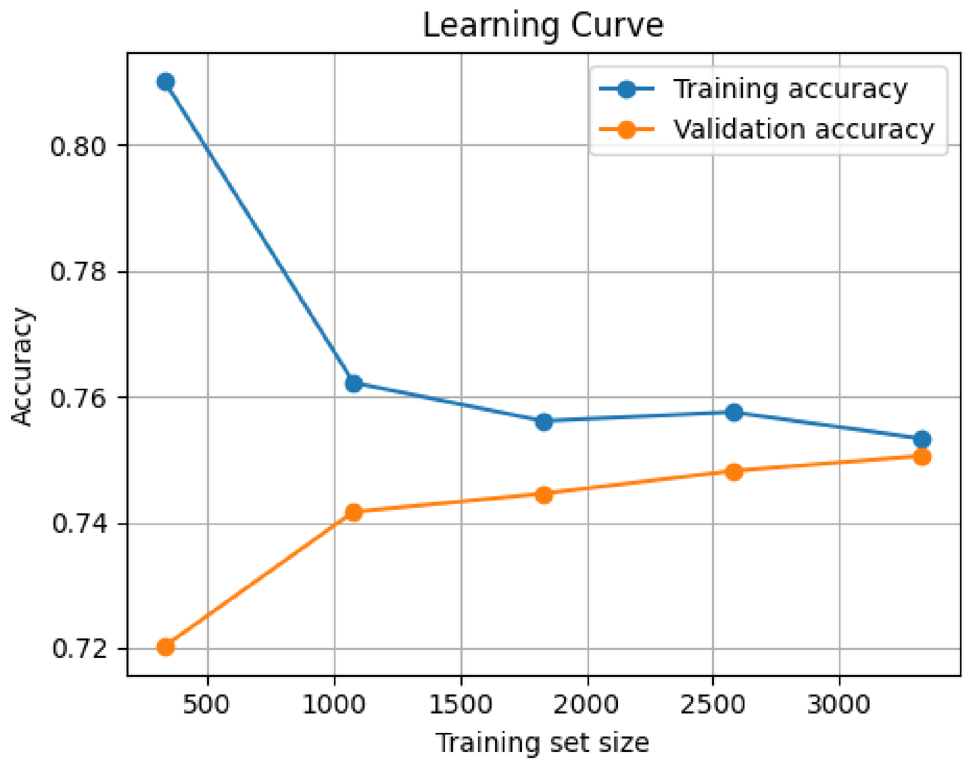
```





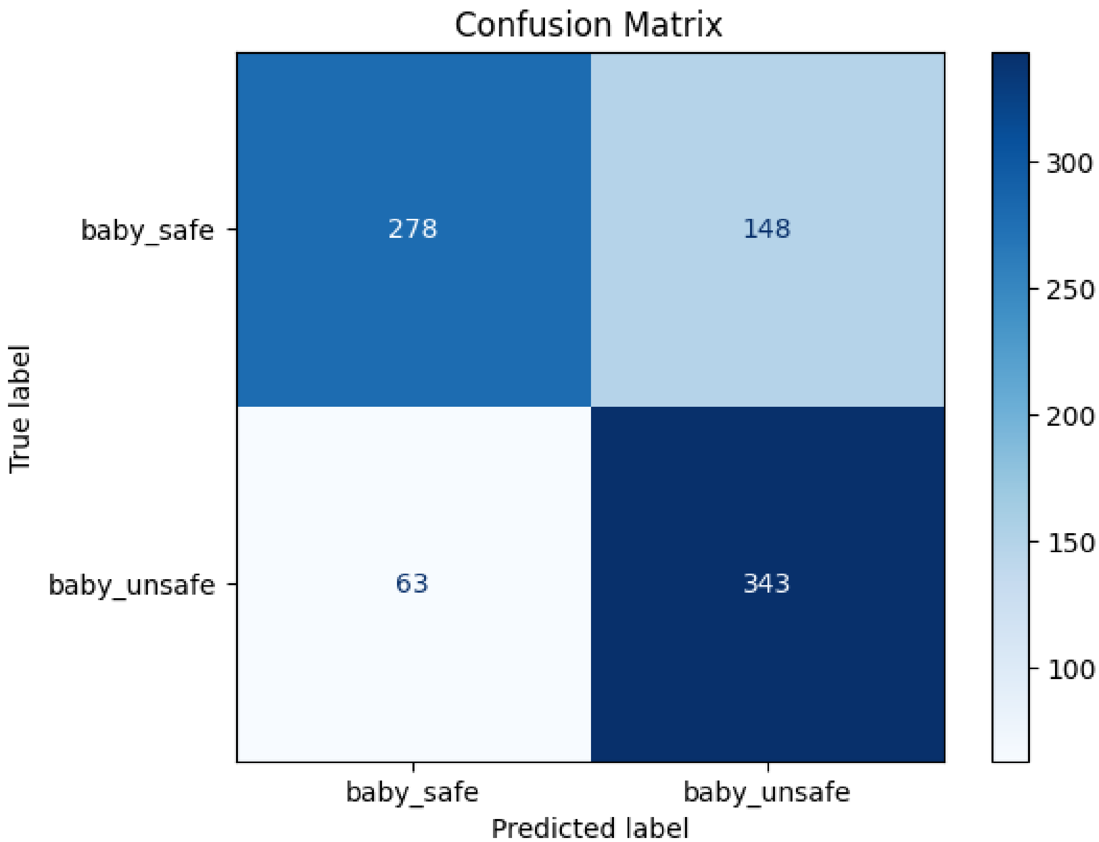

```
Dataset labels:---------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report-------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.82      0.65      0.72       426
 baby_unsafe       0.70      0.84      0.76       406

    accuracy                           0.75       832
   macro avg       0.76      0.75      0.74       832
weighted avg       0.76      0.75      0.74       832

Confusion matrix---------------------------------------
```

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---------------------------------TOP 10 FEATURES
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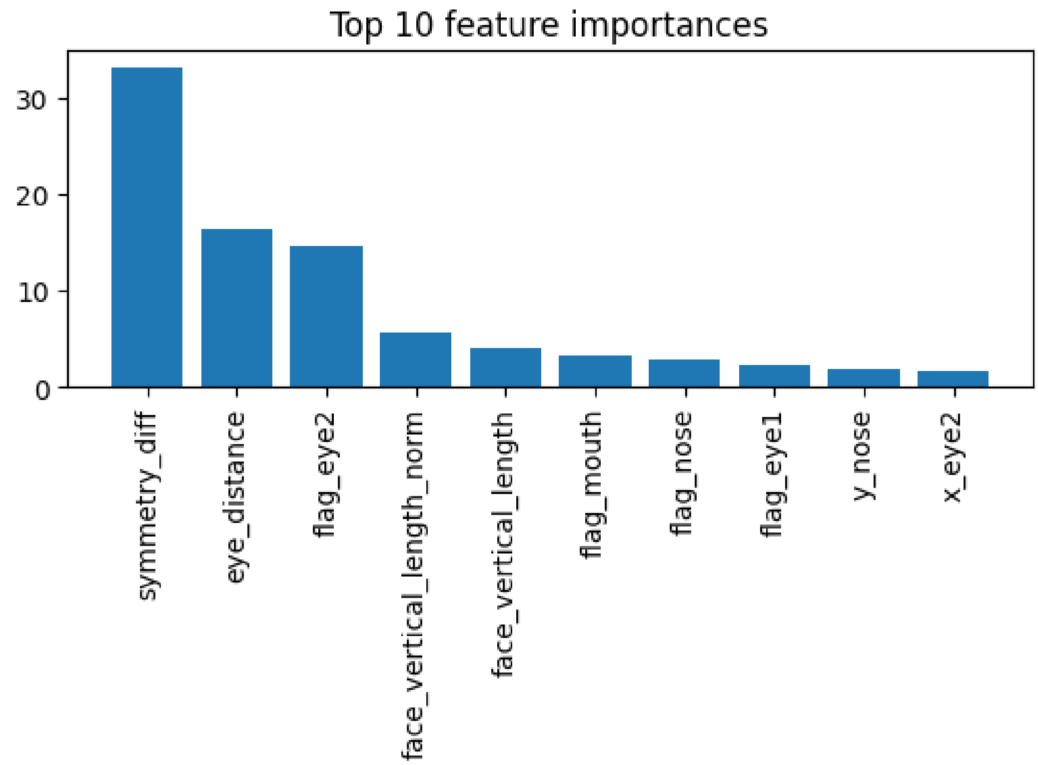
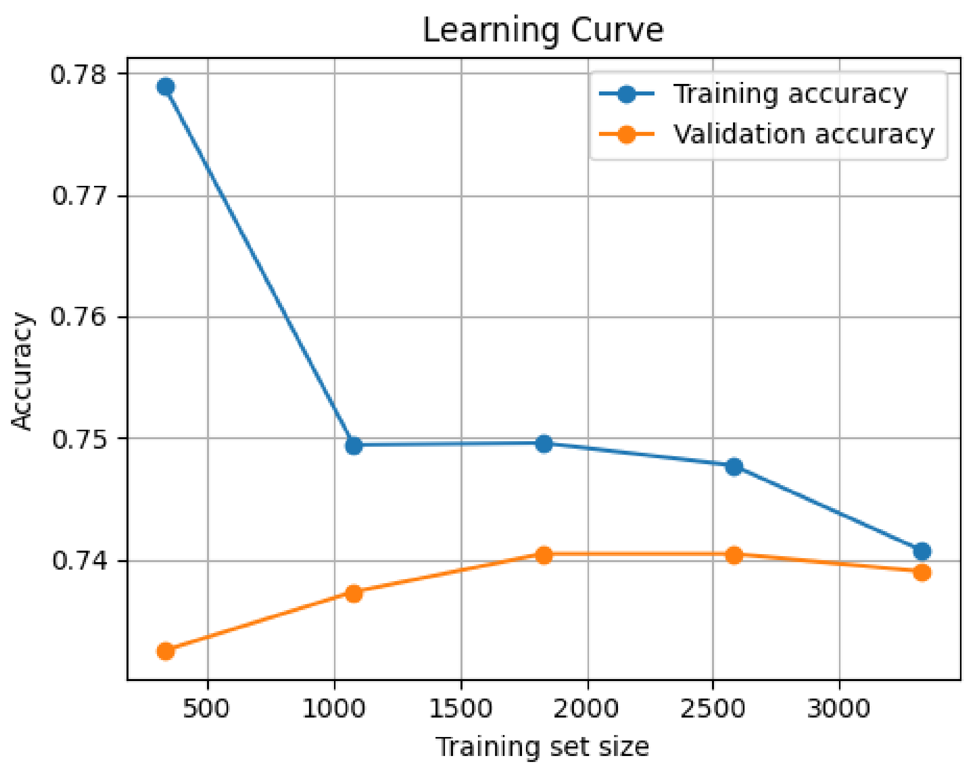
```


Top 10 feature importances
30
20
10
0
symmetry_diff
eye_distance
flag_eye2
face_vertical_length_norm
face_vertical_length
flag_mouth
flag_nose
flag_eye1
y_nose
x_eye2


Learning Curve
Training accuracy
Validation accuracy
0.78
0.77
0.76
0.75
0.74
Accuracy
500
1000
1500
2000
2500
3000
Training set size

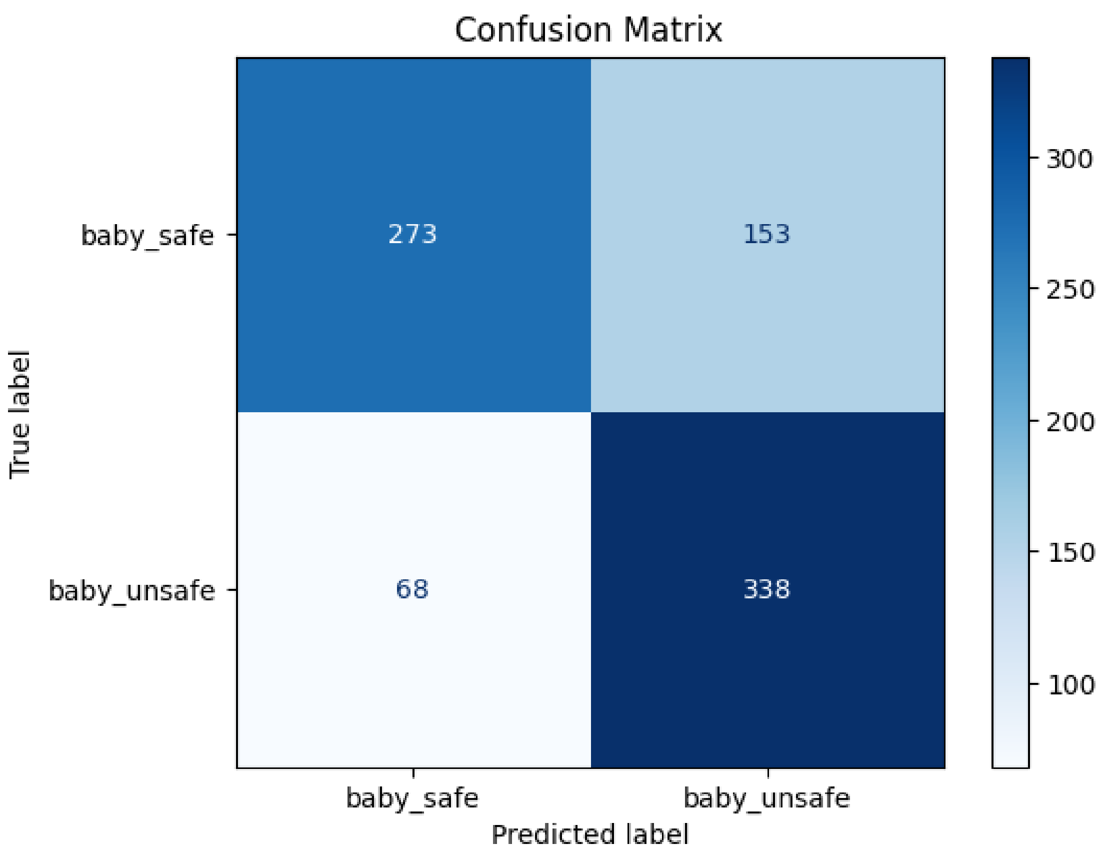
```
Dataset labels:----------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report-------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.80      0.64      0.71       426
 baby_unsafe       0.69      0.83      0.75       406

    accuracy                           0.73       832
   macro avg       0.74      0.74      0.73       832
weighted avg       0.75      0.73      0.73       832

Confusion matrix---------------------------------------
```

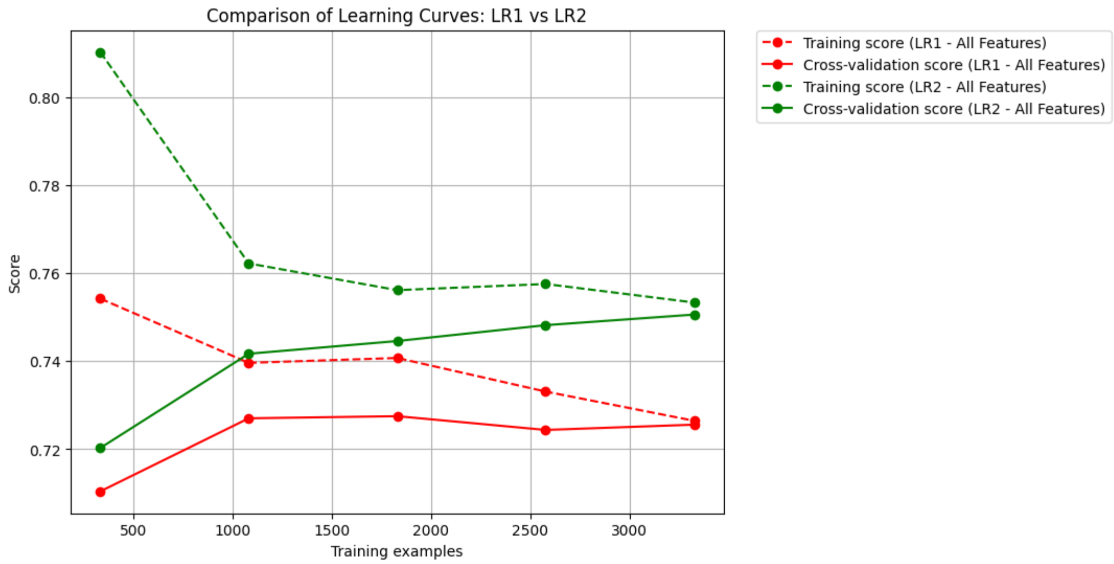


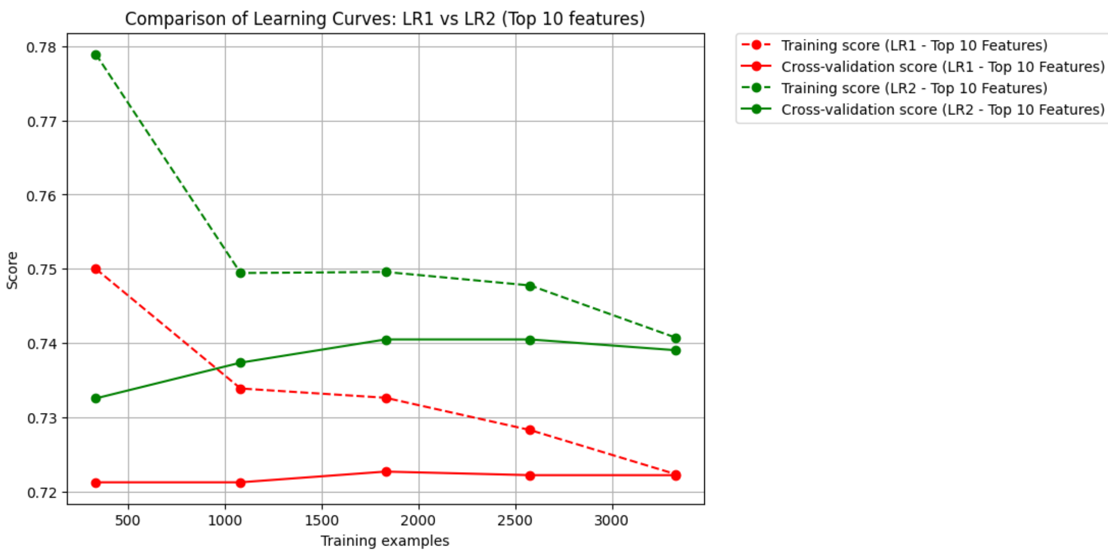
[7]:
```python
# Graph 1:
data_to_plot_1 = [
    (results_lr_1['all_features']['model'], "LR1 - All Features",␣
 ↪results_lr_1['all_features']['X'], results_lr_1['all_features']['y']),
    (results_lr_2['all_features']['model'], "LR2 - All Features",␣
 ↪results_lr_2['all_features']['X'], results_lr_2['all_features']['y'])
]

clf.plot_learning_curve_comparison(
    data_sets=data_to_plot_1,
    title="Comparison of Learning Curves: LR1 vs LR2"
)

# Graph 2:
data_to_plot_2 = [
    (results_lr_1['top_10_features']['model'], "LR1 - Top 10 Features",␣
 ↪results_lr_1['top_10_features']['X'], results_lr_1['top_10_features']['y']),
    (results_lr_2['top_10_features']['model'], "LR2 - Top 10 Features",␣
 ↪results_lr_2['top_10_features']['X'], results_lr_2['top_10_features']['y'])
]

clf.plot_learning_curve_comparison(
    data_sets=data_to_plot_2,
    title="Comparison of Learning Curves: LR1 vs LR2 (Top 10 features)"
)
```





