Introduction

Thank you for taking the time to review my **CSCA-5622 project**. This project explores and compares multiple **supervised machine learning techniques** to assess their effectiveness in addressing a **text classification** task within the context of IT support operations.

By way of background, I currently work in the IT field and approached this project as an initial step toward developing a model capable of **automatically classifying IT service requests**. The broader goal is to design a system that can **intelligently route incoming support tickets** to the appropriate personnel or automated agents, thereby streamlining the triage process and improving operational efficiency.

For this study, I selected the publicly available IT Service Ticket Classification Dataset, which contains a labeled corpus of real-world IT support tickets. These tickets closely resemble the types of requests I encounter in my professional environment, making the dataset a relevant choice for this use case. Due to its size (~14 MB), the raw `.csv` file is not included in this repository; however, it can be downloaded directly from the Kaggle link provided for those wishing to replicate or extend this work.

Problem Statement

In enterprise IT environments, service requests vary widely in nature and often require domain-specific expertise for resolution. For instance:

- A systems administrator may be responsible for resolving technical faults related to Infrastructure Component A.

- An AI-driven agent may handle standardized access requests for Platform B.

In the absence of an automated classification system, such tickets must be manually reviewed and routed to the appropriate resolver group. This manual triage process is not only time-consuming but also introduces the risk of misclassification and delayed resolution.

The aim of this project is to investigate how **machine learning models** can be trained to **automatically classify and route IT support tickets** based on their content. This approach has the potential to significantly reduce human intervention, improve accuracy, and accelerate the overall support workflow.

The scope of this project is limited to **supervised learning methods** introduced in this course. Although more complex architectures (e.g., neural networks) may yield further performance gains, this study is intentionally focused on classical supervised learning techniques covered in the curriculum, in order to evaluate their applicability and effectiveness in this domain.

Exploratory Data Analysis

Import Data

```
import pandas as pd

all_tickets = pd.read_csv('all_tickets_processed_improved_v3.csv')
print(all_tickets.head())
print(f"\n{all_tickets.shape[0]} rows and {all_tickets.shape[1]}
columns")
```

```
                                            Document    Topic_group
0  connection with icon icon dear please setup ic...       Hardware
1  work experience user work experience user hi w...         Access
2  requesting for meeting requesting meeting hi p...       Hardware
3  reset passwords for external accounts re expir...         Access
4  mail verification warning hi has got attached ...  Miscellaneous

47837 rows and 2 columns
```

The `all_tickets` DataFrame consists of two key columns:

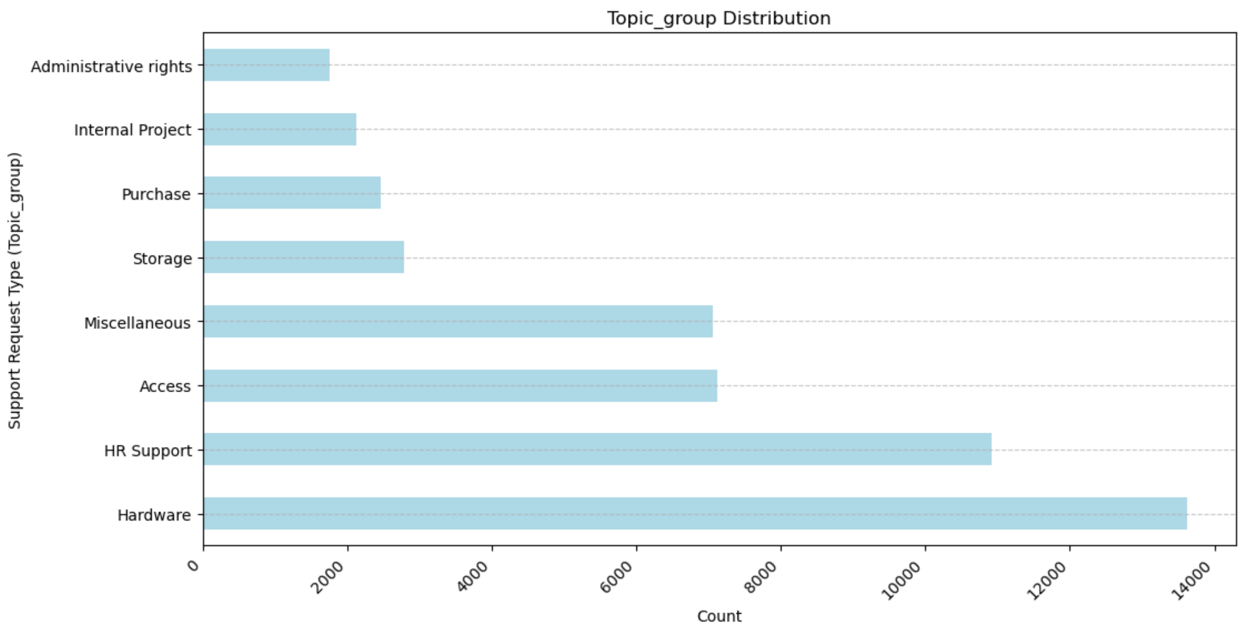
- **`Document`** – containing the textual content of IT support requests.
- **`Topic_group`** – indicating the category or type of each request, which corresponds to the intended routing decision.

In this project, we will approach the classification task as follows:

- Use the text in the `Document` column as the **input features (X)** for our model.
- Use the `Topic_group` column as the **target variable (y)**, representing the classification labels that our model aims to predict.

Distribution of IT Support Request Categories

```
import matplotlib.pyplot as plt

topic_group_counts = all_tickets["Topic_group"].value_counts()

plt.figure(figsize=(12, 6))
topic_group_counts.plot(kind="barh", color='lightblue')
plt.xlabel("Count")
plt.ylabel("Support Request Type (Topic_group)")
plt.title("Topic_group Distribution")
plt.xticks(rotation=45, ha="right")
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```



The distribution of support request categories is imbalanced, with "Hardware" and "HR Support" appearing significantly more frequently than other classes. To maintain consistency and avoid introducing bias, it is important to ensure that both the training and testing datasets reflect this same distribution.

Bag-of-Words Text Representation

We will utilize the Bag-of-Words (BoW) technique for encoding the `Document` text into numerical form.

To give examples from rows 238, 307, and 338 in `all_tickets`:

Row #	`Document` text
238	access re please provide also thanks
307	account for hi please create thank head
338	access great hi please mailbox thank

The Bag-of-Words (BoW) encoding transforms each row of text into a vector where every unique word from the entire corpus is assigned its own column. The values in these columns represent the frequency (i.e., word count) of each word in the corresponding document.

Row #	access	re	please	provide	also	thanks	account	for	hi	create	thank	head	great	mailbox
238	1	1	1	1	1	1	0	0	0	0	0	0	0	0
307	0	0	1	0	0	0	1	1	1	1	1	1	0	0
338	1	0	1	0	0	0	0	0	1	0	1	0	1	1

Data Preparation

Before converting the `Document` column into a bag-of-words matrix, we use the spaCy library to preprocess the text by performing the following steps:

- Tokenization: breaking the text into individual words or tokens
- Stopword removal: filtering out common words like "the", "a", and "an" that carry little meaningful information
- Lemmatization: reducing words to their base or root form (e.g., "running" becomes "run")

These preprocessing steps help improve both the accuracy and efficiency of the model. By eliminating words with low semantic value, we reduce noise in the dataset and allow the model to focus on the more informative terms that are likely to influence classification decisions.