3 3) Random Forest

[8]:
```
random_forest_1, results_rf1 = clf.random_forest(verbose=True)
```

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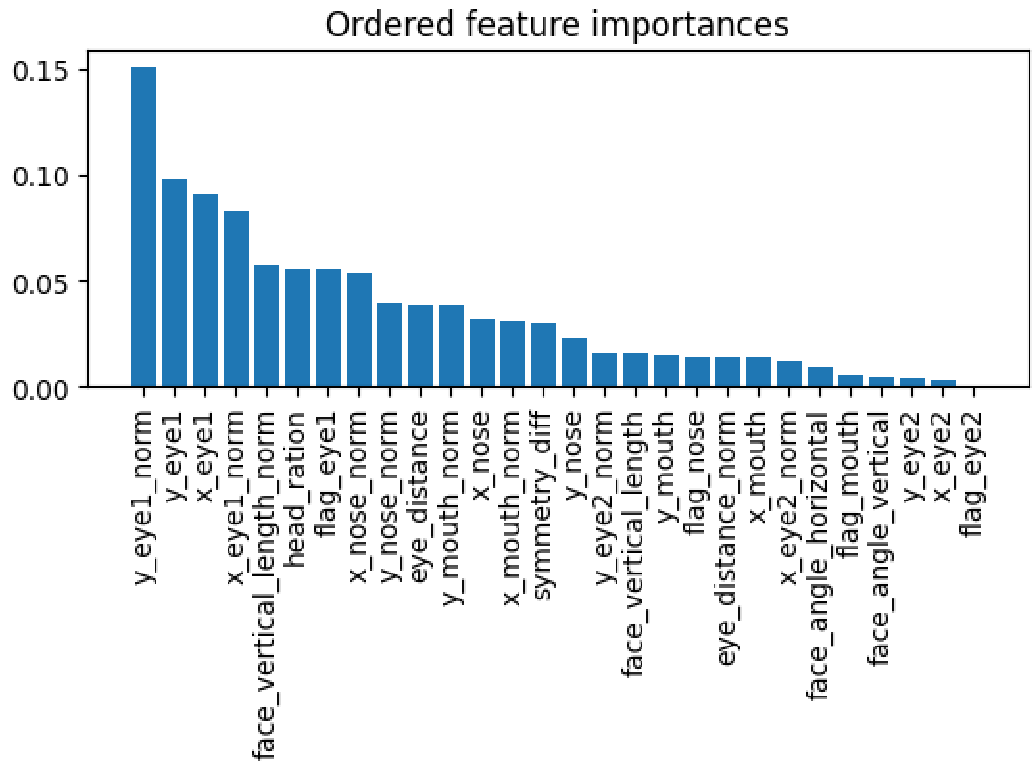
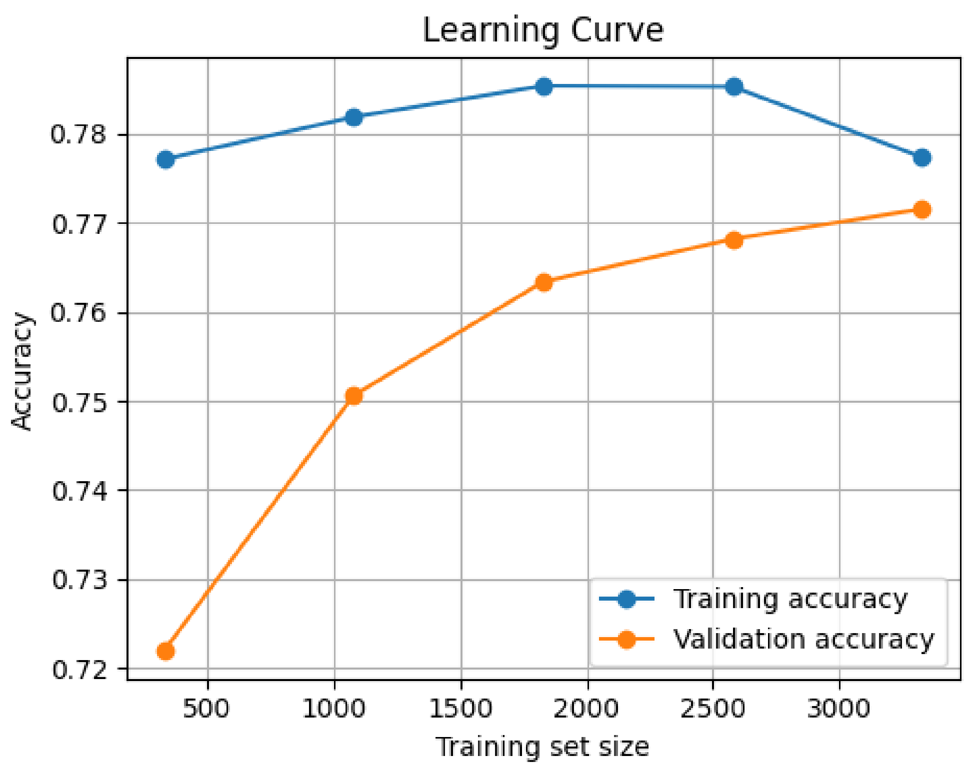
```


Ordered feature importances
0.15
0.10
0.05
0.00
y_eye1_norm
y_eye1
x_eye1
x_eye1_norm
face_vertical_length_norm
head_ration
flag_eye1
x_nose_norm
y_nose_norm
eye_distance
y_mouth_norm
x_nose
x_mouth_norm
symmetry_diff
y_nose
y_eye2_norm
face_vertical_length
y_mouth
flag_nose
eye_distance_norm
x_mouth
x_eye2_norm
face_angle_horizontal
flag_mouth
face_angle_vertical
y_eye2
x_eye2
flag_eye2


Learning Curve
Accuracy
0.78
0.77
0.76
0.75
0.74
0.73
0.72
500
1000
1500
2000
2500
3000
Training set size
Training accuracy
Validation accuracy

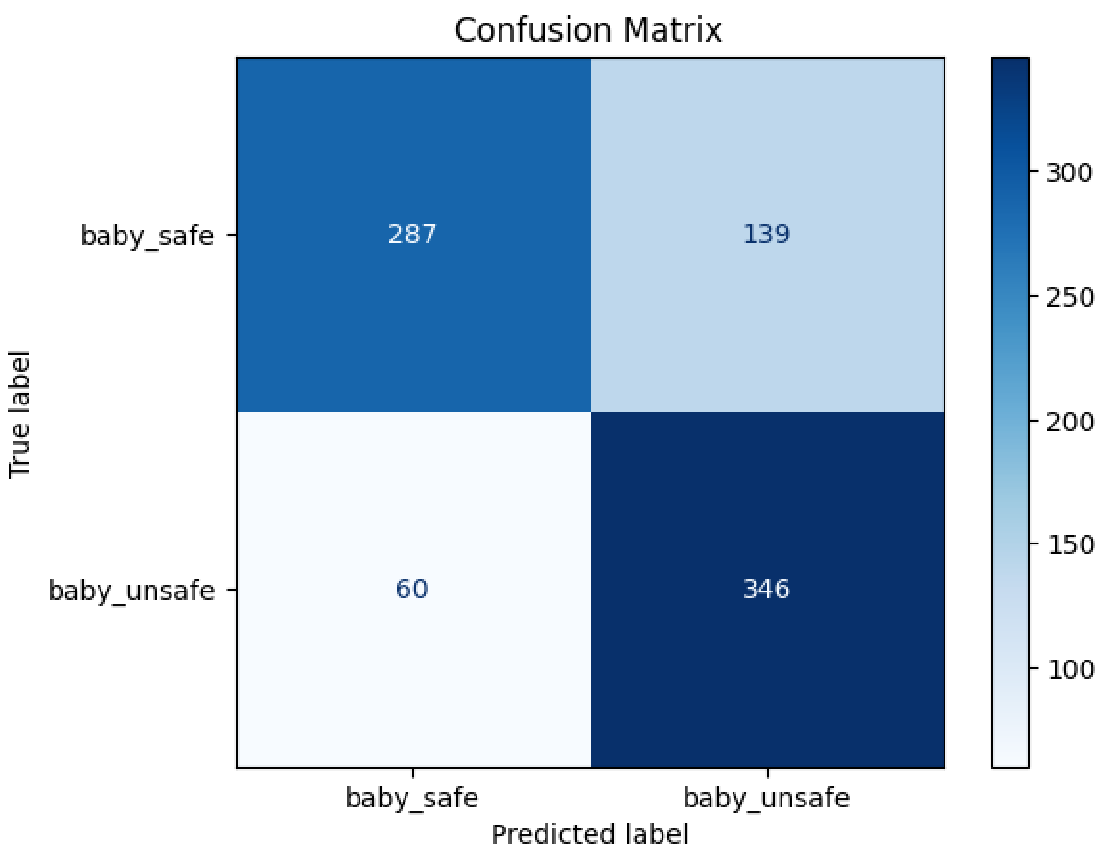
```
Dataset labels:----------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.83      0.67      0.74       426
 baby_unsafe       0.71      0.85      0.78       406

    accuracy                           0.76       832
   macro avg       0.77      0.76      0.76       832
weighted avg       0.77      0.76      0.76       832

Confusion matrix--------------------------------------
```




```
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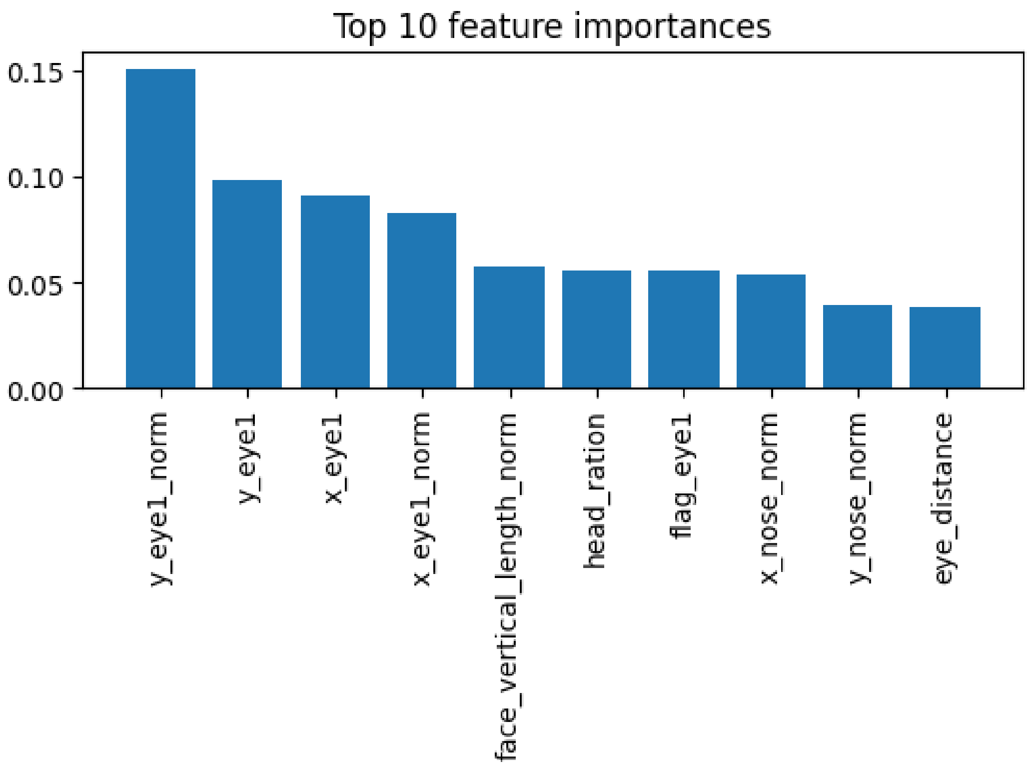
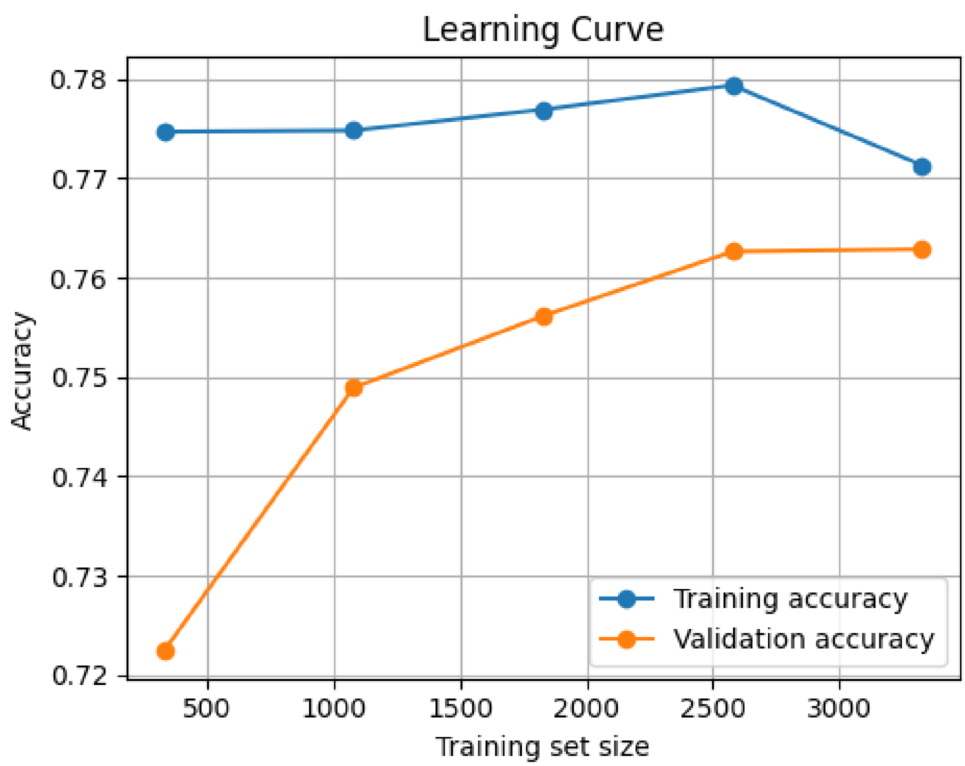
```

---------------------------------TOP 10 FEATURES
ANALYSIS---------------------------------





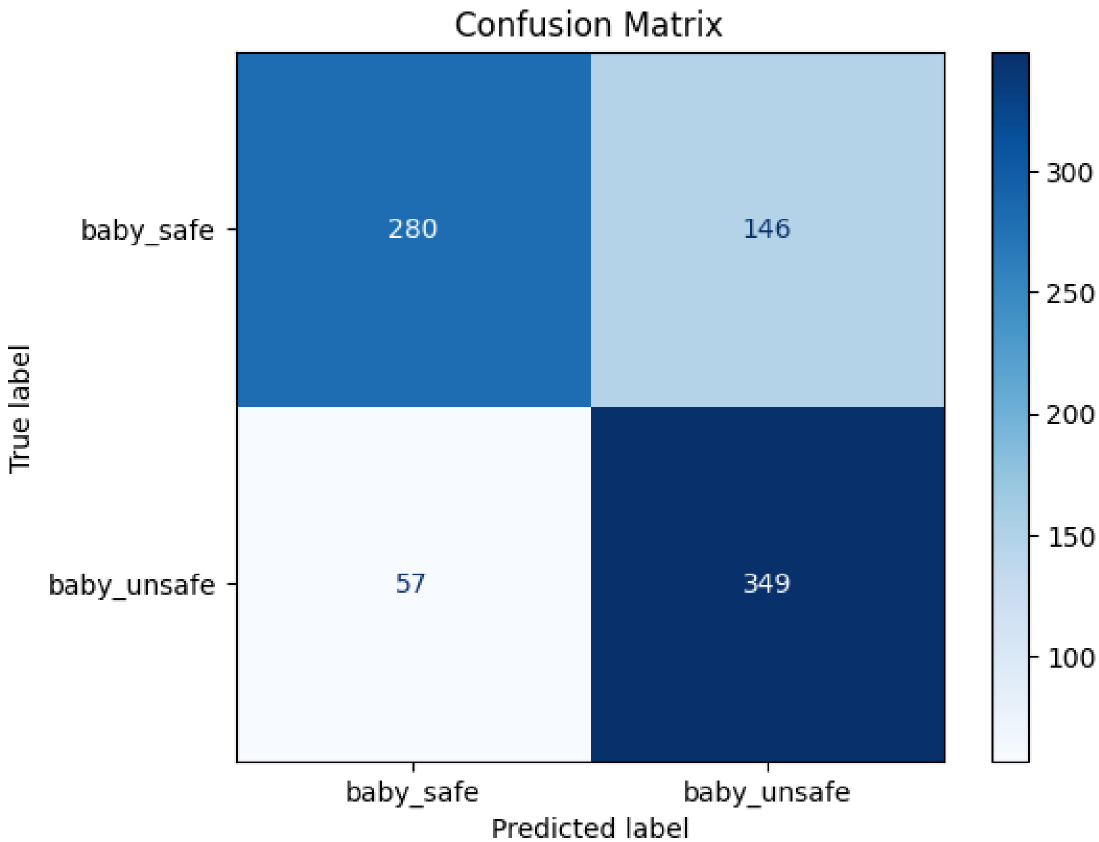

```
Dataset labels:---------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.83      0.66      0.73       426
 baby_unsafe       0.71      0.86      0.77       406

    accuracy                           0.76       832
   macro avg       0.77      0.76      0.75       832
weighted avg       0.77      0.76      0.75       832

Confusion matrix--------------------------------------
```



[9]:
```
param_dist = {
        'n_estimators': randint(200, 1000), # Random number between 100 and 500
        'max_depth': randint(5, 50),      # Random number between 5 and 20
        'min_samples_split': randint(2, 40),
        'min_samples_leaf': randint(1, 25),
        'max_features': ['sqrt', 'log2', 0.5, 0.7, 0.9, None],
        'criterion': ['gini', 'entropy'],
        'max_samples': uniform(0.5, 0.5),
        'bootstrap': [True, False]
}

best_params = clf.optimize_model(random_forest_1, param_dist,verbose=False)
random_forest_2 = RandomForestClassifier(**best_params)
results_rf2 = clf.evaluation_pipeline(random_forest_2,verbose=True)
```

```
Start random search…

Random Search Results:
Best parameters found:  {'bootstrap': True, 'criterion': 'entropy', 'max_depth':
```

```
17, 'max_features': 0.5, 'max_samples': np.float64(0.8473924665198522),
'min_samples_leaf': 2, 'min_samples_split': 7, 'n_estimators': 995}
Best mean cross-validation accuracy:  0.8496696696696697
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--------------------------------------FIRST
ANALYSIS--------------------------------------
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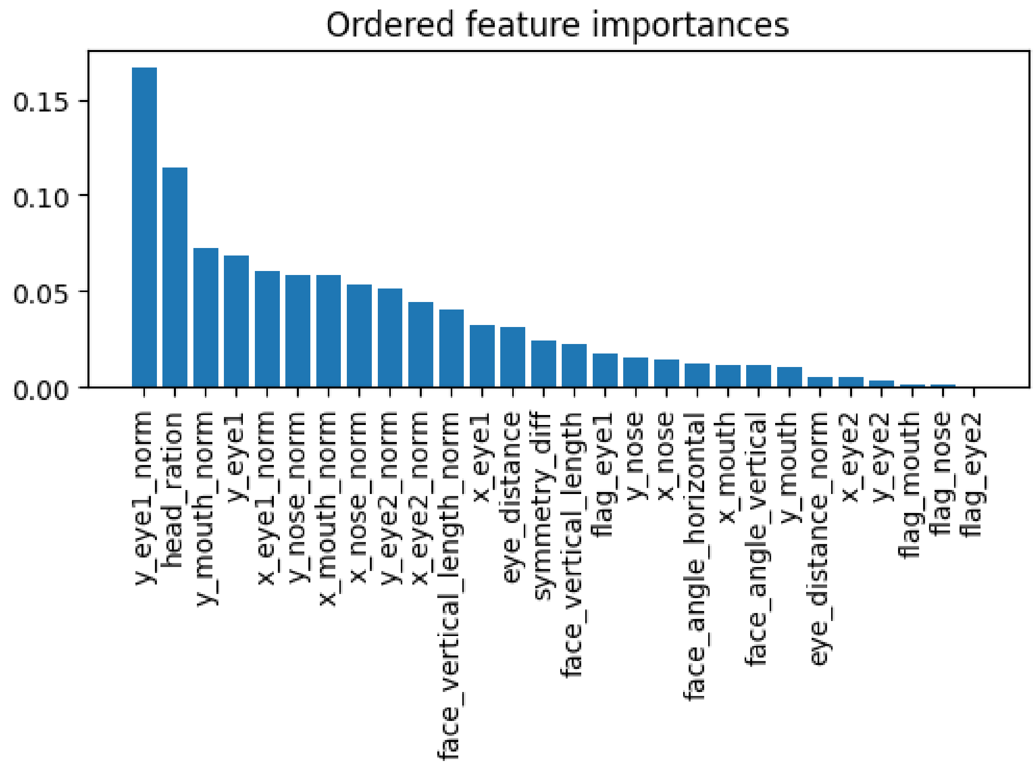
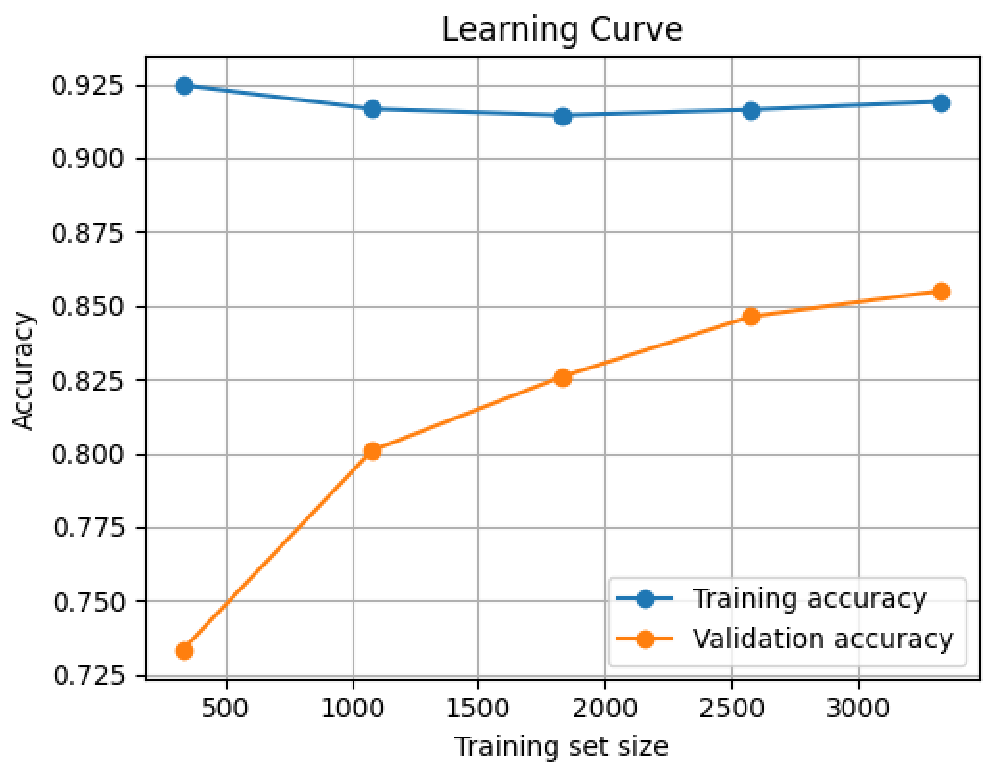




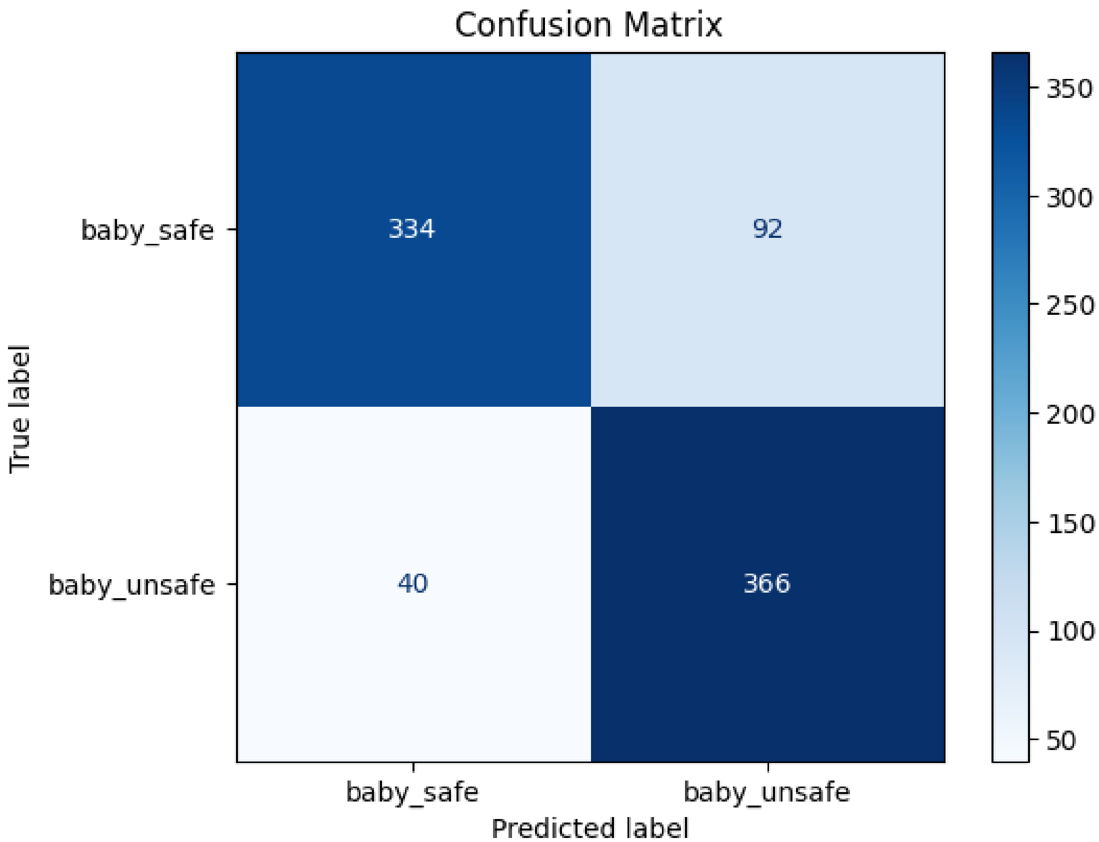

```
Dataset labels:----------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report-------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.89      0.78      0.83       426
 baby_unsafe       0.80      0.90      0.85       406

    accuracy                           0.84       832
   macro avg       0.85      0.84      0.84       832
weighted avg       0.85      0.84      0.84       832

Confusion matrix---------------------------------------
```

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---------------------------------TOP 10 FEATURES
ANALYSIS---------------------------------
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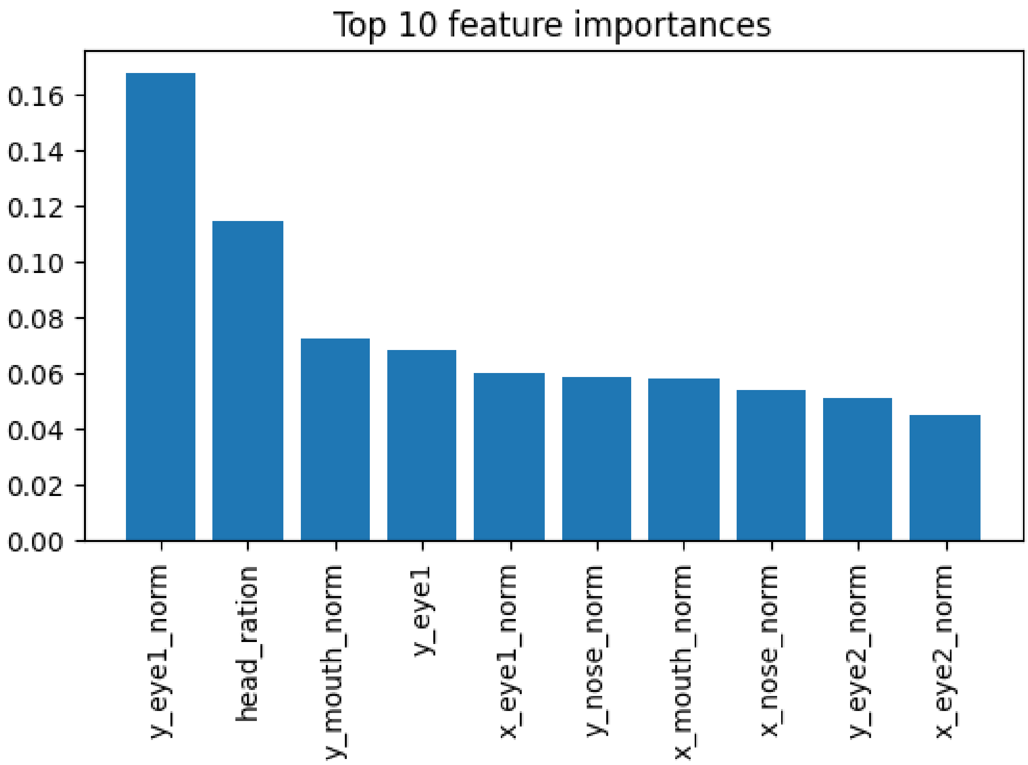
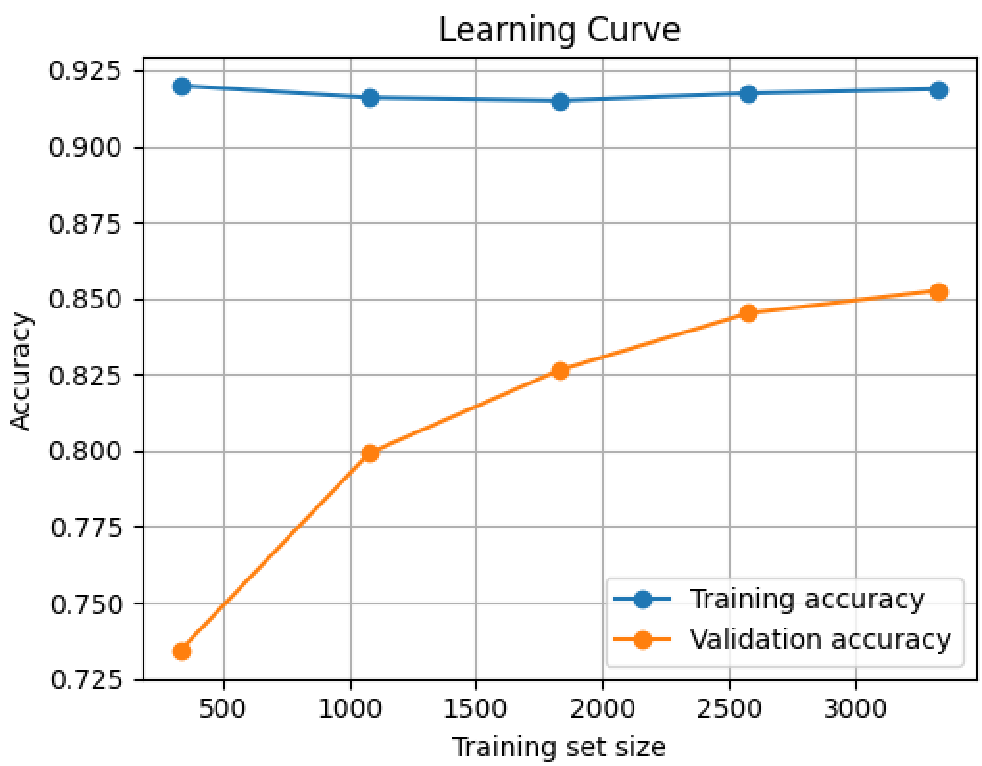
```


Top 10 feature importances
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
y_eye1_norm
head_ration
y_mouth_norm
y_eye1
x_eye1_norm
y_nose_norm
x_mouth_norm
x_nose_norm
y_eye2_norm
x_eye2_norm


Learning Curve
Accuracy
0.925
0.900
0.875
0.850
0.825
0.800
0.775
0.750
0.725
500
1000
1500
2000
2500
3000
Training set size
Training accuracy
Validation accuracy

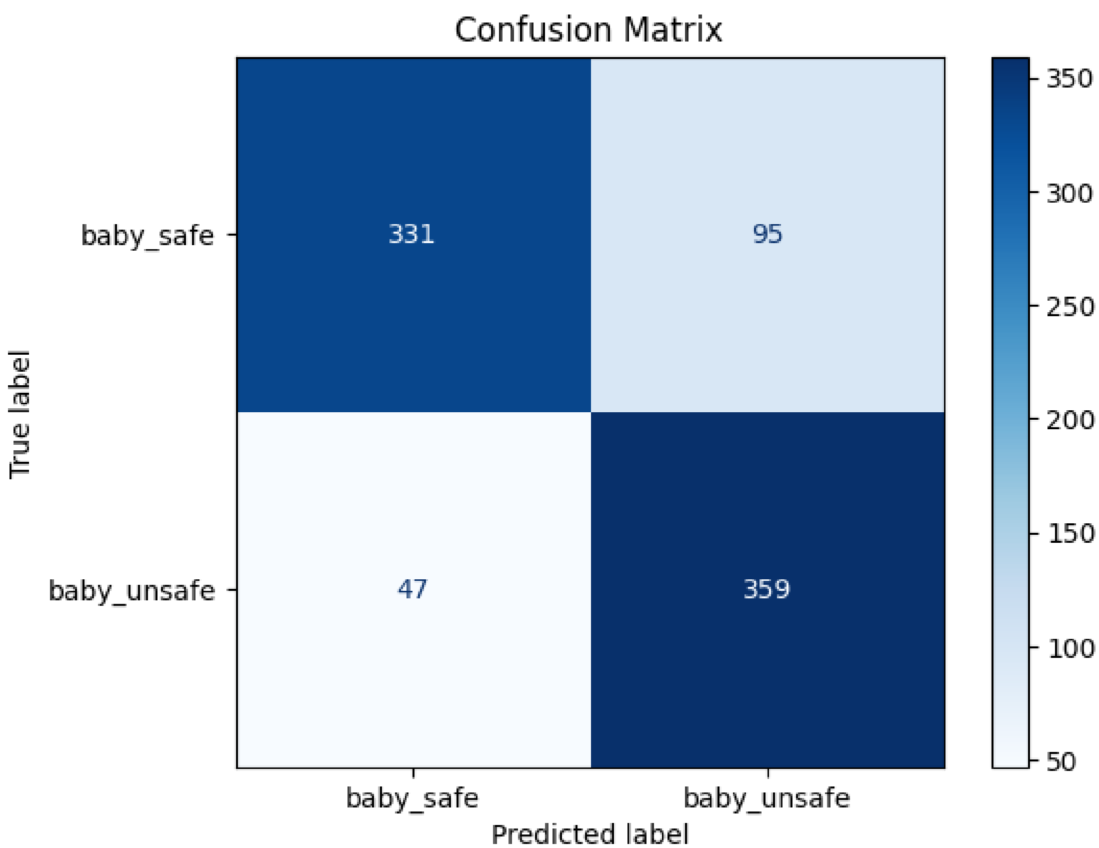
```
Dataset labels:----------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report-------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.88      0.78      0.82       426
 baby_unsafe       0.79      0.88      0.83       406

    accuracy                           0.83       832
   macro avg       0.83      0.83      0.83       832
weighted avg       0.83      0.83      0.83       832