```
import spacy
nlp = spacy.load("en_core_web_sm")

def preprocess_text(text):
    doc = nlp(text.lower())
    cleaned_tokens = [token.lemma_ for token in doc if token.is_alpha
and not token.is_stop]
    return " ".join(cleaned_tokens)

all_tickets["Document"] =
all_tickets["Document"].apply(preprocess_text)
```

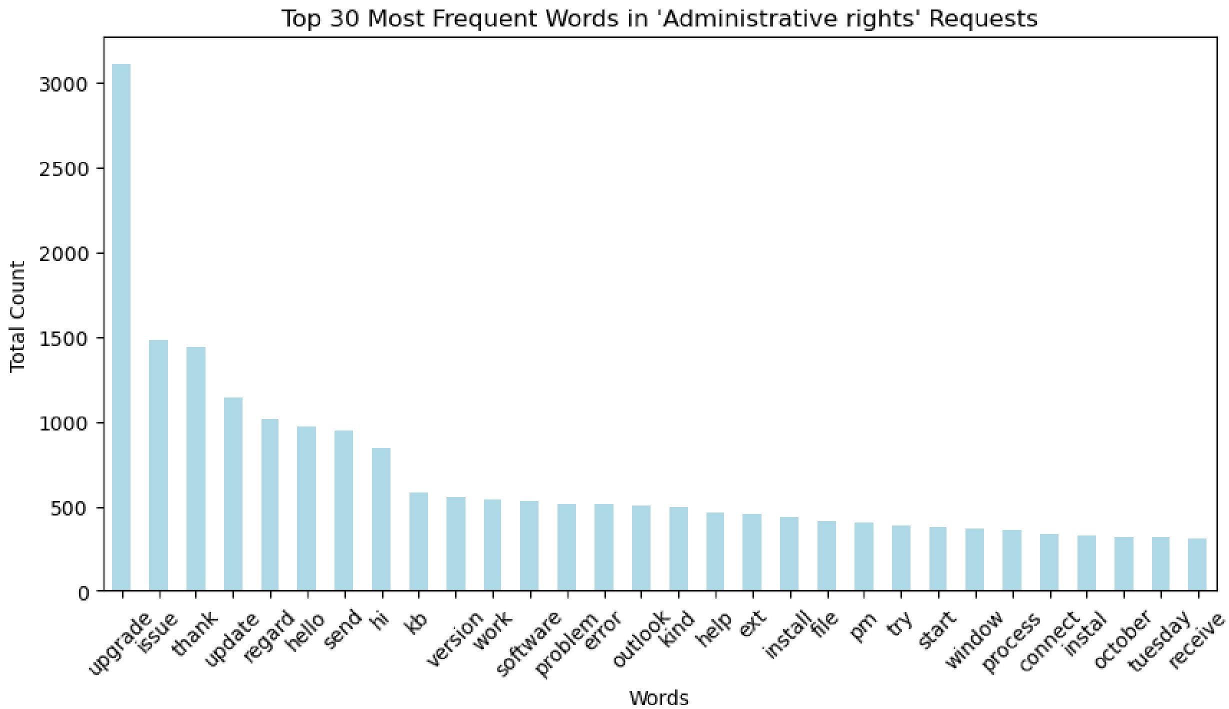
Next, we transform the `Document` column in `all_tickets` into a bag-of-words matrix (X). Then we form a new data frame called `all_tickets_bow_df` rejoining X with the `Topic_group` dependent variable (y).

```
from sklearn.feature_extraction.text import CountVectorizer

# Extract the Document and Topic_group columns from all_tickets
documents = all_tickets["Document"]
y = all_tickets["Topic_group"]

# Apply Bag-of-Words transformation
vectorizer = CountVectorizer(stop_words='english')
bow = vectorizer.fit_transform(documents)
X = pd.DataFrame(bow.toarray(),
columns=vectorizer.get_feature_names_out())

# Rejoin X with y
all_tickets_bow_df = pd.concat([X, y.reset_index(drop=True)], axis=1)
print(f"\n{all_tickets_bow_df.shape[0]} rows and
{all_tickets_bow_df.shape[1]} columns.\n")
```

```
47837 rows and 9298 columns.
```

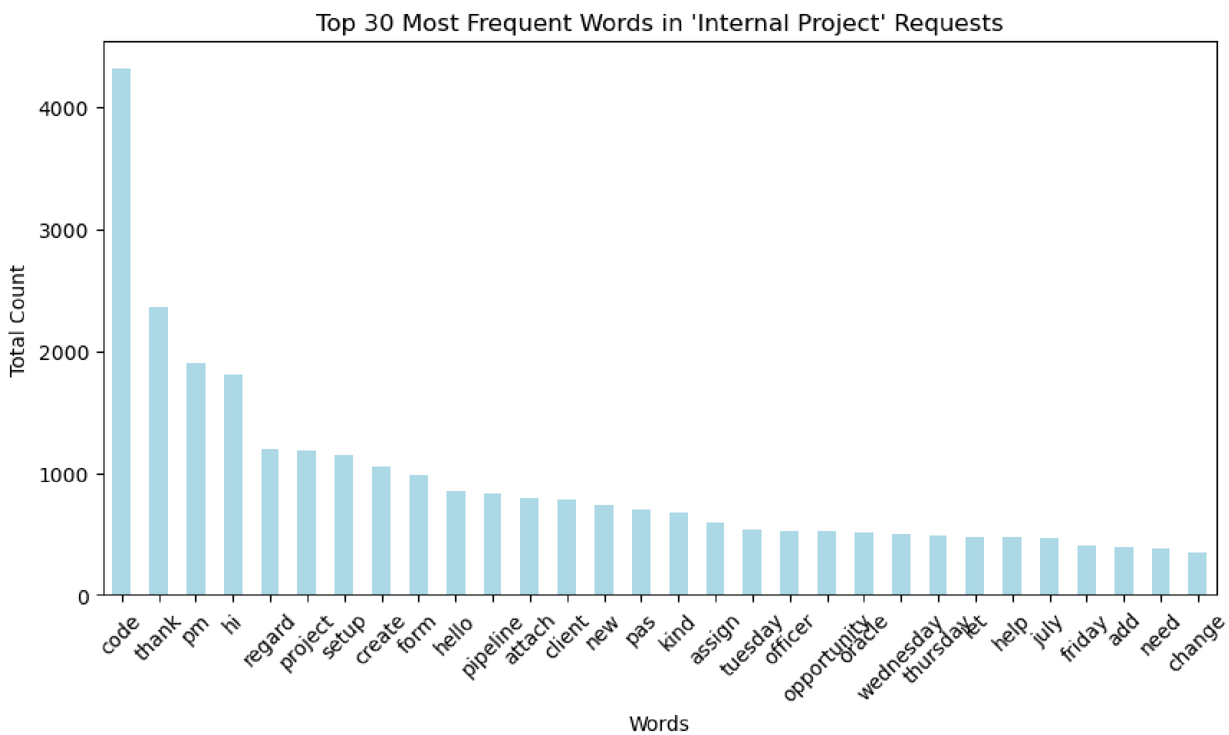
We will examine the 30 most frequent words within each `Topic_group` category. It's worth noting the high occurrence of generic terms such as "hi", "hello", "thank", and "regard", among others. These words are common in support request language but offer limited value for classification, as they appear across multiple categories and do not convey topic-specific meaning.

```
all_tickets_bow_df_Administrative_rights =
all_tickets_bow_df[all_tickets_bow_df["Topic_group"] ==
"Administrative rights"]
word_counts =
all_tickets_bow_df_Administrative_rights.drop(columns=["Topic_group"])
.sum()
top_30_words = word_counts.sort_values(ascending=False).head(30)

import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
top_30_words.plot(kind="bar", color="lightblue")
plt.xlabel("Words")
plt.ylabel("Total Count")
plt.title("Top 30 Most Frequent Words in 'Administrative rights'
Requests")
plt.xticks(rotation=45)
plt.show()