Confusion matrix---------------------------------------
```

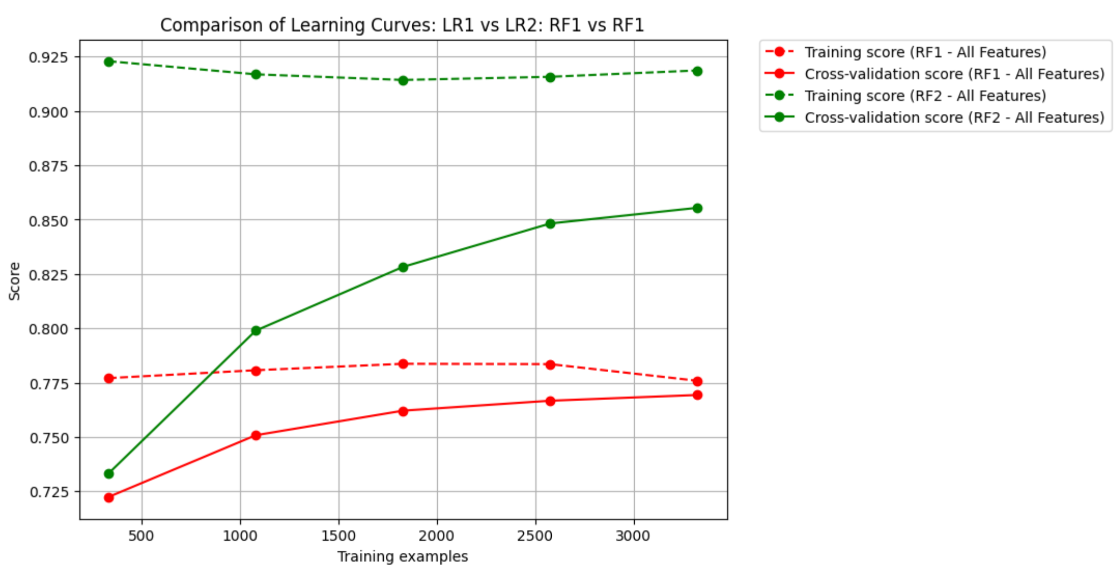


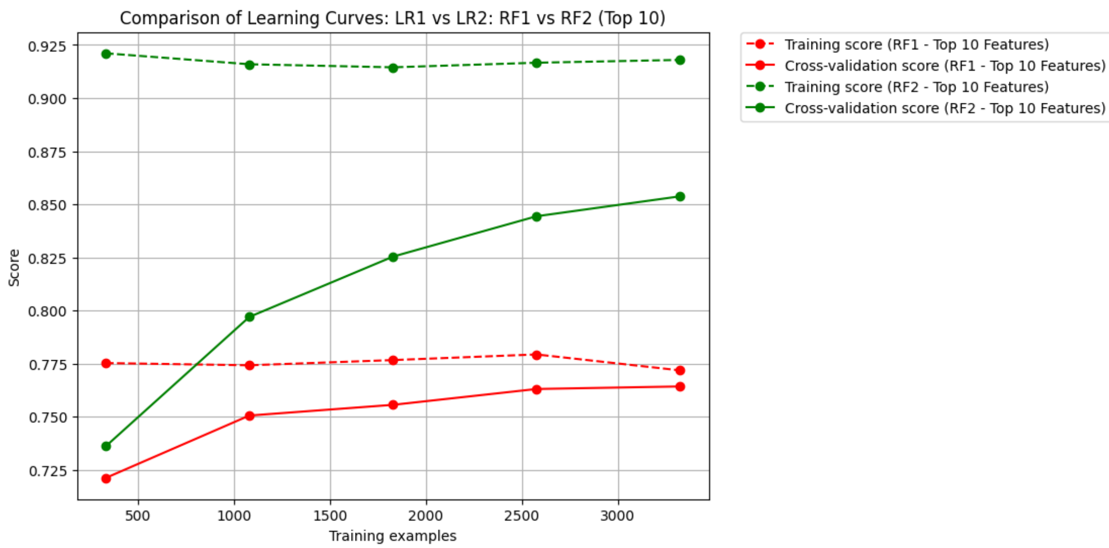
[10]:
```
# Graph 1:
data_to_plot_1 = [
    (results_rf1['all_features']['model'], "RF1 - All Features",␣
↪results_rf1['all_features']['X'], results_rf1['all_features']['y']),
    (results_rf2['all_features']['model'], "RF2 - All Features",␣
↪results_rf2['all_features']['X'], results_rf2['all_features']['y'])
]

clf.plot_learning_curve_comparison(
    data_sets=data_to_plot_1,
    title="Comparison of Learning Curves: LR1 vs LR2: RF1 vs RF1"
)

# Graph 2:
data_to_plot_2 = [
    (results_rf1['top_10_features']['model'], "RF1 - Top 10 Features",␣
↪results_rf1['top_10_features']['X'], results_rf1['top_10_features']['y']),
    (results_rf2['top_10_features']['model'], "RF2 - Top 10 Features",␣
↪results_rf2['top_10_features']['X'], results_rf2['top_10_features']['y'])
]

clf.plot_learning_curve_comparison(
    data_sets=data_to_plot_2,
    title="Comparison of Learning Curves: LR1 vs LR2: RF1 vs RF2 (Top 10)"
)
```





4 4) XGBC

[11]:
```
xgbc_1, results_xgbc_1 = clf.XGBC(verbose=True)
```

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--------------------------------------FIRST
ANALYSIS--------------------------------------
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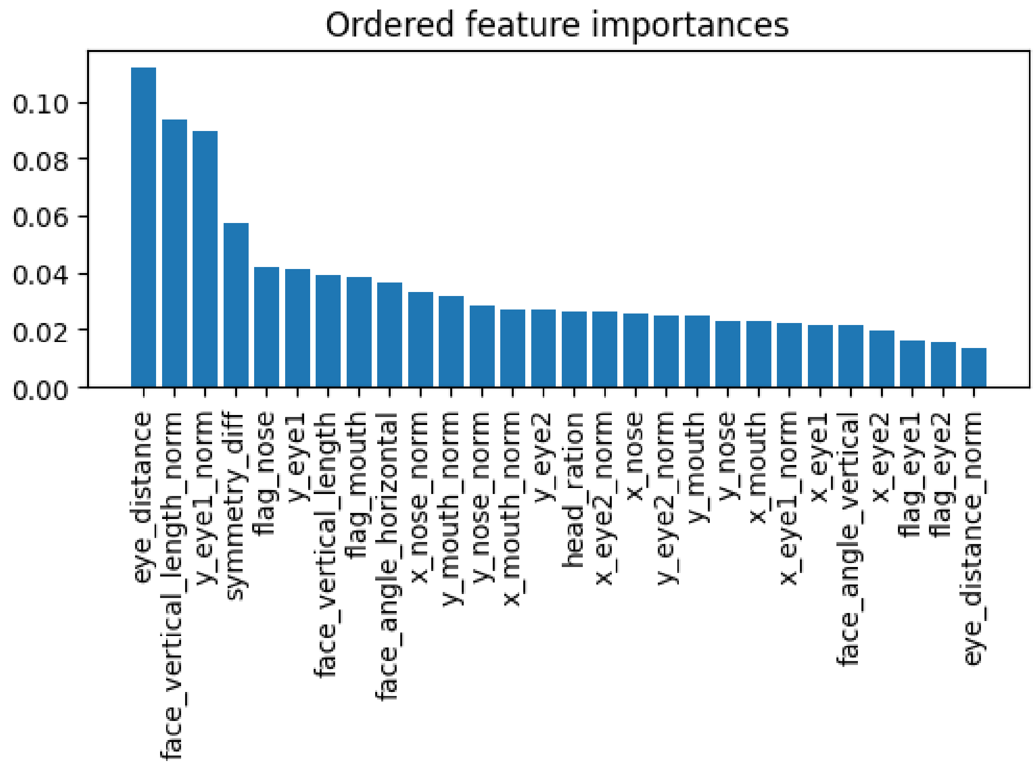
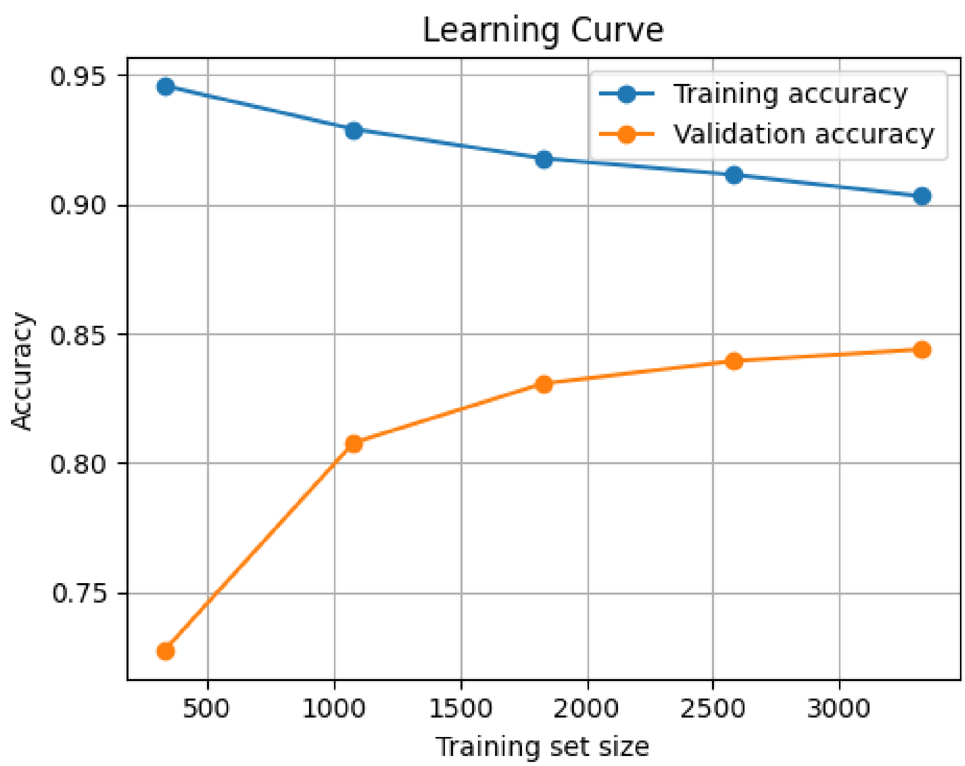
```


Ordered feature importances
0.00
0.02
0.04
0.06
0.08
0.10
eye_distance
face_vertical_length_norm
y_eye1_norm
symmetry_diff
flag_nose
y_eye1
face_vertical_length
flag_mouth
face_angle_horizontal
x_nose_norm
y_mouth_norm
y_nose_norm
x_mouth_norm
y_eye2
head_ration
x_eye2_norm
x_nose
y_eye2_norm
y_mouth
y_nose
x_mouth
x_eye1_norm
x_eye1
face_angle_vertical
x_eye2
flag_eye1
flag_eye2
eye_distance_norm


Learning Curve
Training accuracy
Validation accuracy
Accuracy
0.75
0.80
0.85
0.90
0.95
500
1000
1500
2000
2500
3000
Training set size

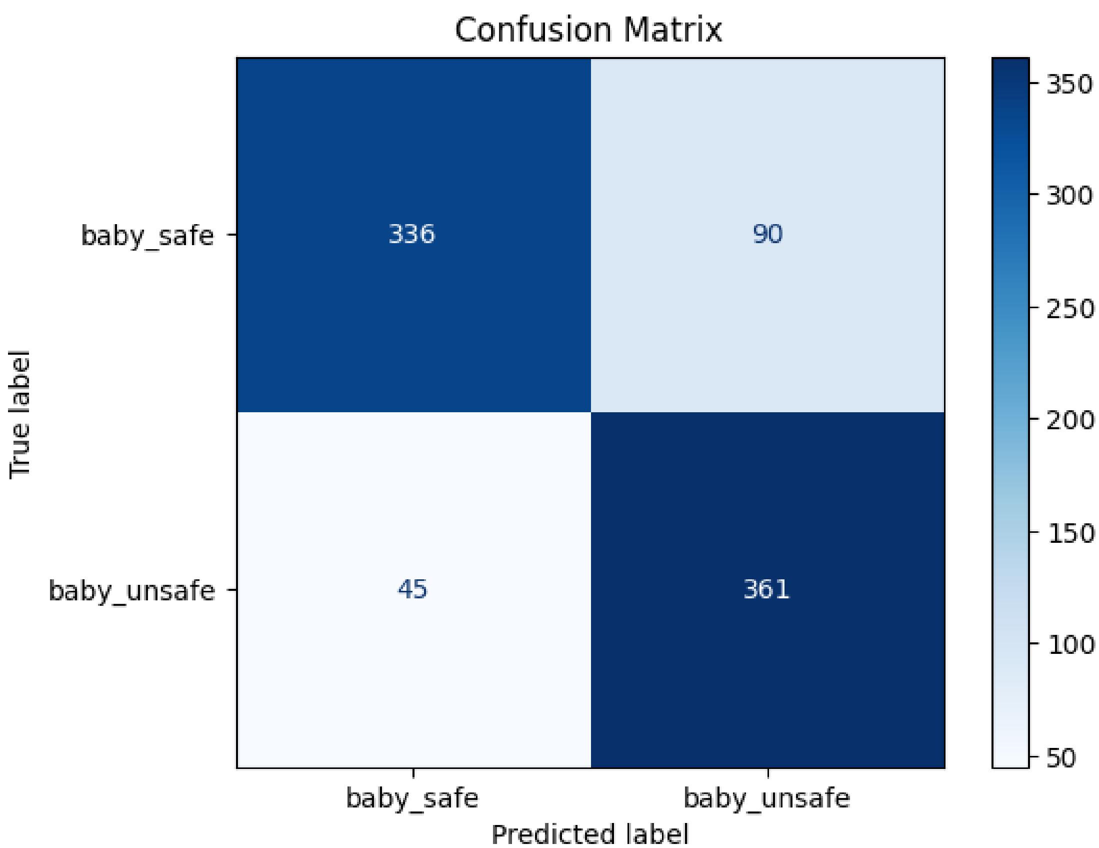
```
Dataset labels:----------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report-------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.88      0.79      0.83       426
 baby_unsafe       0.80      0.89      0.84       406

    accuracy                           0.84       832
   macro avg       0.84      0.84      0.84       832
weighted avg       0.84      0.84      0.84       832

Confusion matrix---------------------------------------
```




```
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```

```
---------------------------------TOP 10 FEATURES
ANALYSIS---------------------------------
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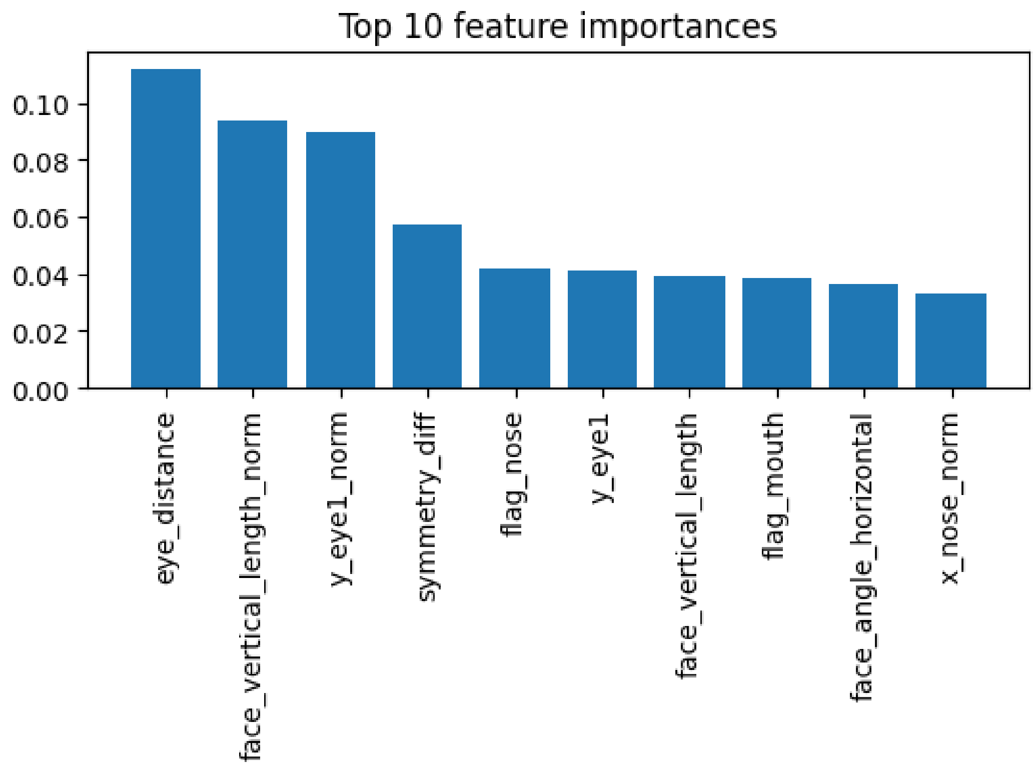
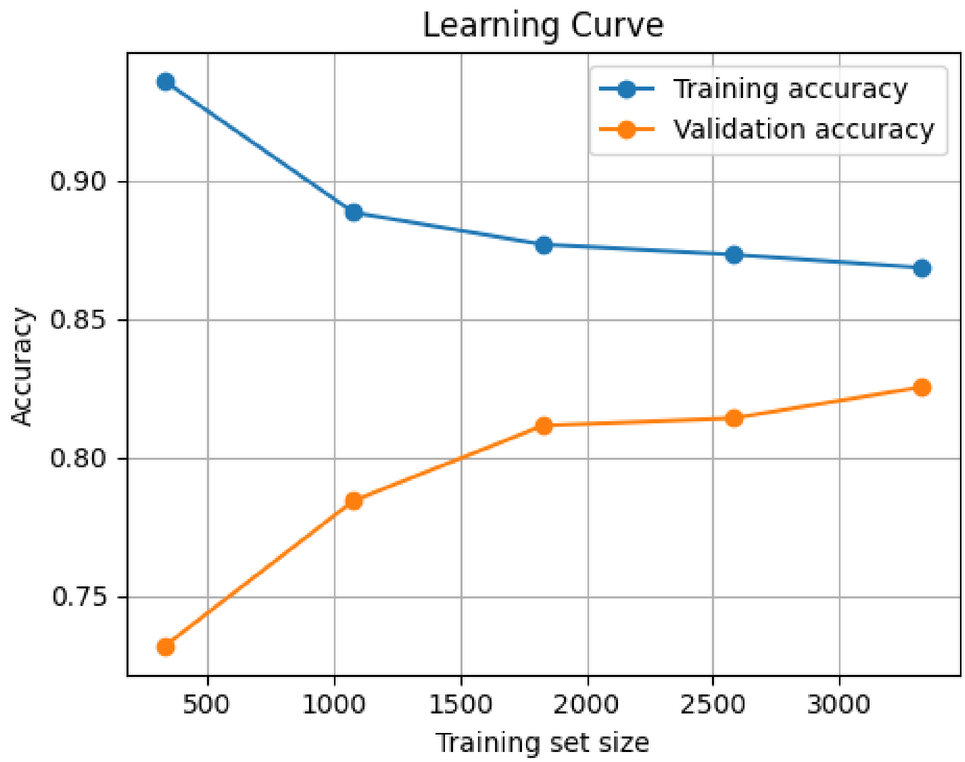
```





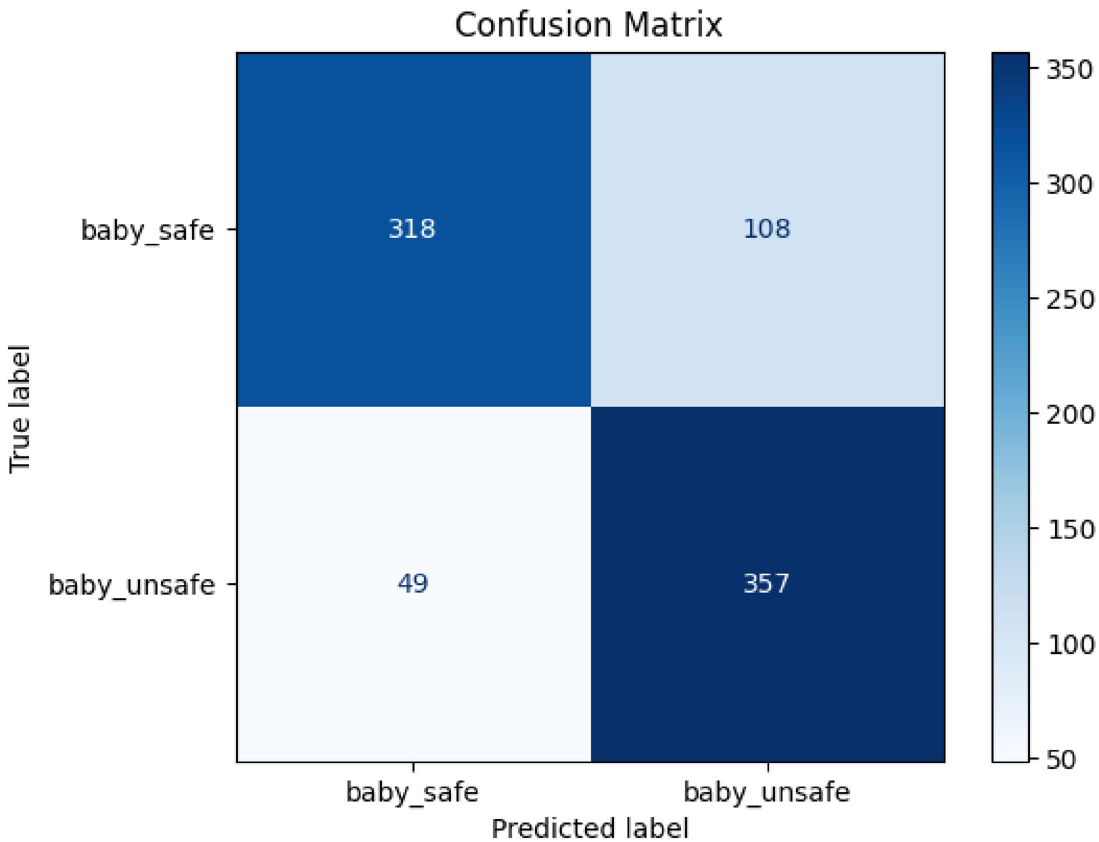

```
Dataset labels:---------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report-----------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.87      0.75      0.80       426
 baby_unsafe       0.77      0.88      0.82       406

    accuracy                           0.81       832
   macro avg       0.82      0.81      0.81       832
weighted avg       0.82      0.81      0.81       832

Confusion matrix-------------------------------------
```



[12]:
```
param_dist = {
    'n_estimators': randint(100, 500), # Numero di alberi da costruire
    'learning_rate': uniform(0.01, 0.3), # Passo di apprendimento
    'max_depth': randint(3, 10), # Profondità massima di un albero
    'subsample': uniform(0.6, 0.4), # Frazione di campioni da usare per␣
 ↪l'addestramento
    'colsample_bytree': uniform(0.6, 0.4), # Frazione di feature da usare per␣
 ↪la costruzione di ogni albero
    'gamma': uniform(0, 0.5) # Riduzione minima della perdita richiesta per␣
 ↪fare un'ulteriore partizione
    }
best_params_xgbc = clf.optimize_model(xgbc_1, param_dist,verbose=False)
xgbc_2 = XGBClassifier(**best_params_xgbc)
results_xgbc_2 = clf.evaluation_pipeline(xgbc_2,verbose=True)
```

```
Start random search…

Random Search Results:
Best parameters found:  {'colsample_bytree': np.float64(0.618786386710022),
```

```
'gamma': np.float64(0.0831416843780397), 'learning_rate':
np.float64(0.23141008492791112), 'max_depth': 5, 'n_estimators': 280,
'subsample': np.float64(0.8412608437865553)}
Best mean cross-validation accuracy:  0.8538783896678634
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-------------------------------------FIRST
ANALYSIS-------------------------------------
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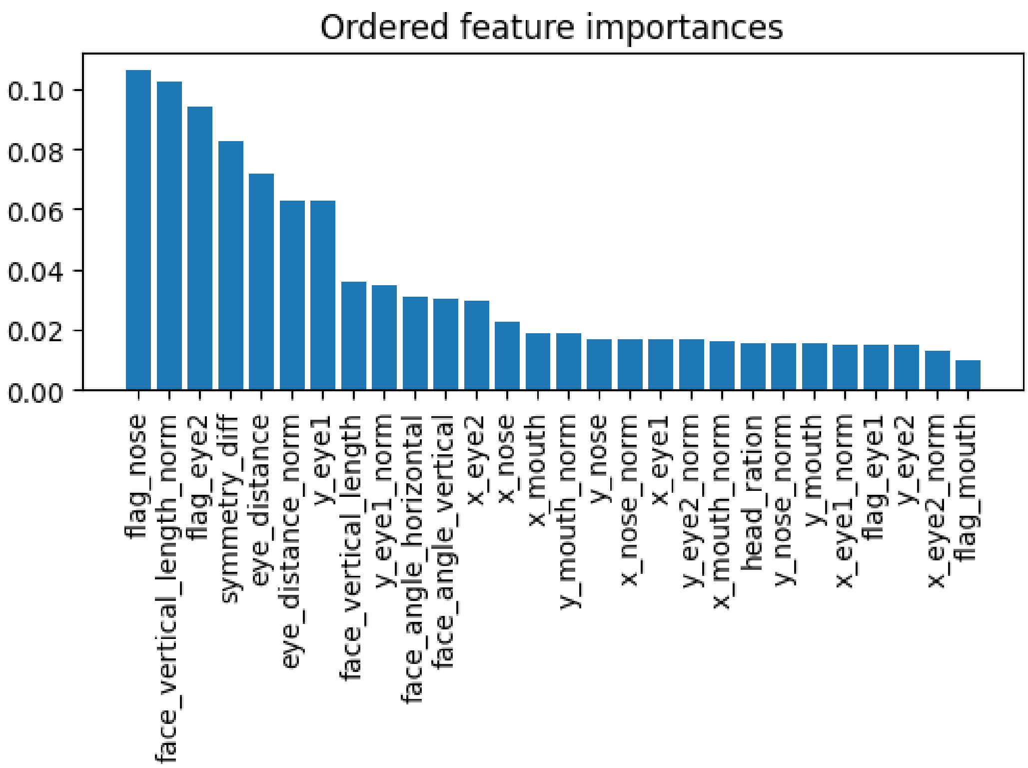
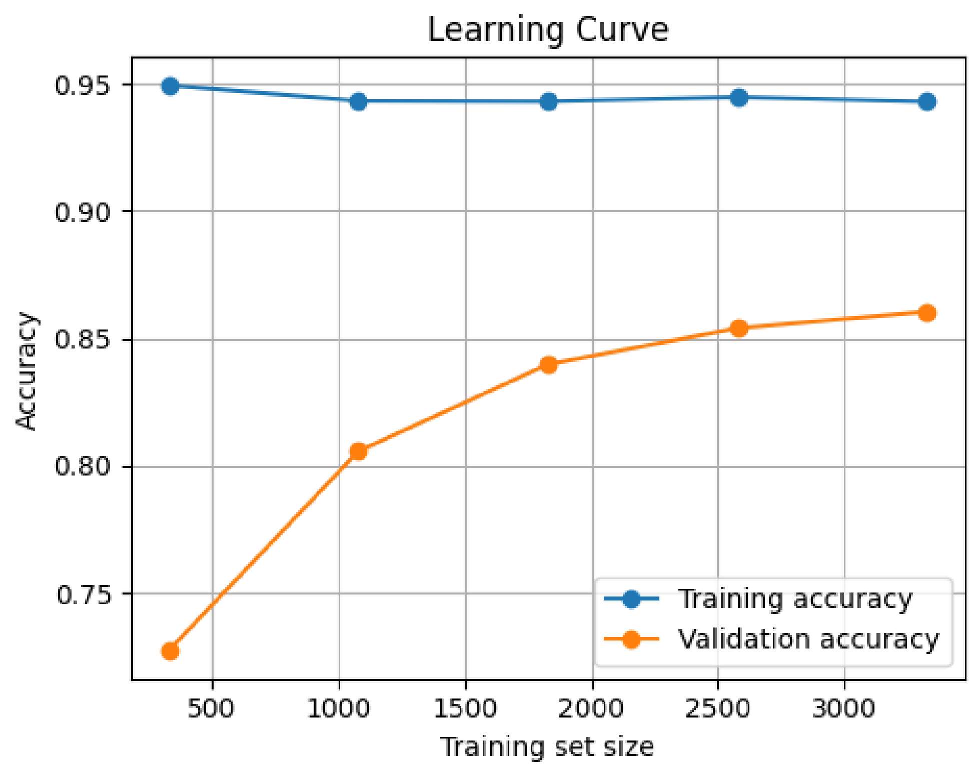
```





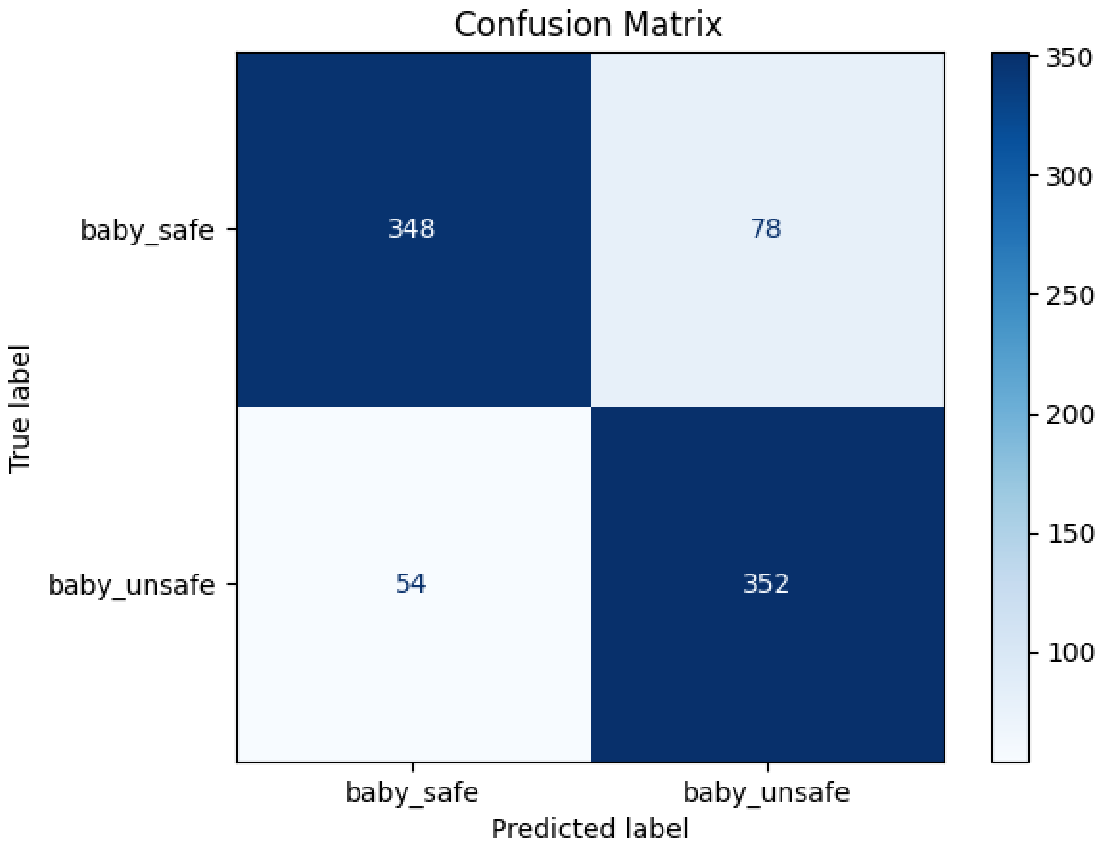

```
Dataset labels:----------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report-------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.87      0.82      0.84       426
 baby_unsafe       0.82      0.87      0.84       406

    accuracy                           0.84       832
   macro avg       0.84      0.84      0.84       832
weighted avg       0.84      0.84      0.84       832

Confusion matrix---------------------------------------
```




```
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---------------------------------TOP 10 FEATURES
ANALYSIS---------------------------------
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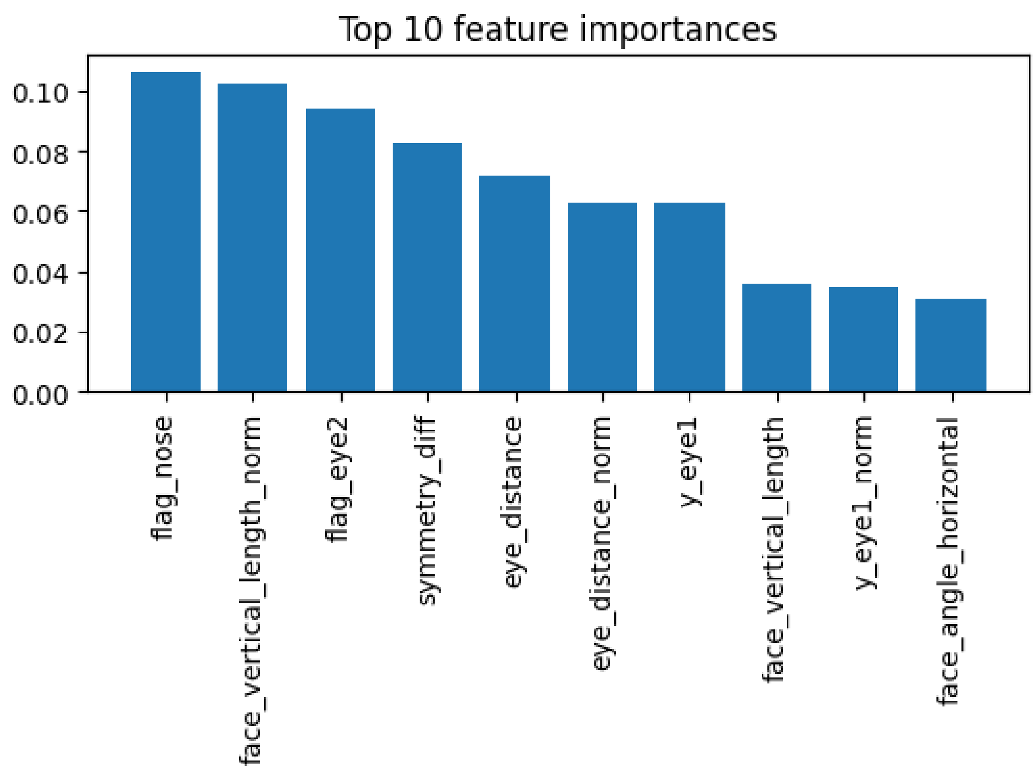
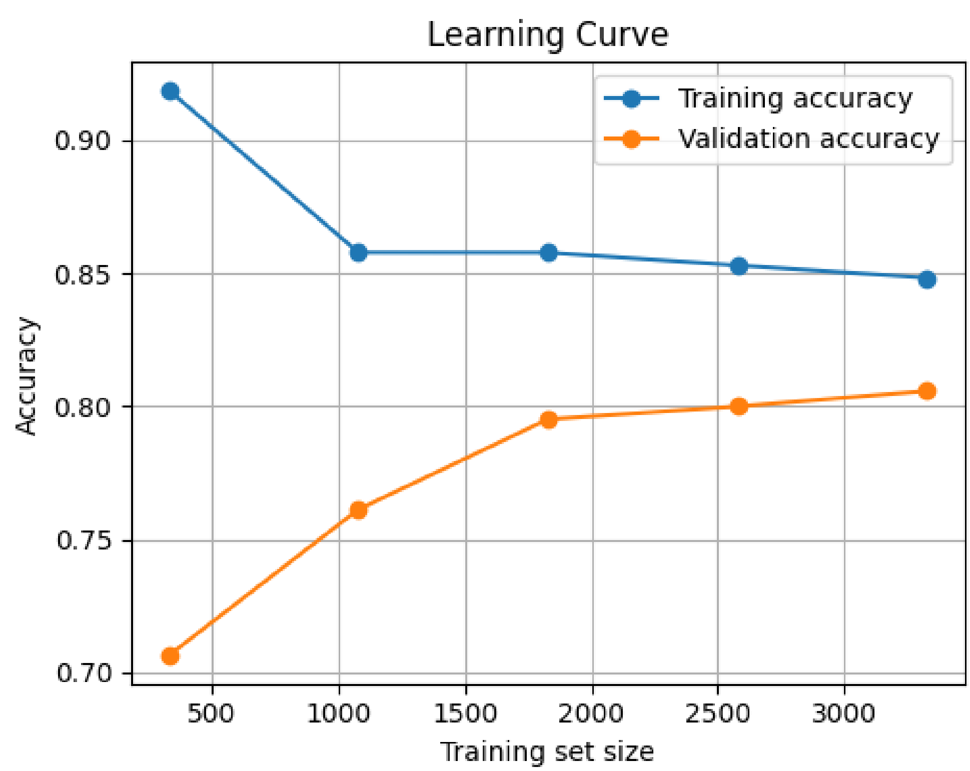
```


Top 10 feature importances
0.10
0.08
0.06
0.04
0.02
0.00
flag_nose
face_vertical_length_norm
flag_eye2
symmetry_diff
eye_distance
eye_distance_norm
y_eye1
face_vertical_length
y_eye1_norm
face_angle_horizontal


Learning Curve
Training accuracy
Validation accuracy
0.90
0.85
0.80
0.75
0.70
Accuracy
500
1000
1500
2000
2500
3000
Training set size

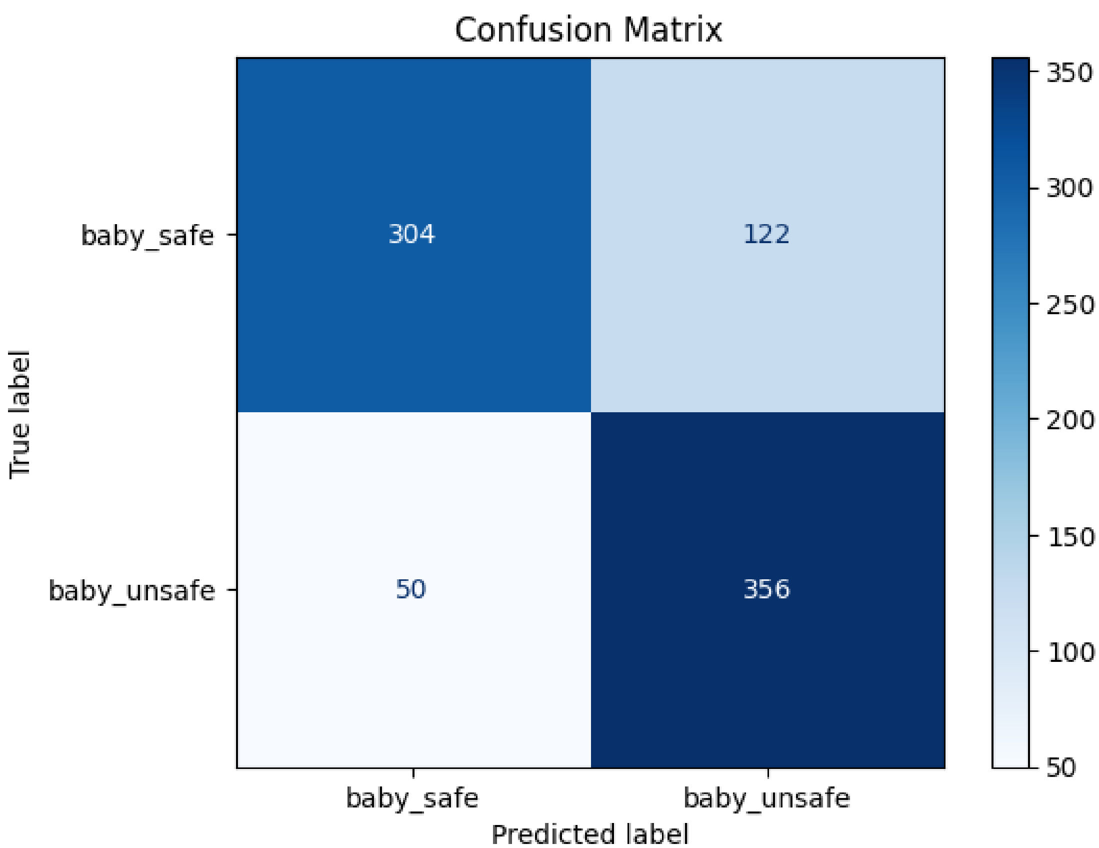
```
Dataset labels:----------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report-------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.86      0.71      0.78       426
 baby_unsafe       0.74      0.88      0.81       406

    accuracy                           0.79       832
   macro avg       0.80      0.80      0.79       832
weighted avg       0.80      0.79      0.79       832