print(top_30_words)
```



upgrade	3111
issue	1483
thank	1439
update	1144
regard	1018
hello	972
send	950
hi	841
kb	578
version	555
work	536
software	530
problem	514
error	512
outlook	504
kind	500
help	465
ext	458
install	437
file	408
pm	399
try	385
start	376
window	366
process	357
connect	335
instal	323

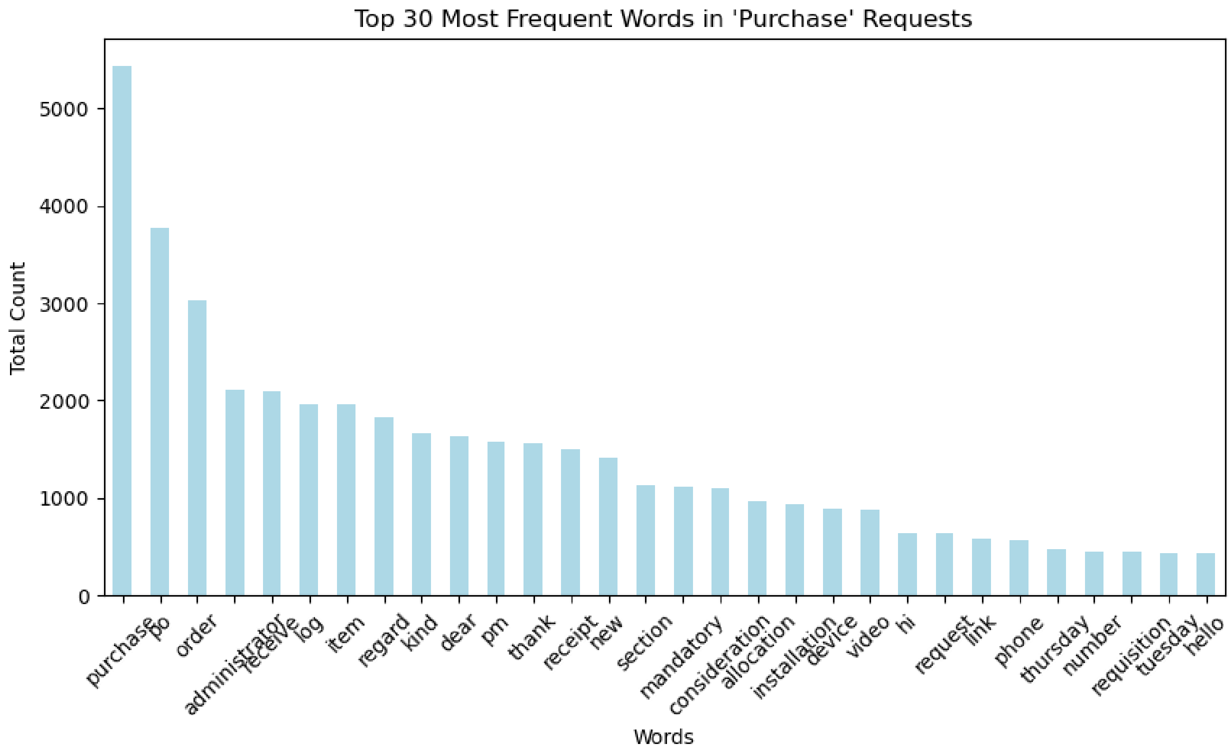
```
october      318
tuesday      317
receive      306
dtype: int64

all_tickets_bow_df_Internal_Project =
all_tickets_bow_df[all_tickets_bow_df["Topic_group"] == "Internal
Project"]
word_counts =
all_tickets_bow_df_Internal_Project.drop(columns=["Topic_group"]).sum(
)
top_30_words = word_counts.sort_values(ascending=False).head(30)

import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
top_30_words.plot(kind="bar", color="lightblue")
plt.xlabel("Words")
plt.ylabel("Total Count")
plt.title("Top 30 Most Frequent Words in 'Internal Project' Requests")
plt.xticks(rotation=45)
plt.show()

print(top_30_words)
```




```
code             4316
thank            2355
```

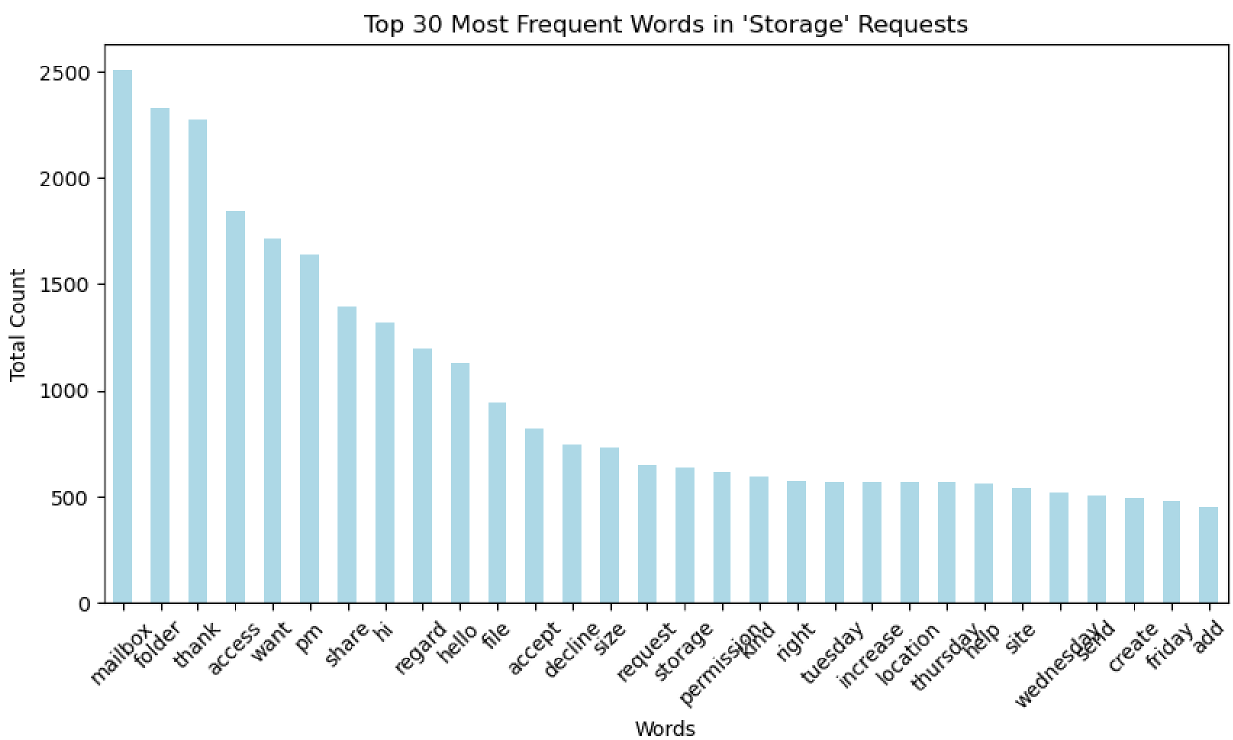
```
pm             1903
hi             1804
regard         1199
project        1181
setup          1147
create         1057
form            978
hello           854
pipeline        835
attach          792
client          784
new             730
pas             699
kind            672
assign          595
tuesday         535
officer         522
opportunity     520
oracle          507
wednesday       495
thursday        486
let             475
help            472
july            470
friday          404
add             388
need            387
change          350
dtype: int64
```

```
all_tickets_bow_df_Purchase =
all_tickets_bow_df[all_tickets_bow_df["Topic_group"] == "Purchase"]
word_counts =
all_tickets_bow_df_Purchase.drop(columns=["Topic_group"]).sum()
top_30_words = word_counts.sort_values(ascending=False).head(30)

import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
top_30_words.plot(kind="bar", color="lightblue")
plt.xlabel("Words")
plt.ylabel("Total Count")
plt.title("Top 30 Most Frequent Words in 'Purchase' Requests")
plt.xticks(rotation=45)
plt.show()

print(top_30_words)
```



purchase	5440
po	3764
order	3031
administrator	2112
receive	2099
log	1967
item	1955
regard	1825
kind	1658
dear	1640
pm	1578
thank	1560
receipt	1502
new	1411
section	1123
mandatory	1115
consideration	1101
allocation	971
installation	931
device	890
video	875
hi	642
request	640
link	577
phone	562
thursday	474

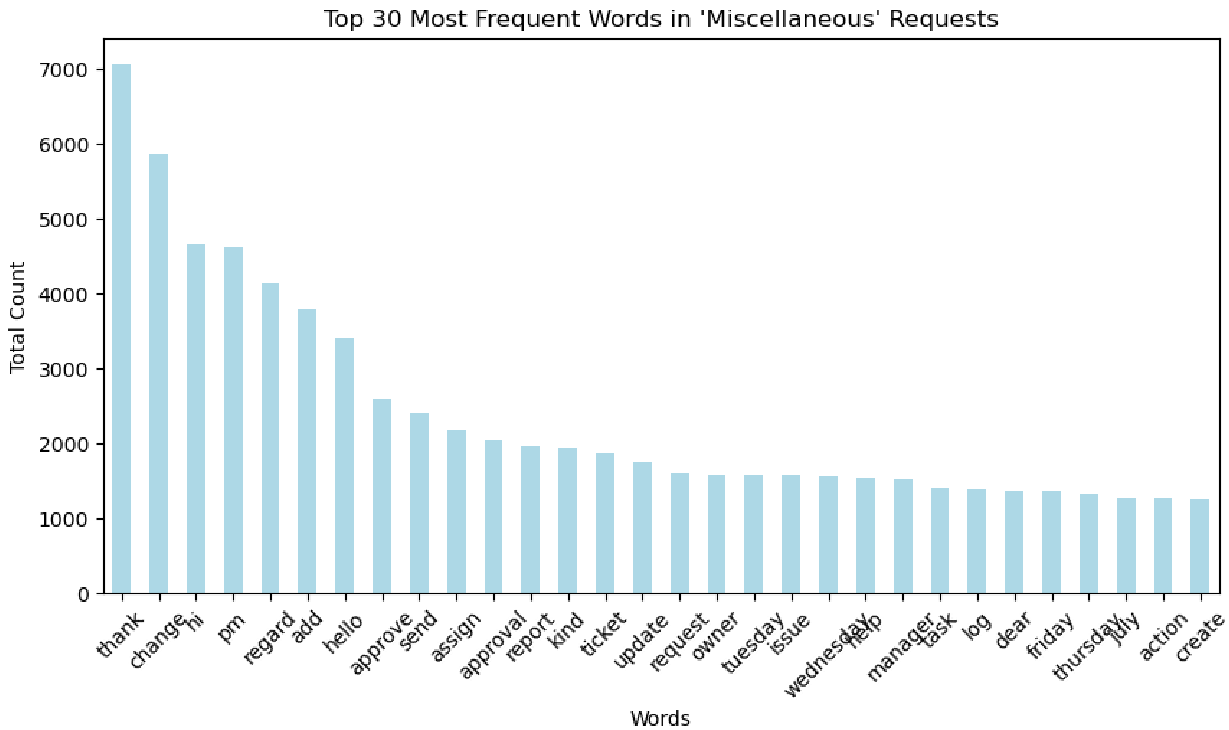
```
number             444
requisition        441
tuesday            439
hello              439
dtype: int64

all_tickets_bow_df_Storage =
all_tickets_bow_df[all_tickets_bow_df["Topic_group"] == "Storage"]
word_counts =
all_tickets_bow_df_Storage.drop(columns=["Topic_group"]).sum()
top_30_words = word_counts.sort_values(ascending=False).head(30)

import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
top_30_words.plot(kind="bar", color="lightblue")
plt.xlabel("Words")
plt.ylabel("Total Count")
plt.title("Top 30 Most Frequent Words in 'Storage' Requests")
plt.xticks(rotation=45)
plt.show()

print(top_30_words)
```




```
mailbox         2503
folder          2326
```

```
thank          2272
access         1843
want           1717
pm             1636
share          1395
hi             1315
regard         1196
hello          1124
file            944
accept          819
decline         747
size            734
request         649
storage         636
permission      615
kind            592
right           575
tuesday         569
increase        567
location        566
thursday        564
help            557
site            540
wednesday       520
send            505
create          491
friday          475
add             453
dtype: int64
```

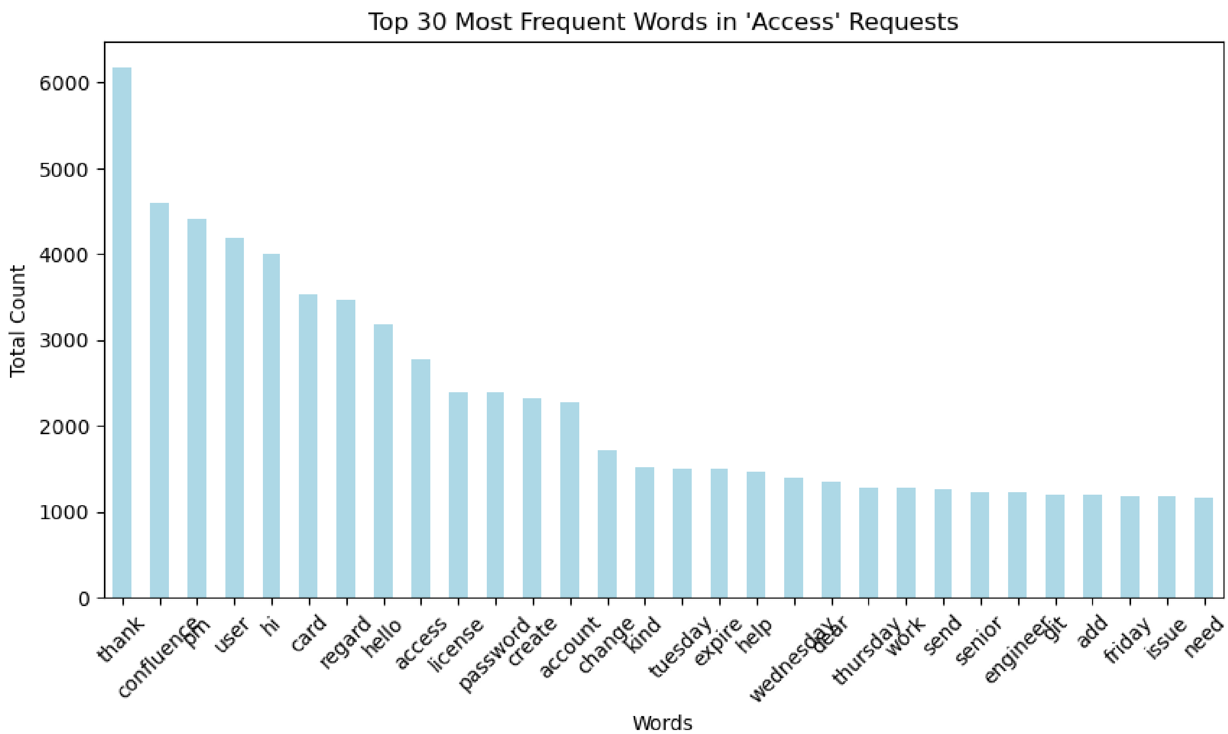
```
all_tickets_bow_df_Miscellaneous =
all_tickets_bow_df[all_tickets_bow_df["Topic_group"] ==
"Miscellaneous"]
word_counts =
all_tickets_bow_df_Miscellaneous.drop(columns=["Topic_group"]).sum()
top_30_words = word_counts.sort_values(ascending=False).head(30)

import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
top_30_words.plot(kind="bar", color="lightblue")
plt.xlabel("Words")
plt.ylabel("Total Count")
plt.title("Top 30 Most Frequent Words in 'Miscellaneous' Requests")
plt.xticks(rotation=45)
plt.show()