Confusion matrix---------------------------------------
```

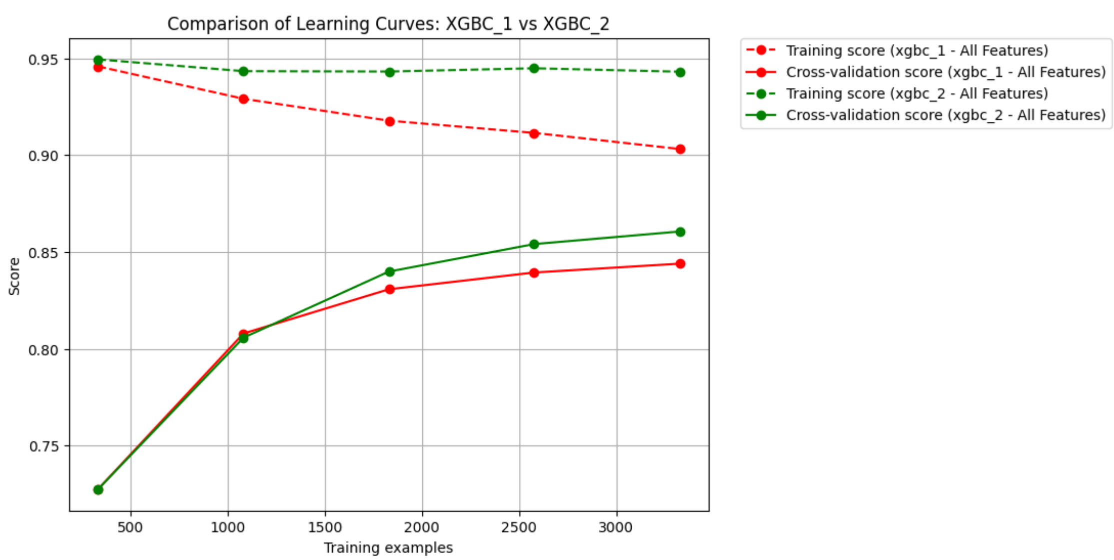


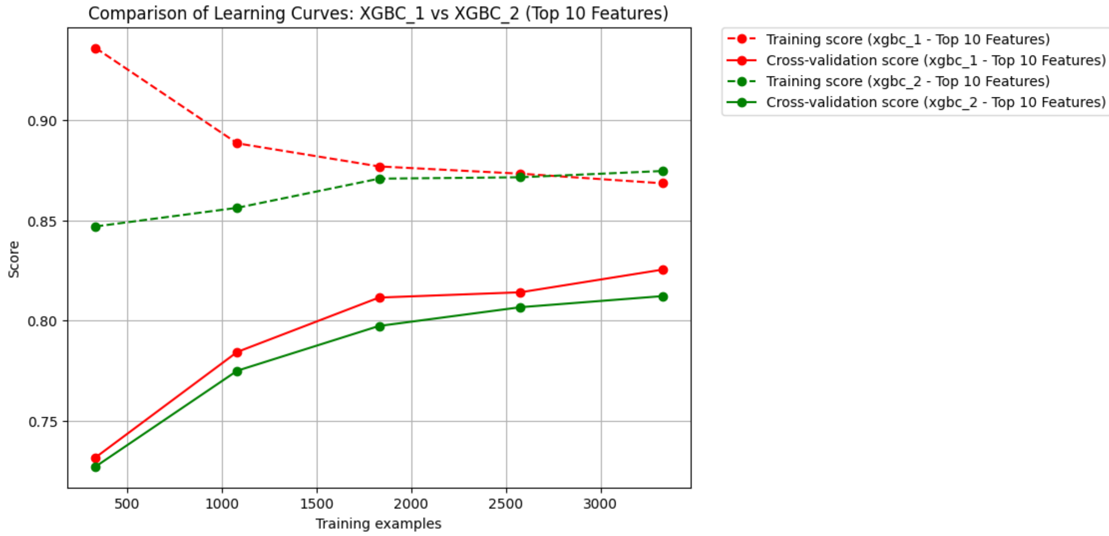
[13]:
```
# Graph 1:
data_to_plot_1 = [
    (results_xgbc_1['all_features']['model'], "xgbc_1 - All Features",␣
 ↪results_xgbc_1['all_features']['X'], results_xgbc_1['all_features']['y']),
    (results_xgbc_2['all_features']['model'], "xgbc_2 - All Features",␣
 ↪results_xgbc_2['all_features']['X'], results_xgbc_2['all_features']['y'])
]

clf.plot_learning_curve_comparison(
    data_sets=data_to_plot_1,
    title="Comparison of Learning Curves: XGBC_1 vs XGBC_2"
)

# Graph 2:
data_to_plot_2 = [
    (results_xgbc_1['top_10_features']['model'], "xgbc_1 - Top 10 Features",␣
 ↪results_xgbc_1['top_10_features']['X'],␣
 ↪results_xgbc_1['top_10_features']['y']),
    (results_rf2['top_10_features']['model'], "xgbc_2 - Top 10 Features",␣
 ↪results_xgbc_2['top_10_features']['X'],␣
 ↪results_xgbc_2['top_10_features']['y'])
]

clf.plot_learning_curve_comparison(
    data_sets=data_to_plot_2,
    title="Comparison of Learning Curves: XGBC_1 vs XGBC_2 (Top 10 Features)"
)
```





5 5) Bagging

[14]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier
base_clf = DecisionTreeClassifier(random_state=42)
bagging_1, results_bag_1 = clf.bagging(base_clf=base_clf,verbose=True)
```

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--------------------------------------FIRST
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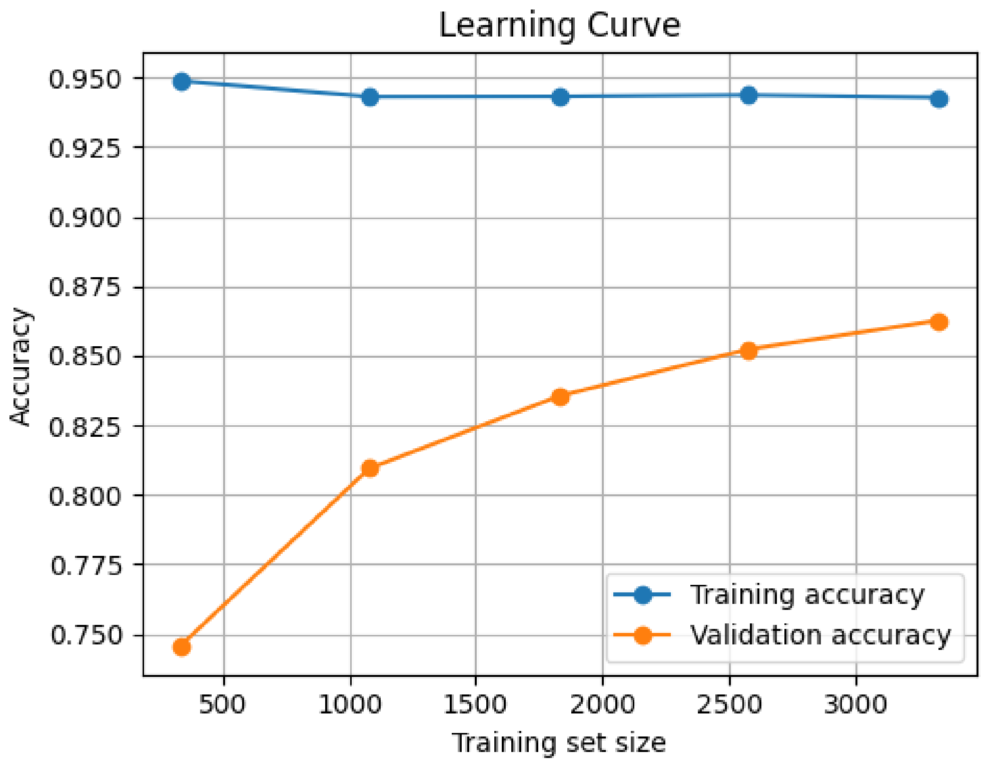
```



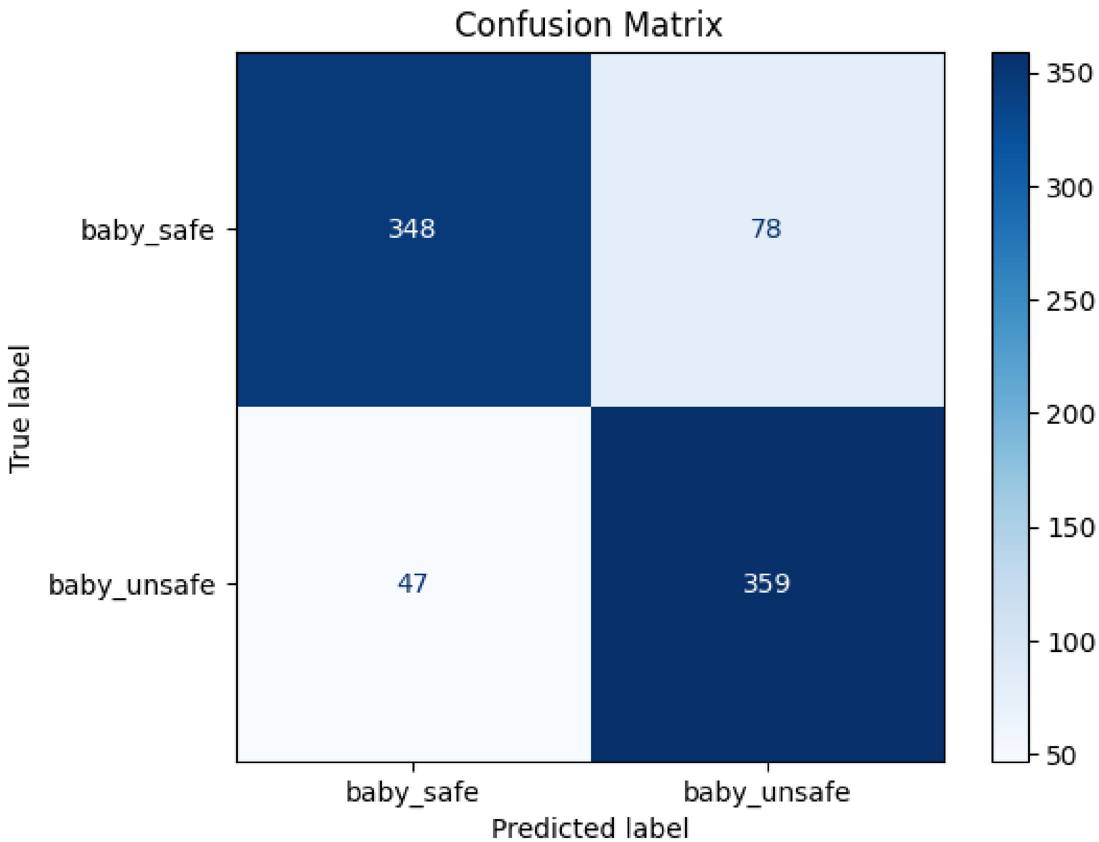

```
Dataset labels:----------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report---------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.88      0.82      0.85       426
 baby_unsafe       0.82      0.88      0.85       406

    accuracy                           0.85       832
   macro avg       0.85      0.85      0.85       832
weighted avg       0.85      0.85      0.85       832

Confusion matrix---------------------------------------
```



[15]:
```
# Definisci il dizionario dei parametri per la ricerca casuale
param_grid = {
    'n_estimators': randint(100, 500),
    'max_samples': uniform(0.5, 1),
    'max_features': uniform(0.5, 1),
    'bootstrap_features': [True, False],
    'estimator__max_depth': randint(1,30),
    'estimator__min_samples_split': randint(2, 20)
}

best_params_bagging = clf.optimize_model(model=bagging_1,␣
↪param_grid=param_grid, verbose=False)

dt_params = {
    'max_depth': best_params_bagging.pop('estimator__max_depth'),
    'min_samples_split': best_params_bagging.pop('estimator__min_samples_split')
}

bagging_2 = BaggingClassifier(
```

```
    estimator=DecisionTreeClassifier(random_state=42,**dt_params),
    **best_params_bagging)

results_bagging_2 = clf.evaluation_pipeline(bagging_2,verbose=True)
```

```
Start random search…

Random Search Results:
Best parameters found:  {'bootstrap_features': True, 'estimator__max_depth': 22,
'estimator__min_samples_split': 3, 'max_features':
np.float64(0.7541636490697388), 'max_samples': np.float64(0.7952905884189387),
'n_estimators': 372}
Best mean cross-validation accuracy:  0.8541800447063604
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--------------------------------------FIRST
ANALYSIS--------------------------------------
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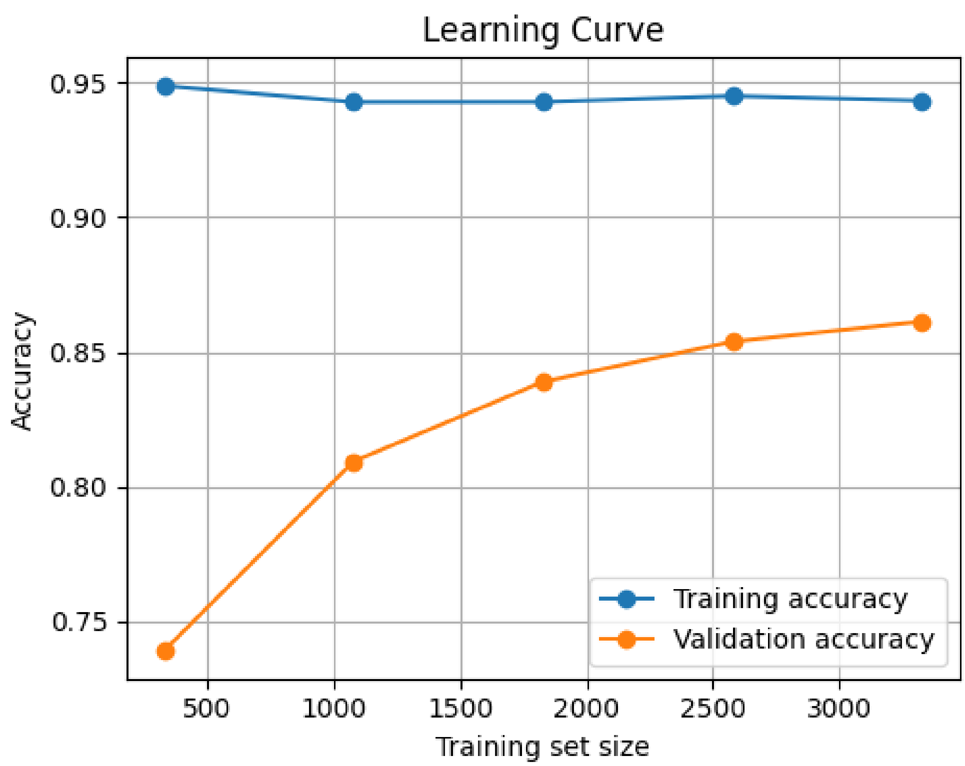
```




```
Dataset labels:----------------------------------------
```

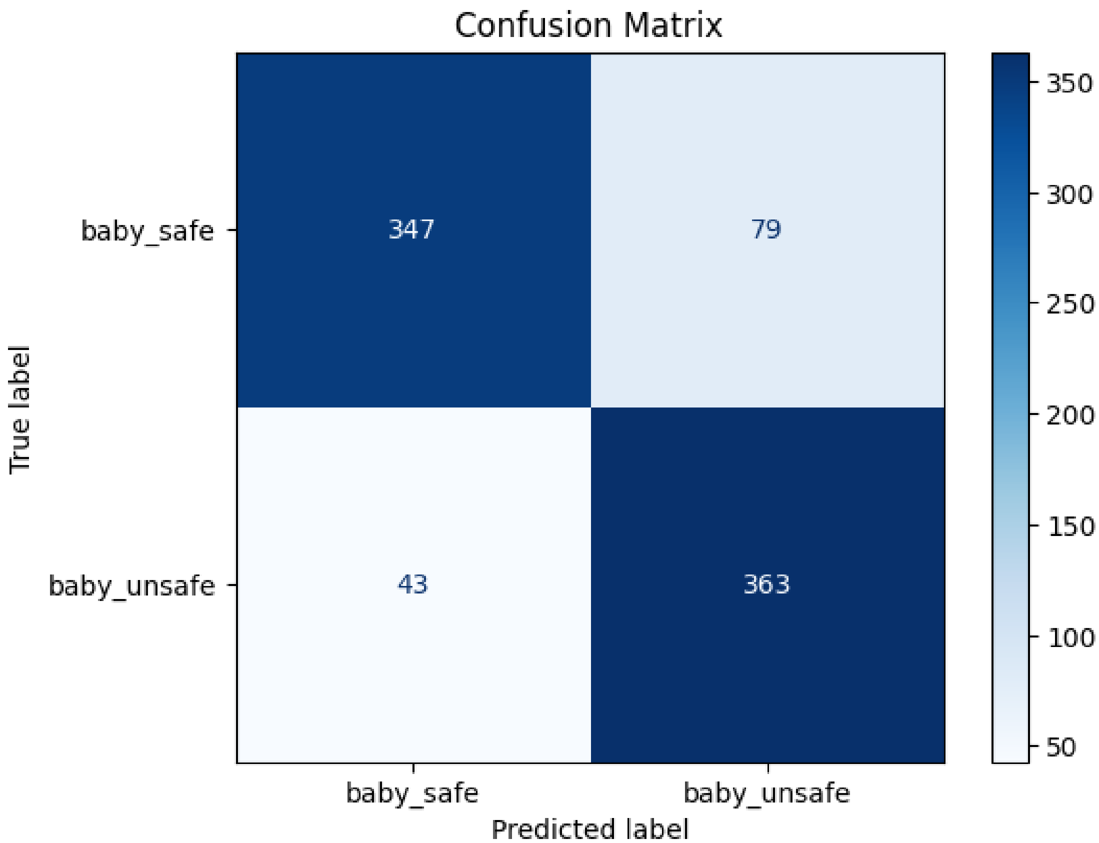
```
{'baby_safe': 0, 'baby_unsafe': 1}