print(top_30_words)
```




```
thank          7046
change         5853
hi             4660
pm             4605
regard         4140
add            3778
hello          3405
approve        2597
send           2402
assign         2181
approval       2036
report         1954
kind           1933
ticket         1866
update         1759
request        1592
owner          1571
tuesday        1571
issue          1570
wednesday      1550
help           1540
manager        1518
task           1413
log            1379
dear           1367
friday         1356
thursday       1332
```

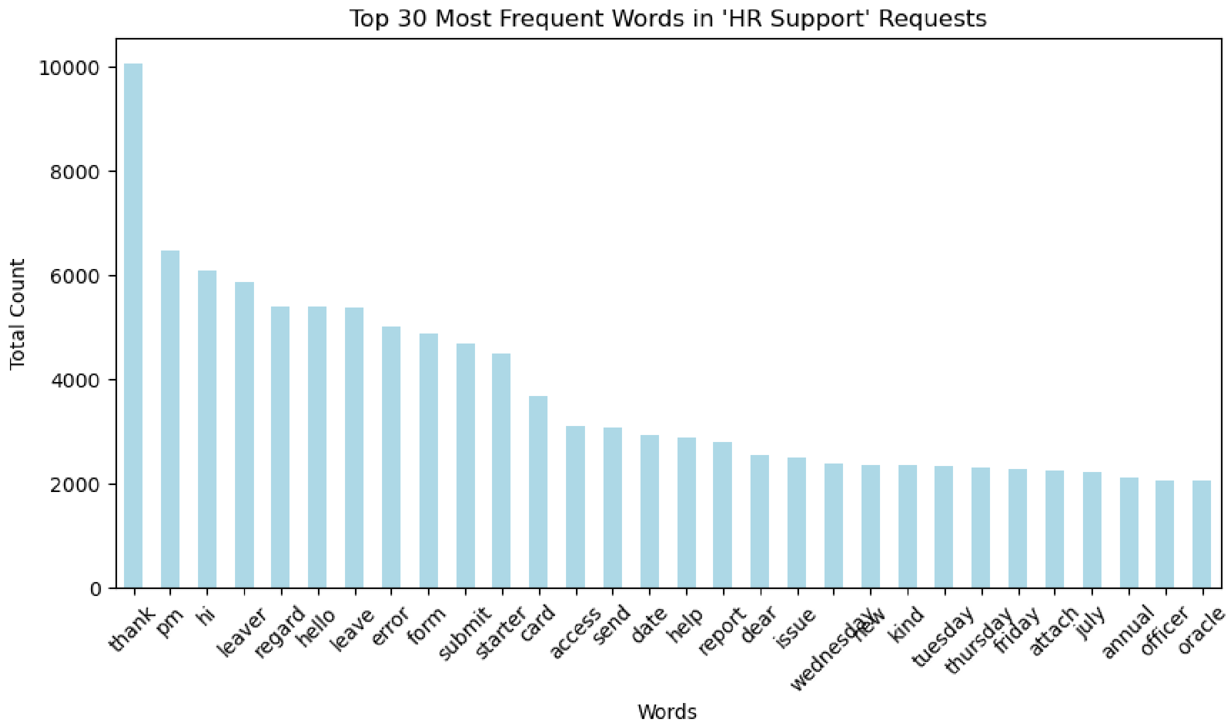
```
july          1276
action        1264
create        1253
dtype: int64
```

```
all_tickets_bow_df_Access =
all_tickets_bow_df[all_tickets_bow_df["Topic_group"] == "Access"]
word_counts =
all_tickets_bow_df_Access.drop(columns=["Topic_group"]).sum()
top_30_words = word_counts.sort_values(ascending=False).head(30)

import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
top_30_words.plot(kind="bar", color="lightblue")
plt.xlabel("Words")
plt.ylabel("Total Count")
plt.title("Top 30 Most Frequent Words in 'Access' Requests")
plt.xticks(rotation=45)
plt.show()

print(top_30_words)
```




```
thank         6166
confluence    4587
pm            4401
```

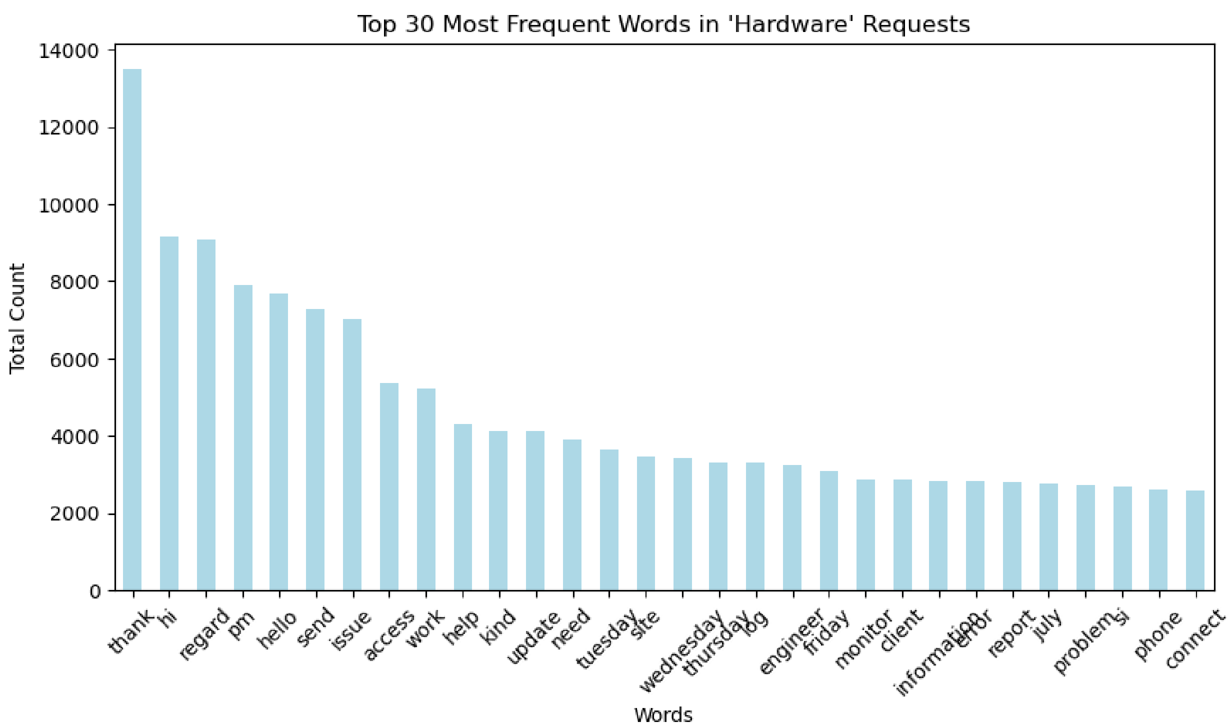
```
user          4186
hi            4001
card          3533
regard        3463
hello         3182
access        2775
license       2395
password      2385
create        2319
account       2277
change        1719
kind          1517
tuesday       1493
expire        1490
help          1470
wednesday     1404
dear          1347
thursday      1284
work          1282
send          1268
senior        1234
engineer      1229
git           1199
add           1199
friday        1186
issue         1177
need          1158
dtype: int64

all_tickets_bow_df_HR_Support =
all_tickets_bow_df[all_tickets_bow_df["Topic_group"] == "HR Support"]
word_counts =
all_tickets_bow_df_HR_Support.drop(columns=["Topic_group"]).sum()
top_30_words = word_counts.sort_values(ascending=False).head(30)

import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
top_30_words.plot(kind="bar", color="lightblue")
plt.xlabel("Words")
plt.ylabel("Total Count")
plt.title("Top 30 Most Frequent Words in 'HR Support' Requests")
plt.xticks(rotation=45)
plt.show()

print(top_30_words)
```



thank	10041
pm	6477
hi	6092
leaver	5859
regard	5397
hello	5383
leave	5358
error	5020
form	4885
submit	4678
starter	4494
card	3667
access	3097
send	3060
date	2945
help	2870
report	2799
dear	2542
issue	2482
wednesday	2374
new	2359
kind	2356
tuesday	2339
thursday	2291
friday	2279
attach	2239
july	2230

```
annual         2113
officer        2065
oracle         2057
dtype: int64
```

```
all_tickets_bow_df_Hardware =
all_tickets_bow_df[all_tickets_bow_df["Topic_group"] == "Hardware"]
word_counts =
all_tickets_bow_df_Hardware.drop(columns=["Topic_group"]).sum()
top_30_words = word_counts.sort_values(ascending=False).head(30)

import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
top_30_words.plot(kind="bar", color="lightblue")
plt.xlabel("Words")
plt.ylabel("Total Count")
plt.title("Top 30 Most Frequent Words in 'Hardware' Requests")
plt.xticks(rotation=45)
plt.show()

print(top_30_words)
```




```
thank          13482
hi              9143
regard          9075
pm              7903
```

```
hello          7666
send           7274
issue          7007
access         5360
work           5238
help           4285
kind           4130
update         4100
need           3883
tuesday        3636
site           3468
wednesday      3413
thursday       3308
log            3302
engineer       3242
friday         3105
monitor        2882
client         2875
information    2833
error          2822
report         2796
july           2767
problem        2734
si             2688
phone          2611
connect        2584
dtype: int64
```

To reduce noise, we'll drop the high-frequency words "hello", "hi", "regard", and "thank" from `all_tickets_bow_df`.

```
all_tickets_bow_df = all_tickets_bow_df.drop(columns=["hi", "hello",
"regard", "thank"])
```

We now split the data into train and test sets. We'll use the `stratify=y` parameter in `train_test_split` to ensure the class distribution in the train and test sets matches the distribution in the original `all_tickets` data.

```
from sklearn.model_selection import train_test_split

X = all_tickets_bow_df.drop(columns=["Topic_group"])
y = all_tickets_bow_df["Topic_group"]

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42, stratify=y)

print(f"Training set: {X_train.shape[0]} rows and {X_train.shape[1]}
columns")
```

```
print(f"Test set: {X_test.shape[0]} rows and {X_test.shape[1]}
columns")
```

```
Training set: 38269 rows and 9293 columns
Test set: 9568 rows and 9293 columns
```

Model Building and Analysis

Logistic Regression (unweighted)

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

log_reg_unweighted = LogisticRegression(max_iter=1000,
random_state=42)
log_reg_unweighted.fit(X_train, y_train)
y_pred_log_reg_unweighted = log_reg_unweighted.predict(X_test)

print("Logistic Regression Performance:")
print(f"Accuracy: {accuracy_score(y_test,
y_pred_log_reg_unweighted):.4f}")
print("\nClassification Report:\n", classification_report(y_test,
y_pred_log_reg_unweighted))
```

```
Logistic Regression Performance:
Accuracy: 0.8336

Classification Report:
                        precision    recall  f1-score   support

                Access       0.88      0.88      0.88      1425
 Administrative rights       0.79      0.70      0.74       352
            HR Support       0.83      0.84      0.84      2183
              Hardware       0.80      0.82      0.81      2724
      Internal Project       0.87      0.84      0.85       424
         Miscellaneous       0.79      0.79      0.79      1412
              Purchase       0.95      0.88      0.92       493
               Storage       0.88      0.88      0.88       555

              accuracy                           0.83      9568
             macro avg       0.85      0.83      0.84      9568
          weighted avg       0.83      0.83      0.83      9568
```

Logistic Regression (weighted)

```
log_reg_weighted = LogisticRegression(max_iter=1000, random_state=42,
class_weight='balanced')
log_reg_weighted.fit(X_train, y_train)
y_pred_log_reg_weighted = log_reg_weighted.predict(X_test)
```

```
print("Logistic Regression Performance:")
print(f"Accuracy: {accuracy_score(y_test,
y_pred_log_reg_weighted):.4f}")
print("\nClassification Report:\n", classification_report(y_test,
y_pred_log_reg_weighted))
```

```
Logistic Regression Performance:
Accuracy: 0.8272

Classification Report:
                         precision    recall  f1-score   support

                 Access       0.87      0.89      0.88      1425
Administrative rights       0.63      0.80      0.71       352
             HR Support       0.85      0.83      0.84      2183
               Hardware       0.85      0.76      0.80      2724
       Internal Project       0.77      0.90      0.83       424
          Miscellaneous       0.77      0.82      0.80      1412
               Purchase       0.89      0.91      0.90       493
                Storage       0.84      0.91      0.87       555

               accuracy                           0.83      9568
              macro avg       0.81      0.85      0.83      9568
           weighted avg       0.83      0.83      0.83      9568
```

KNN

```
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred_knn = knn.predict(X_test)

print("KNN Performance:")
print(f"Accuracy: {accuracy_score(y_test, y_pred_knn):.4f}")
print("\nClassification Report:\n", classification_report(y_test,
y_pred_knn))
```

```
KNN Performance:
Accuracy: 0.7181

Classification Report:
                         precision    recall  f1-score   support

                 Access       0.76      0.81      0.79      1425
Administrative rights       0.59      0.52      0.55       352
             HR Support       0.59      0.88      0.71      2183
               Hardware       0.80      0.62      0.70      2724
       Internal Project       0.80      0.67      0.73       424
```

```
      Miscellaneous       0.74      0.59      0.66      1412
           Purchase       0.95      0.84      0.89       493
            Storage       0.85      0.72      0.78       555

           accuracy                           0.72      9568
          macro avg       0.76      0.71      0.72      9568
       weighted avg       0.74      0.72      0.72      9568
```

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier

dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)

print("Decision Tree Performance:")
print(f"Accuracy: {accuracy_score(y_test, y_pred_dt):.4f}")
print("\nClassification Report:\n", classification_report(y_test,
y_pred_dt))
```

```
Decision Tree Performance:
Accuracy: 0.7652

Classification Report:
                        precision    recall  f1-score   support

               Access       0.83      0.84      0.84      1425
Administrative rights       0.73      0.68      0.71       352
           HR Support       0.79      0.78      0.78      2183
             Hardware       0.74      0.74      0.74      2724
     Internal Project       0.73      0.77      0.75       424
        Miscellaneous       0.69      0.71      0.70      1412
             Purchase       0.88      0.83      0.85       493
              Storage       0.82      0.77      0.80       555

             accuracy                           0.77      9568
            macro avg       0.77      0.77      0.77      9568
         weighted avg       0.77      0.77      0.77      9568
```

Random Forest (100 estimators)

```
from sklearn.ensemble import RandomForestClassifier

rf1 = RandomForestClassifier(n_estimators=100, random_state=42)
rf1.fit(X_train, y_train)
y_pred_rf1 = rf1.predict(X_test)
```

```python
print("Random Forest Performance:")
print(f"Accuracy: {accuracy_score(y_test, y_pred_rf1):.4f}")
print("\nClassification Report:\n", classification_report(y_test,
y_pred_rf1))
```

```
Random Forest Performance:
Accuracy: 0.8314

Classification Report:
                          precision    recall  f1-score   support

                 Access       0.88      0.86      0.87      1425
Administrative rights       0.92      0.59      0.72       352
             HR Support       0.83      0.86      0.85      2183
               Hardware       0.77      0.87      0.81      2724
       Internal Project       0.89      0.80      0.85       424
          Miscellaneous       0.81      0.76      0.79      1412
               Purchase       0.97      0.86      0.91       493
                Storage       0.94      0.81      0.87       555

               accuracy                           0.83      9568
              macro avg       0.88      0.80      0.83      9568
           weighted avg       0.84      0.83      0.83      9568
```

Random Forest (300 estimators)

```python
rf2 = RandomForestClassifier(n_estimators=300, random_state=42)
rf2.fit(X_train, y_train)
y_pred_rf2 = rf2.predict(X_test)

print("Random Forest Performance:")
print(f"Accuracy: {accuracy_score(y_test, y_pred_rf2):.4f}")
print("\nClassification Report:\n", classification_report(y_test,
y_pred_rf2))
```

```
Random Forest Performance:
Accuracy: 0.8378

Classification Report:
                          precision    recall  f1-score   support

                 Access       0.90      0.86      0.88      1425
Administrative rights       0.94      0.59      0.73       352
             HR Support       0.85      0.86      0.85      2183
               Hardware       0.77      0.88      0.82      2724
       Internal Project       0.89      0.80      0.84       424
          Miscellaneous       0.81      0.78      0.79      1412
               Purchase       0.96      0.86      0.91       493
                Storage       0.94      0.81      0.87       555
```

```
              accuracy                           0.84      9568
             macro avg       0.88      0.80      0.84      9568
          weighted avg       0.84      0.84      0.84      9568
```

Random Forest (600 estimators)

```
rf3 = RandomForestClassifier(n_estimators=600, random_state=42)
rf3.fit(X_train, y_train)
y_pred_rf3 = rf3.predict(X_test)

print("Random Forest Performance:")
print(f"Accuracy: {accuracy_score(y_test, y_pred_rf3):.4f}")
print("\nClassification Report:\n", classification_report(y_test, 
y_pred_rf3))
```

```
Random Forest Performance:
Accuracy: 0.8424

Classification Report:
                         precision    recall  f1-score   support

                Access       0.90      0.87      0.89      1425
Administrative rights       0.92      0.64      0.75       352
            HR Support       0.85      0.87      0.86      2183
              Hardware       0.78      0.88      0.83      2724
      Internal Project       0.89      0.79      0.84       424
         Miscellaneous       0.81      0.78      0.79      1412
              Purchase       0.96      0.86      0.91       493
               Storage       0.94      0.81      0.87       555

              accuracy                           0.84      9568
             macro avg       0.88      0.81      0.84      9568
          weighted avg       0.85      0.84      0.84      9568
```

Support Vector Machine (linear)