Report--------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.89      0.81      0.85       426
 baby_unsafe       0.82      0.89      0.86       406

    accuracy                           0.85       832
   macro avg       0.86      0.85      0.85       832
weighted avg       0.86      0.85      0.85       832

Confusion matrix----------------------------------------
```



6 6) Ensamble

[16]:
```
voting_clf_soft = VotingClassifier(
    estimators=[('lr', lr_2), ('rf', random_forest_2), ('xgb', xgbc_2),␣
 ↪('bagging', bagging_2)],
    voting='soft'  # 'hard' per la maggioranza, 'soft' per le probabilità
)

results_voting_soft = clf.
 ↪evaluation_pipeline(voting_clf_soft,verbose=True,is_ensemble=True)
```

```
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--------------------------------------FIRST
ANALYSIS-------------------------------------
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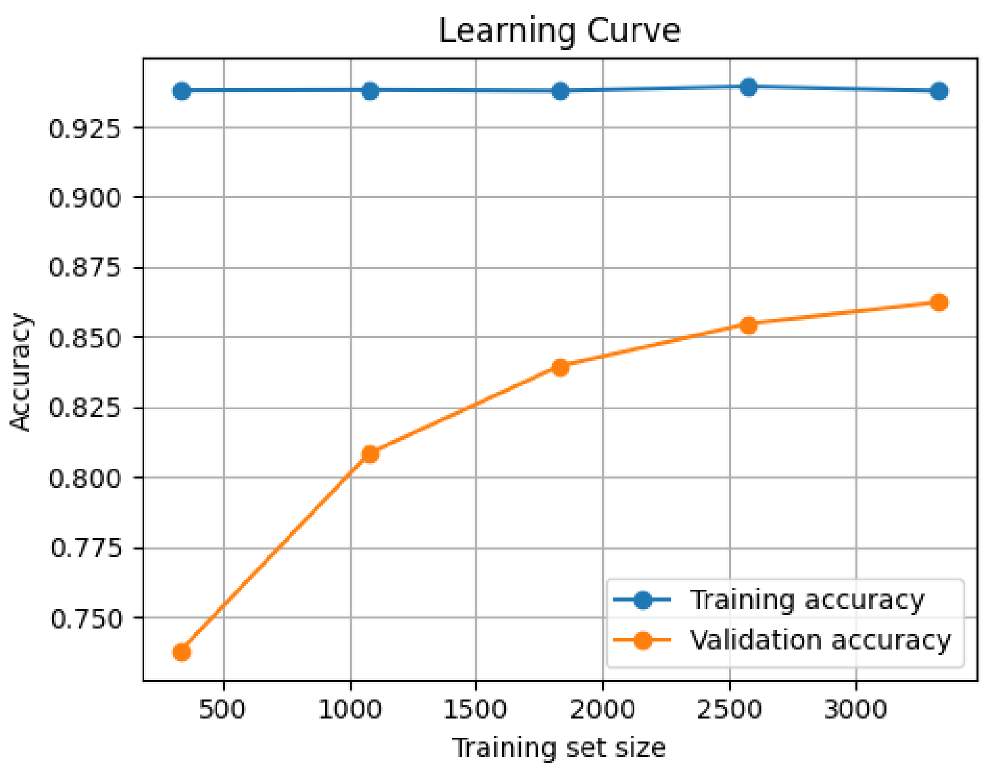
```




```
Dataset labels:---------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

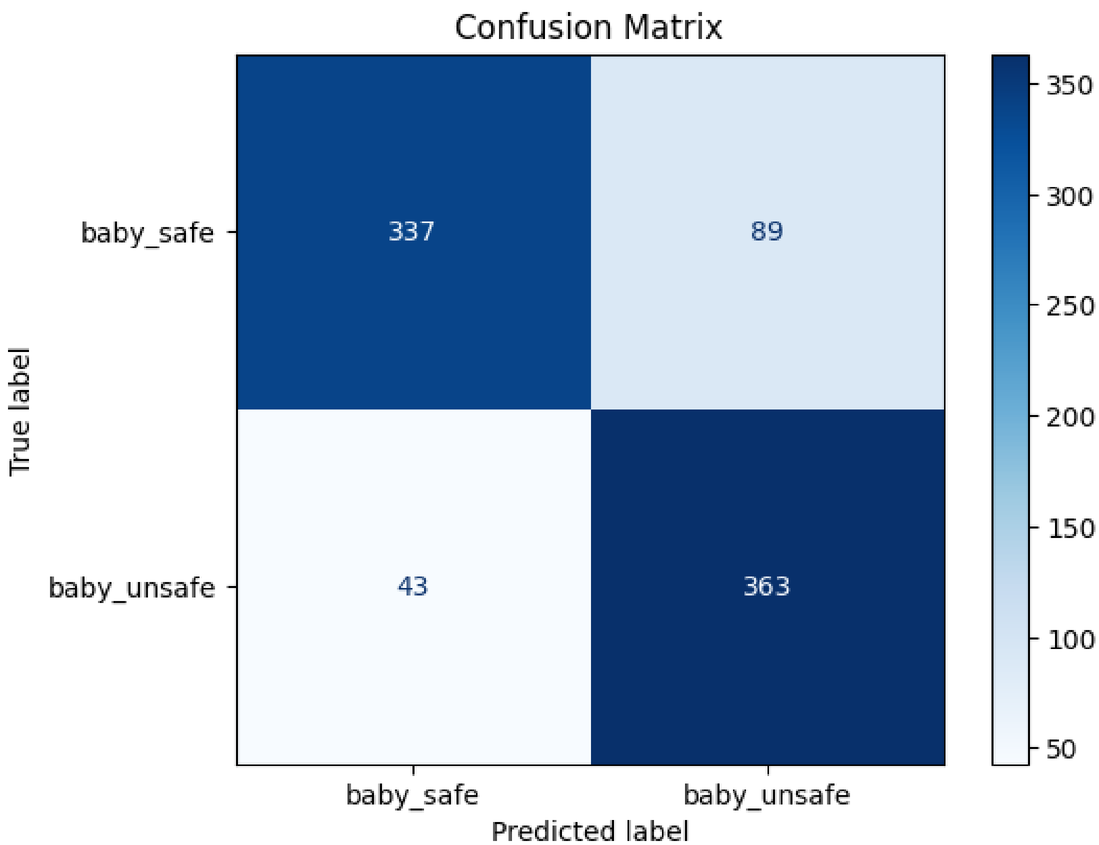
Report------------------------------------------------
```

```
              precision    recall  f1-score   support

   baby_safe       0.89      0.79      0.84       426
 baby_unsafe       0.80      0.89      0.85       406

    accuracy                           0.84       832
   macro avg       0.84      0.84      0.84       832
weighted avg       0.85      0.84      0.84       832

Confusion matrix---------------------------------------
```



[17]:

```
top_10_features_idx = results_lr_2['top_10_features']['top_features_idx']

results_voting_soft = clf.ensemble_on_top_features(
    ensemble_clf=voting_clf_soft,
    top_features_idx=top_10_features_idx,
    verbose=True
)
```

```
--------------------------------------------------------------------------------
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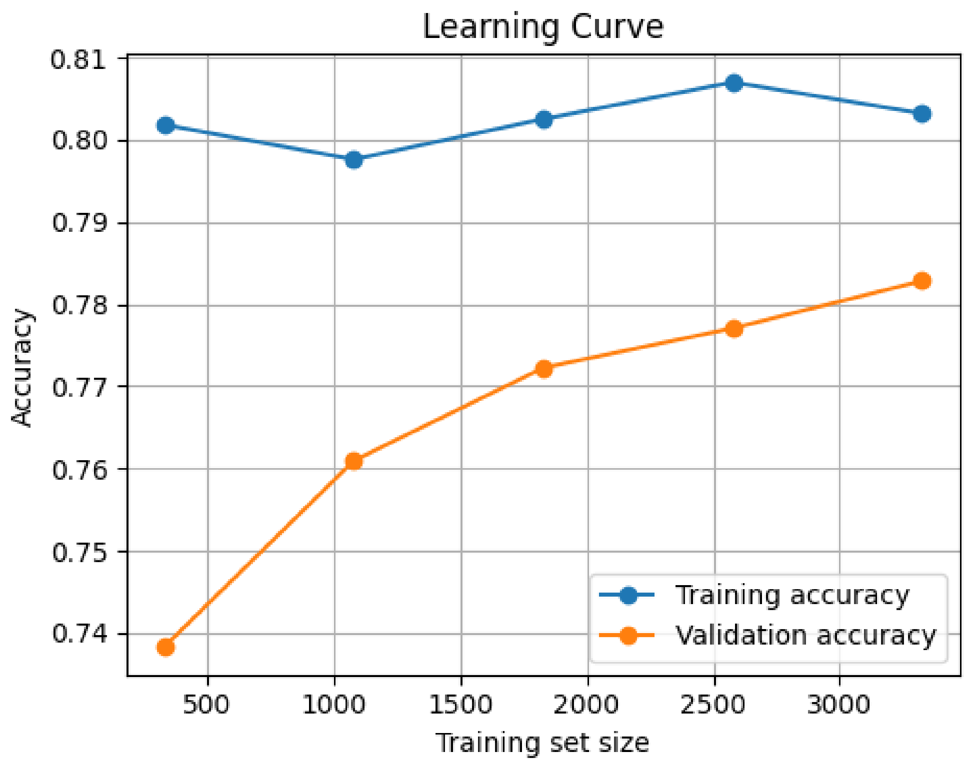
```

```
-----------------------ENSEMBLE MODEL EVALUATION ON TOP 10
FEATURES-----------------------
--------------------------------------------------------------------------------
----------
```



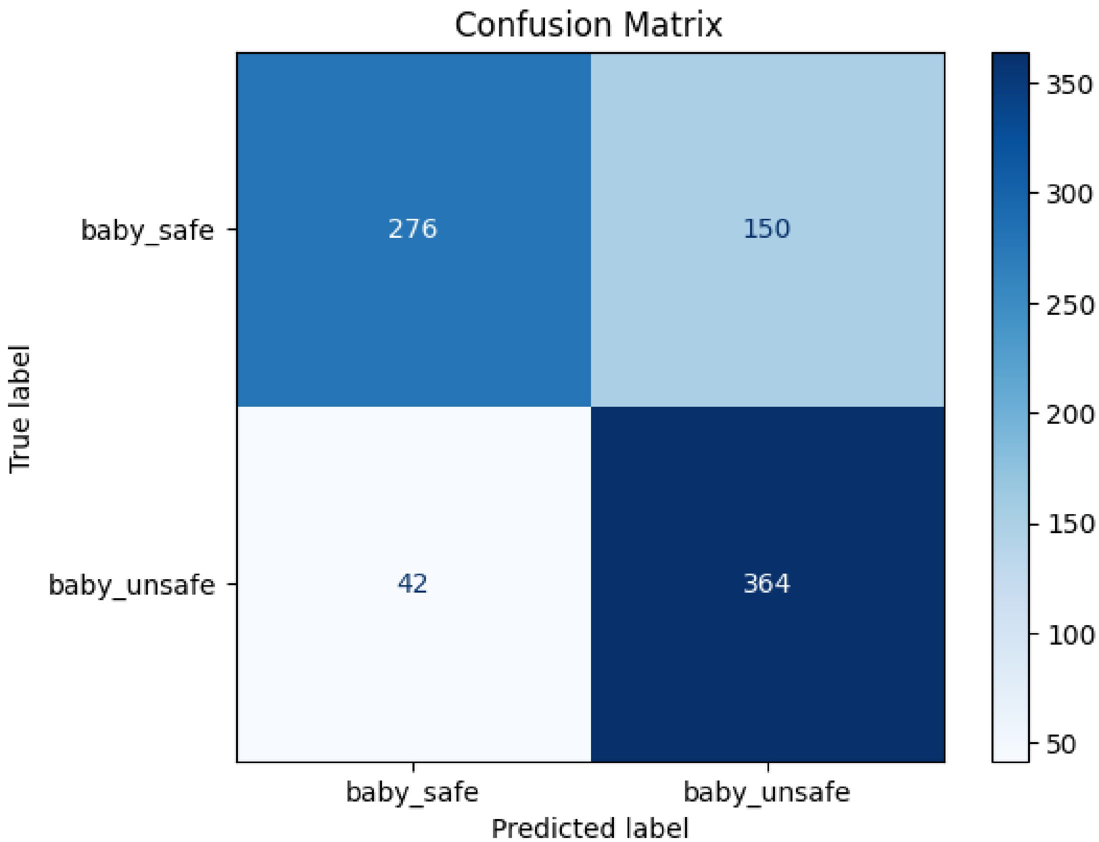

```
Dataset labels:----------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report--------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.87      0.65      0.74       426
 baby_unsafe       0.71      0.90      0.79       406

    accuracy                           0.77       832
   macro avg       0.79      0.77      0.77       832
weighted avg       0.79      0.77      0.77       832

Confusion matrix---------------------------------------
```



[18]:
```
from sklearn.calibration import CalibratedClassifierCV
# Calibrazione dei modelli per migliorare le probabilità
# Per la Regressione Logistica, la calibrazione è solitamente meno necessaria,␣
↪ma è una buona pratica
calibrated_lr = CalibratedClassifierCV(lr_2, method='isotonic', cv=5)

# Per il Random Forest e altri modelli basati su alberi, la calibrazione è␣
↪molto utile
calibrated_rf = CalibratedClassifierCV(random_forest_2, method='isotonic', cv=5)

# Anche per XGBoost, la calibrazione può aiutare
calibrated_xgbc = CalibratedClassifierCV(xgbc_2, method='isotonic', cv=5)

calibrated_bagging = CalibratedClassifierCV(bagging_2, method='isotonic', cv=5)

# Creazione del VotingClassifier utilizzando i modelli calibrati
# Nota: La calibrazione richiede 'voting='soft' per funzionare correttamente
voting_clf_soft_calibrated = VotingClassifier(
    estimators=[
```

```
        ('lr_calibrated', calibrated_lr),
        ('rf_calibrated', calibrated_rf),
        ('xgbc_calibrated', calibrated_xgbc),
        ('bagging_calibrated', calibrated_bagging)
    ],
    voting='soft'
)
results_voting_soft_calibrated = clf.
 ↪evaluation_pipeline(voting_clf_soft,verbose=True,is_ensemble=True)
```

```
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--------------------------------------FIRST
ANALYSIS--------------------------------------
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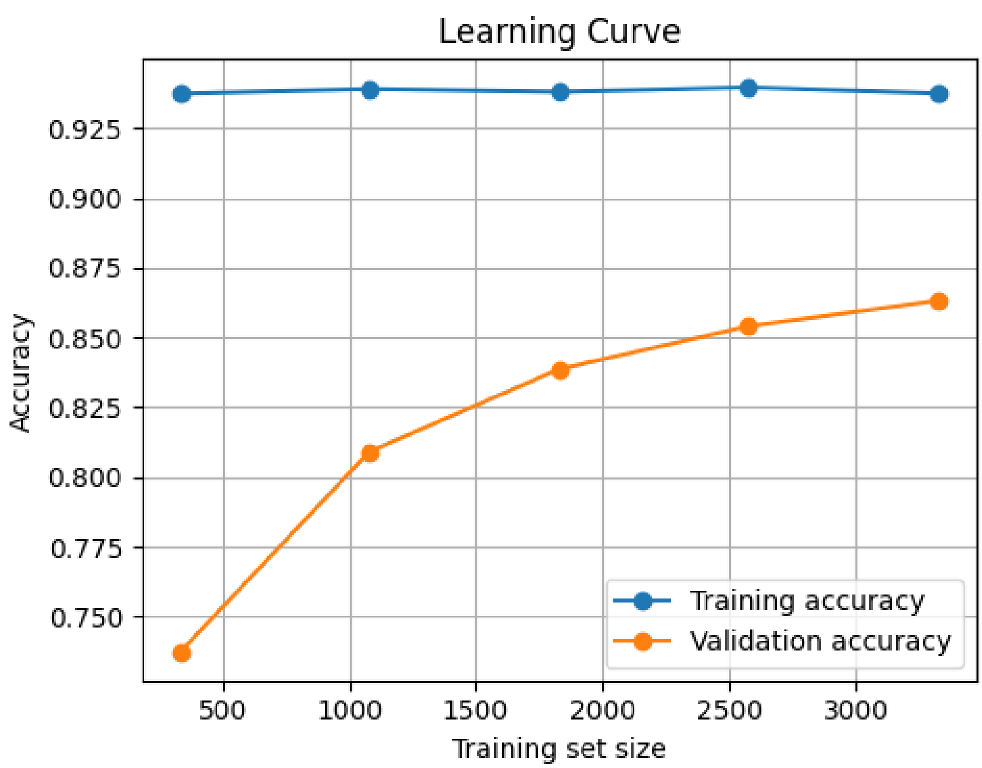
```



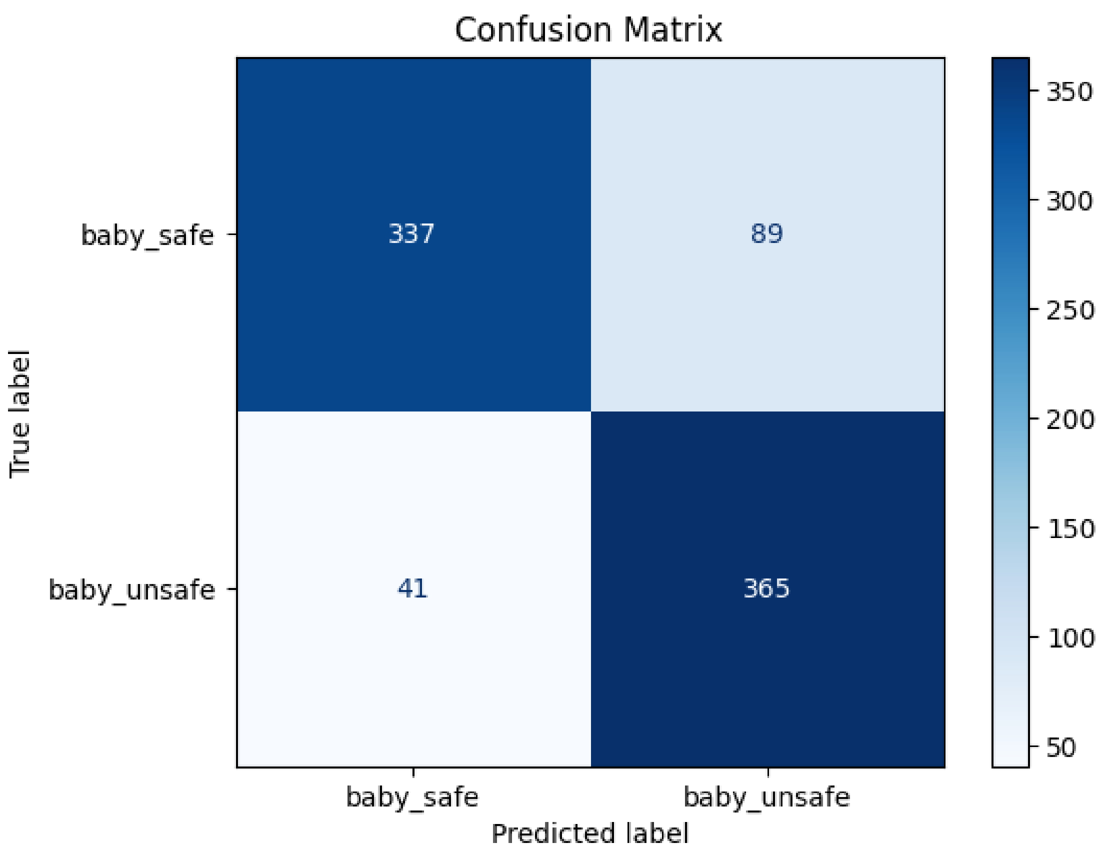