```
from sklearn.svm import SVC

svm_linear = SVC(kernel="linear", random_state=42)
svm_linear.fit(X_train, y_train)
y_pred_svm_linear = svm_linear.predict(X_test)

print("SVM Performance:")
print(f"Accuracy: {accuracy_score(y_test, y_pred_svm_linear):.4f}")
print("\nClassification Report:\n", classification_report(y_test, 
y_pred_svm_linear))
```

```
SVM Performance:
Accuracy: 0.8308

Classification Report:
                        precision    recall  f1-score   support

                Access       0.86      0.90      0.88      1425
Administrative rights       0.77      0.72      0.74       352
            HR Support       0.81      0.85      0.83      2183
              Hardware       0.82      0.81      0.82      2724
      Internal Project       0.86      0.83      0.85       424
         Miscellaneous       0.80      0.77      0.78      1412
              Purchase       0.93      0.90      0.92       493
               Storage       0.89      0.86      0.87       555

              accuracy                           0.83      9568
             macro avg       0.84      0.83      0.84      9568
          weighted avg       0.83      0.83      0.83      9568
```

Support Vector Machine (RBF kernel)

```
from sklearn.svm import SVC

svm_rbf = SVC(kernel="rbf", random_state=42)
svm_rbf.fit(X_train, y_train)
y_pred_svm_rbf = svm_rbf.predict(X_test)

print("SVM Performance (RBF):")
print(f"Accuracy: {accuracy_score(y_test, y_pred_svm_rbf):.4f}")
print("\nClassification Report:\n", classification_report(y_test, 
y_pred_svm_rbf))
```

```
SVM Performance (RBF):
Accuracy: 0.8304

Classification Report:
                        precision    recall  f1-score   support

                Access       0.89      0.85      0.87      1425
Administrative rights       0.90      0.59      0.71       352
            HR Support       0.84      0.85      0.85      2183
              Hardware       0.75      0.88      0.81      2724
      Internal Project       0.89      0.75      0.82       424
         Miscellaneous       0.83      0.76      0.79      1412
              Purchase       0.97      0.87      0.92       493
               Storage       0.93      0.81      0.86       555

              accuracy                           0.83      9568
             macro avg       0.88      0.80      0.83      9568
```

```
    weighted avg       0.84      0.83      0.83      9568
```

AdaBoost (100 estimators)

```python
from sklearn.ensemble import AdaBoostClassifier

adaboost1 = AdaBoostClassifier(n_estimators=100, random_state=42)
adaboost1.fit(X_train, y_train)
y_pred_ab1 = adaboost1.predict(X_test)

print("AdaBoost Performance:")
print(f"Accuracy: {accuracy_score(y_test, y_pred_ab1):.4f}")
print("\nClassification Report:\n", classification_report(y_test,
y_pred_ab1))
```

```
AdaBoost Performance:
Accuracy: 0.4278

Classification Report:
                         precision    recall  f1-score   support

                 Access       0.90      0.13      0.23      1425
Administrative rights       0.80      0.19      0.31       352
             HR Support       0.72      0.27      0.40      2183
               Hardware       0.34      0.93      0.50      2724
      Internal Project       0.80      0.46      0.59       424
         Miscellaneous       0.25      0.06      0.10      1412
               Purchase       0.97      0.66      0.79       493
                Storage       0.83      0.17      0.28       555

               accuracy                           0.43      9568
              macro avg       0.70      0.36      0.40      9568
           weighted avg       0.60      0.43      0.38      9568
```

AdaBoost (300 estimators)

```python
base_estimator = DecisionTreeClassifier(max_depth=3, random_state=42)
adaboost2 = AdaBoostClassifier(estimator=base_estimator,
n_estimators=300, random_state=42)
adaboost2.fit(X_train, y_train)
y_pred_ab2 = adaboost2.predict(X_test)


print("AdaBoost Performance:")
print(f"Accuracy: {accuracy_score(y_test, y_pred_ab2):.4f}")
print("\nClassification Report:\n", classification_report(y_test,
y_pred_ab2))
```

```
AdaBoost Performance:
Accuracy: 0.7240

Classification Report:
                         precision    recall  f1-score   support

                 Access       0.84      0.72      0.78      1425
  Administrative rights       0.78      0.62      0.69       352
             HR Support       0.78      0.70      0.74      2183
               Hardware       0.60      0.81      0.69      2724
       Internal Project       0.76      0.76      0.76       424
          Miscellaneous       0.71      0.56      0.62      1412
               Purchase       0.94      0.85      0.89       493
                Storage       0.90      0.73      0.81       555

               accuracy                           0.72      9568
              macro avg       0.79      0.72      0.75      9568
           weighted avg       0.74      0.72      0.73      9568
```

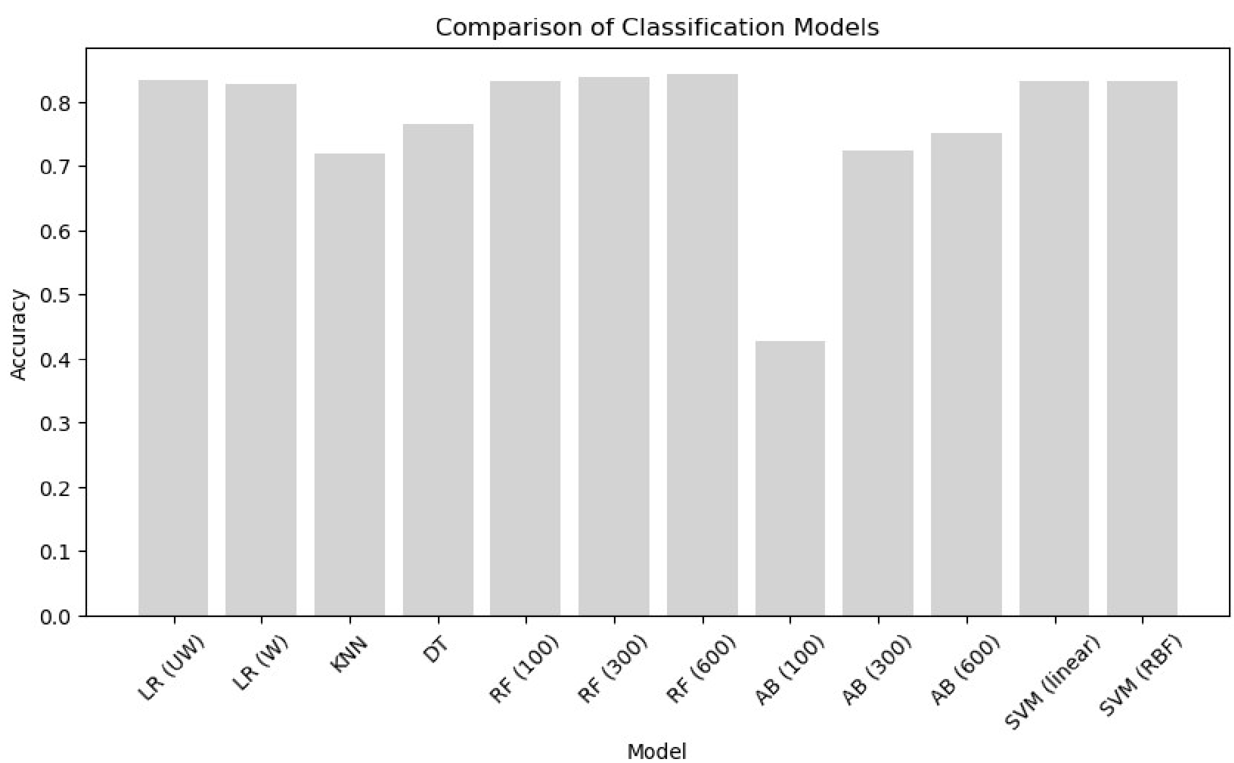
AdaBoost (600 estimators)

```
base_estimator = DecisionTreeClassifier(max_depth=4, random_state=42)
adaboost3 = AdaBoostClassifier(estimator=base_estimator,
n_estimators=600, random_state=42)
adaboost3.fit(X_train, y_train)
y_pred_ab3 = adaboost3.predict(X_test)

print("AdaBoost Performance:")
print(f"Accuracy: {accuracy_score(y_test, y_pred_ab3):.4f}")
print("\nClassification Report:\n", classification_report(y_test,
y_pred_ab3))
```