```
Dataset labels:----------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report-------------------------------------------------
              precision    recall  f1-score   support
```

```
   baby_safe       0.89      0.79      0.84       426
 baby_unsafe       0.80      0.90      0.85       406

    accuracy                           0.84       832
   macro avg       0.85      0.85      0.84       832
weighted avg       0.85      0.84      0.84       832

Confusion matrix---------------------------------------
```

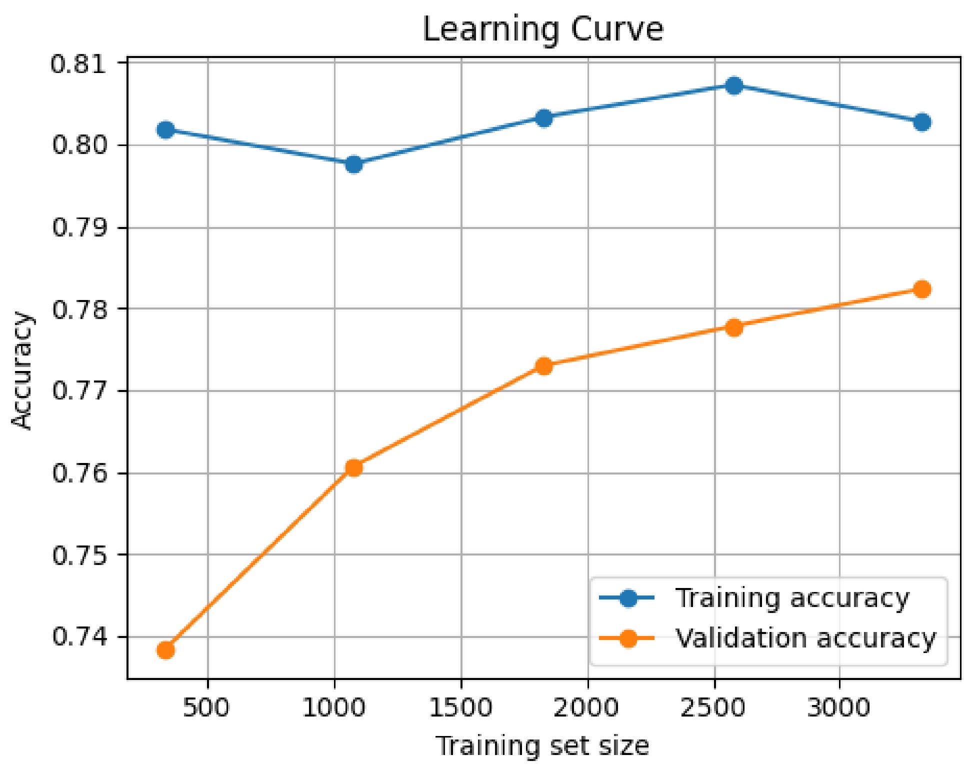


[19]:
```
top_10_features_idx = results_lr_2['top_10_features']['top_features_idx']

clf.ensemble_on_top_features(
    ensemble_clf=voting_clf_soft,
    top_features_idx=top_10_features_idx,
    verbose=True
)
```

```
--------------------------------------------------------------------------------
----------
-----------------------ENSEMBLE MODEL EVALUATION ON TOP 10
```

```
FEATURES-----------------------
--------------------------------------------------------------------------------
----------
```



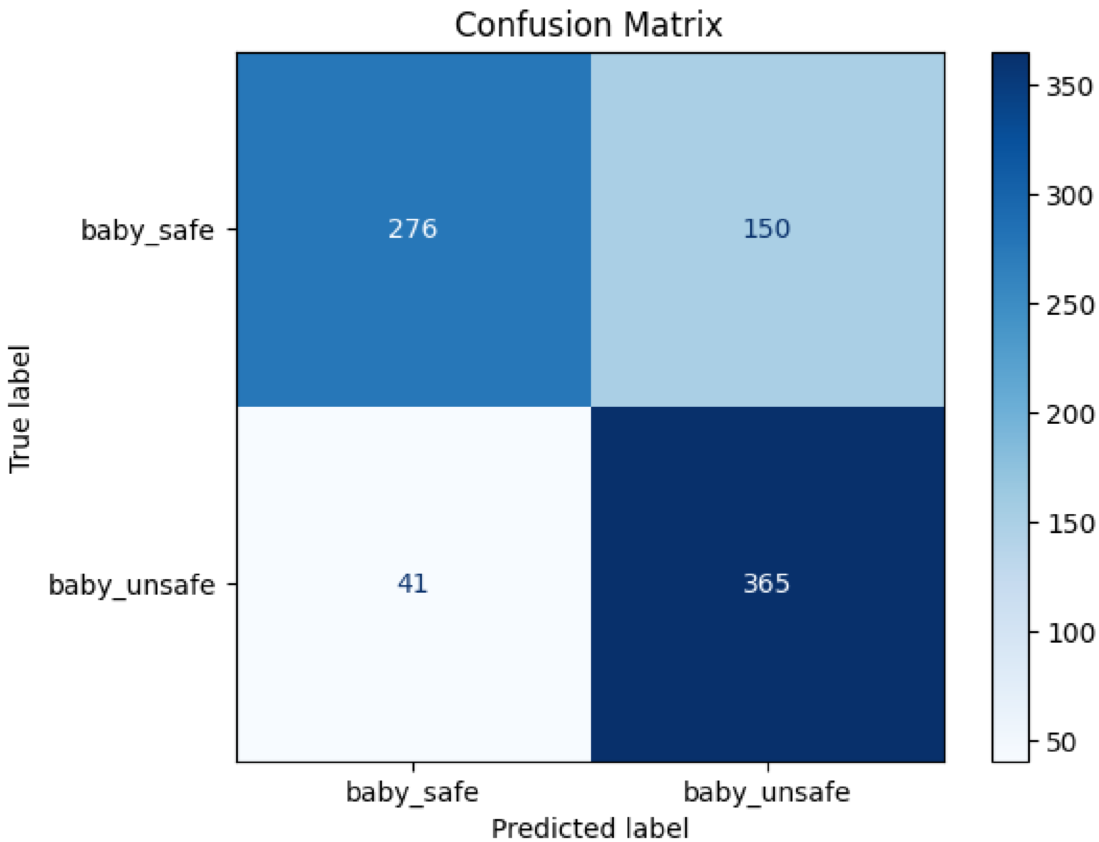

```
Dataset labels:---------------------------------------
{'baby_safe': 0, 'baby_unsafe': 1}

Report------------------------------------------------
              precision    recall  f1-score   support

   baby_safe       0.87      0.65      0.74       426
 baby_unsafe       0.71      0.90      0.79       406

    accuracy                           0.77       832
   macro avg       0.79      0.77      0.77       832
weighted avg       0.79      0.77      0.77       832

Confusion matrix--------------------------------------
```



[19]:
```
{'top_10_features': {'model': VotingClassifier(estimators=[('lr',
LogisticRegression(C=np.float64(530.0369711220895),
                                                   l1_ratio=0.1,
                                                   solver='liblinear')),
                               ('rf',
                                RandomForestClassifier(criterion='entropy',
                                                       max_depth=17,
                                                       max_features=0.5,
max_samples=np.float64(0.8473924665198522),
                                                       min_samples_leaf=2,
                                                       min_samples_split=7,
                                                       n_estimators=995)),
                               ('xgb',
                                XGBClassifier(base_score=None, booster=None,…
                                              monotone_constraints=None,
                                              multi_strategy=None,
                                              n_estimators=280, n_jobs=None,
                                              num_parallel_tree=None, …)),
                               ('bagging',
                                BaggingClassifier(bootstrap_features=True,
```

```
estimator=DecisionTreeClassifier(max_depth=22,
   min_samples_split=3,
   random_state=42),
max_features=np.float64(0.7541636490697388),
max_samples=np.float64(0.7952905884189387),
                                                  n_estimators=372))],
                   voting='soft'),
  'X': array([[          0,           -1,             0, …,             0,
-1,           -1],
         [          0,           -1,             0, …,             0,           -1,
-1],
         [          0,           -1,             0, …,             0,           -1,
-1],
         …,
         [   0.051653,       0.1172,             1, …,             1,      0.20079,
0.71437],
         [  0.0070473,     0.067337,             1, …,             1,      0.23225,
0.51004],
         [          0,           -1,             0, …,             0,           -1,
-1]]),
  'y': array([1, 0, 1, …, 0, 0, 1])}}
```

7 Compare all the models

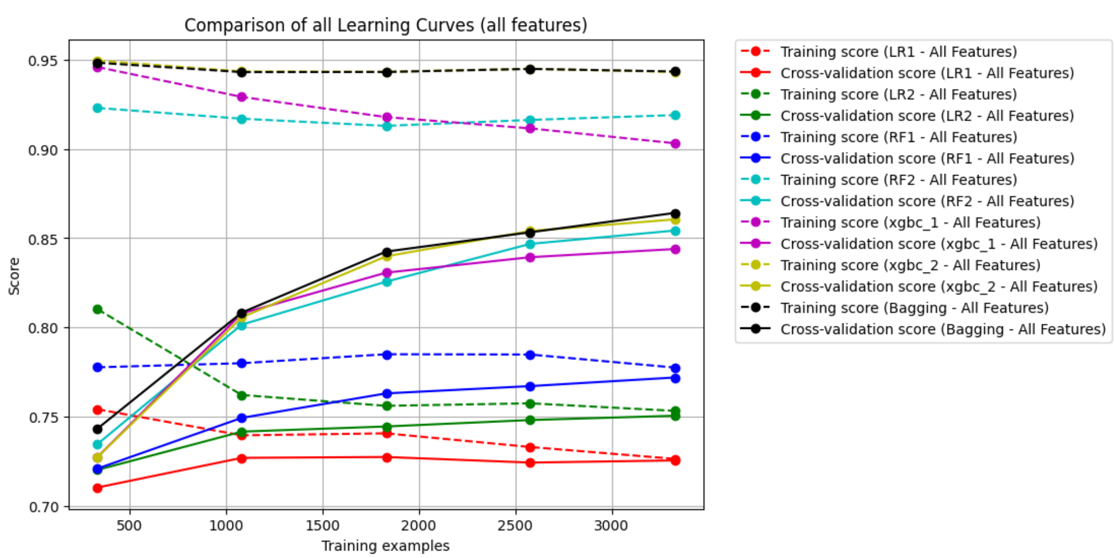
[ ]:
```
data_to_plot_1 = [
        (results_lr_1['all_features']['model'], "LR1 - All Features",␣
 ↪results_lr_1['all_features']['X'], results_lr_1['all_features']['y']),
        (results_lr_2['all_features']['model'], "LR2 - All Features",␣
 ↪results_lr_2['all_features']['X'], results_lr_2['all_features']['y']),
        (results_rf1['all_features']['model'], "RF1 - All Features",␣
 ↪results_rf1['all_features']['X'], results_rf1['all_features']['y']),
        (results_rf2['all_features']['model'], "RF2 - All Features",␣
 ↪results_rf2['all_features']['X'], results_rf2['all_features']['y']),
        (results_xgbc_1['all_features']['model'], "xgbc_1 - All Features",␣
 ↪results_xgbc_1['all_features']['X'], results_xgbc_1['all_features']['y']),
        (results_xgbc_2['all_features']['model'], "xgbc_2 - All Features",␣
 ↪results_xgbc_2['all_features']['X'], results_xgbc_2['all_features']['y']),
        (results_bagging_2['all_features']['model'], "Bagging - All Features",␣
 ↪results_bagging_2['all_features']['X'],␣
 ↪results_bagging_2['all_features']['y'])
]

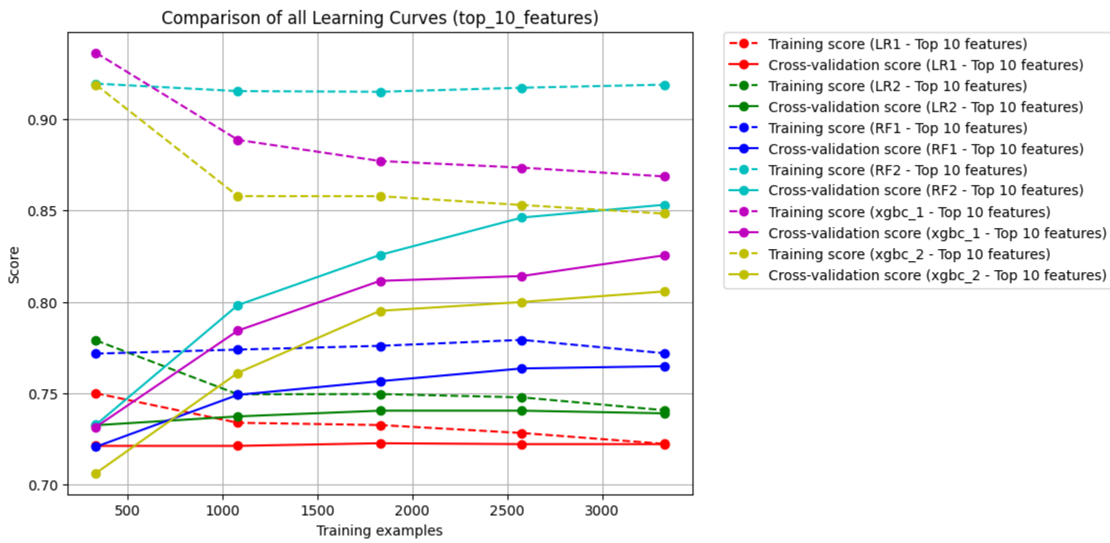
data_to_plot_2 = [
        (results_lr_1['top_10_features']['model'], "LR1 - Top 10 features",␣
 ↪results_lr_1['top_10_features']['X'], results_lr_1['top_10_features']['y']),
```

```
        (results_lr_2['top_10_features']['model'], "LR2 - Top 10 features",␣
↪results_lr_2['top_10_features']['X'], results_lr_2['top_10_features']['y']),
        (results_rf1['top_10_features']['model'], "RF1 - Top 10 features",␣
↪results_rf1['top_10_features']['X'], results_rf1['top_10_features']['y']),
        (results_rf2['top_10_features']['model'], "RF2 - Top 10 features",␣
↪results_rf2['top_10_features']['X'], results_rf2['top_10_features']['y']),
        (results_xgbc_1['top_10_features']['model'], "xgbc_1 - Top 10␣
↪features", results_xgbc_1['top_10_features']['X'],␣
↪results_xgbc_1['top_10_features']['y']),
        (results_xgbc_2['top_10_features']['model'], "xgbc_2 - Top 10␣
↪features", results_xgbc_2['top_10_features']['X'],␣
↪results_xgbc_2['top_10_features']['y'])
]

clf.plot_learning_curve_comparison(data_sets=data_to_plot_1, title="Comparison␣
↪of all Learning Curves (all features)"
)
clf.plot_learning_curve_comparison(data_sets=data_to_plot_2, title="Comparison␣
↪of all Learning Curves (top_10_features)"
)

clf.plot_learning_curve_comparison(data_sets=data_to_plot_1+ data_to_plot_2,␣
↪title="Comparison of all Learning Curves",figsize=(30,15)
)
```





8 General Model Analysis and Conclusion

Our comprehensive analysis of various classification models has provided clear insights into their performance with both the full feature set and the top 10 most relevant features.

Model Performance with All Features Performance with Top 10 Features Logistic Regression Good baseline. Slight performance drop, showing the value of additional features. Random Forest Excellent. Excellent. XGBoost Excellent, often matching or slightly surpassing Random Forest. Excellent, demonstrating robustness with fewer features. BaggingClassifier Excellent. N/A. Ensemble (VotingClassifier) Excellent performance, with a minor improvement over the best individual model. Excellent performance, with a minor improvement over the best individual model. Best Individual Models

Most Powerful Model: XGBoost emerged as the strongest individual classifier. It is a robust, efficient, and highly predictive model that performs consistently well on both the full and reduced feature sets.

Most Efficient Model: The Random Forest is a close second. It offers excellent performance with less implementation complexity and great stability. While XGBoost is marginally better, Random Forest remains a reliable and powerful choice.

The Overall Best Model: The Ensemble

The absolute best model is the VotingClassifier . While individual models like XGBoost were very strong, the ensemble's ability to combine their strengths and compensate for their weaknesses led to a more robust and accurate final prediction.

9 Save Notebook

[22]:
```
os.environ["PATH"] = "/Library/TeX/texbin:" + os.environ["PATH"]
file_manager.save_as_pdf(ipynbname.path())
```

```
[NbConvertApp] Converting notebook /Users/lorenzodimaio/Download/SIDS_revelation
_project/pipeline_terry/classsifier_parameter.ipynb to pdf
[NbConvertApp] Support files will be in /Users/lorenzodimaio/Download/SIDS_revel
ation_project/pipeline_terry/reports/classsifier_parameter(2025-08-29)_files/
[NbConvertApp] Writing 110617 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 2228742 bytes to /Users/lorenzodimaio/Download/SIDS_revel
ation_project/pipeline_terry/reports/classsifier_parameter(2025-08-29).pdf
```