```
AdaBoost Performance:
Accuracy: 0.7504

Classification Report:
                         precision    recall  f1-score   support

                 Access       0.84      0.78      0.81      1425
  Administrative rights       0.66      0.68      0.67       352
             HR Support       0.81      0.75      0.78      2183
               Hardware       0.67      0.76      0.72      2724
       Internal Project       0.63      0.85      0.72       424
          Miscellaneous       0.76      0.61      0.68      1412
               Purchase       0.85      0.88      0.86       493
                Storage       0.84      0.79      0.82       555

               accuracy                           0.75      9568
              macro avg       0.76      0.76      0.76      9568
```

```
            weighted avg       0.76      0.75      0.75      9568
```

```python
model_scores = {
    "LR (UW)": accuracy_score(y_test, y_pred_log_reg_unweighted),
    "LR (W)": accuracy_score(y_test, y_pred_log_reg_weighted),
    "KNN": accuracy_score(y_test, y_pred_knn),
    "DT": accuracy_score(y_test, y_pred_dt),
    "RF (100)": accuracy_score(y_test, y_pred_rf1),
    "RF (300)": accuracy_score(y_test, y_pred_rf2),
    "RF (600)": accuracy_score(y_test, y_pred_rf3),
    "AB (100)": accuracy_score(y_test, y_pred_ab1),
    "AB (300)": accuracy_score(y_test, y_pred_ab2),
    "AB (600)": accuracy_score(y_test, y_pred_ab3),
    "SVM (linear)": accuracy_score(y_test, y_pred_svm_linear),
    "SVM (RBF)": accuracy_score(y_test, y_pred_svm_rbf)
}

plt.figure(figsize=(10, 5))
plt.bar(model_scores.keys(), model_scores.values(), color="lightgrey")
plt.xlabel("Model")
plt.ylabel("Accuracy")
plt.title("Comparison of Classification Models")
plt.xticks(rotation=45)
plt.show()
```



Model Training Time (mac M1 processor - single core utilization)

Model	Training Time
Logistic Regression (unweighted)	1 minute 37 seconds
Logistic Regression (weighted)	1 minute 19 seconds
KNN	1 minute 4 seconds
Decision Tree	23 seconds
Random Forest (100 estimators)	1 minute 23 seconds
Random Forest (300 estimators)	3 minutes 59 seconds
Random Forest (600 estimators)	7 minutes 55 seconds
Support Vector Machine (linear)	28 minutes 46 seconds
Support Vector Machine (RBF kernel)	49 minutes 52 seconds
AdaBoost (100 estimators)	3 minutes 17 seconds
AdaBoost (300 estimators)	16 minutes 4 seconds
AdaBoost (600 estimators)	39 minutes 31 seconds

Reflections on Model Performance

Among the models evaluated, **Logistic Regression** performed notably well, achieving an accuracy of **83.3%**, which was nearly equivalent to the best-performing model—**Random Forest**. This outcome is particularly striking given the simplicity of Logistic Regression, suggesting that a linear decision boundary is sufficient to capture a significant portion of the underlying patterns in the data. Additionally, Logistic Regression offered the advantage of **fast training time** (approximately 1.5 minutes), making it a practical choice for rapid iteration.

A significant challenge in this project was the **high dimensionality** of the dataset, with nearly **10,000 bag-of-words features**. This complexity likely impacted the performance of **Support Vector Machines (SVM)**, both with linear and RBF kernels. Training times were substantial—around **29 minutes for the linear SVM** and nearly **50 minutes for the RBF variant**—making them less viable for experimentation in this context.

The performance of **AdaBoost** was unexpectedly low, with a maximum accuracy of only **~75%**. Given that AdaBoost is built on decision trees, it was initially assumed to perform comparably to Random Forest. However, its reliance on boosting weak learners may be less effective in a high-dimensional feature space, where simple decision stumps are insufficient for capturing complex patterns. Despite increasing the number of learners and the maximum depth (up to 300 learners), improvements were marginal. Further increasing model complexity could enhance performance, but this comes at the cost of significantly higher computational demands—placing AdaBoost among the most resource-intensive models tested, alongside SVM.

Random Forest, on the other hand, emerged as the top performer, balancing accuracy and interpretability. Given its strong results, it was selected for further hyperparameter tuning in the subsequent phase of the project.

Hyperparameter Tuning for Random Forest

Given that the Random Forest model achieved the highest accuracy in the initial evaluation, I proceeded to explore **hyperparameter tuning** to determine whether performance could be further optimized. Specifically, I focused on the impact of **limiting tree depth**, hypothesizing that unrestricted tree growth may lead to **overfitting**, reducing the model's generalization to unseen data.

The earlier `rf3` model was trained with the default setting `max_depth=None`, allowing trees to grow until nodes are pure (i.e., each leaf contains only a single class). While this can increase training accuracy, it often results in models that are overly complex and prone to overfitting. To address this, I tested whether **constraining the depth** of the trees could improve model generalization.

To evaluate this, I conducted a **grid search** over a range of hyperparameters, with particular focus on varying tree depth. The grid search included the following parameters:

- **n_estimators**: Number of trees in the ensemble.
- **max_depth**: Maximum depth of each tree (tested at 10, 20, and 30).
- **min_samples_split**: Minimum number of samples required to split an internal node.
- **min_samples_leaf**: Minimum number of samples required to be present at a leaf node.

The grid search was performed using **3-fold cross-validation** on the training set to assess how different combinations of these hyperparameters influenced model performance. The primary goal was to test the hypothesis that limiting tree depth could reduce overfitting and lead to better validation accuracy.

```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

rf_param_grid = {
    'n_estimators': [600, 800, 1000],
    'max_depth': [10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

rf = RandomForestClassifier(random_state=42, n_jobs=-1)
rf_grid_search = GridSearchCV(estimator=rf, param_grid=rf_param_grid,
                              cv=3, verbose=2, n_jobs=-1)
rf_grid_search.fit(X_train, y_train)

print("Best Parameters:", rf_grid_search.best_params_)
print("Best Accuracy:", rf_grid_search.best_score_)
```

```
Fitting 3 folds for each of 81 candidates, totalling 243 fits
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=2,
```

```
n_estimators=600; total time= 1.3min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=2,
n_estimators=600; total time= 1.3min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=2,
n_estimators=600; total time= 1.3min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=5,
n_estimators=600; total time= 1.4min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=2,
n_estimators=800; total time= 1.5min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=2,
n_estimators=800; total time= 1.5min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=2,
n_estimators=800; total time= 1.5min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=2,
n_estimators=1000; total time= 1.6min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=2,
n_estimators=1000; total time= 1.6min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=2,
n_estimators=1000; total time= 1.6min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=5,
n_estimators=600; total time=  57.5s
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=5,
n_estimators=600; total time=  57.6s
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=5,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=5,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=5,
n_estimators=800; total time= 1.0min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=10,
n_estimators=600; total time=  58.3s
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=10,
n_estimators=600; total time= 1.0min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=5,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=5,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=5,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=10,
n_estimators=600; total time=  41.7s
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=10,
n_estimators=800; total time=  55.9s
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=10,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=10,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=2,
n_estimators=600; total time=  55.4s
```

```
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=2,
n_estimators=600; total time=  57.1s
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=2,
n_estimators=600; total time=  55.8s
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=10,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=10,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=1, min_samples_split=10,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=2,
n_estimators=800; total time=  58.3s
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=2,
n_estimators=800; total time=  51.7s
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=2,
n_estimators=800; total time= 1.0min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=5,
n_estimators=600; total time=  58.5s
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=5,
n_estimators=600; total time=  55.1s
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=5,
n_estimators=600; total time=  57.5s
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=2,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=5,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=2,
n_estimators=1000; total time= 1.3min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=2,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=5,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=5,
n_estimators=800; total time= 1.0min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=5,
n_estimators=1000; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=10,
n_estimators=600; total time=  59.5s
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=10,
n_estimators=600; total time=  59.0s
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=10,
n_estimators=600; total time=  58.5s
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=5,
n_estimators=1000; total time= 1.3min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=10,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=10,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=5,
```

```
n_estimators=1000; total time= 1.3min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=10,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=10,
n_estimators=1000; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=2,
n_estimators=600; total time=  58.4s
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=2,
n_estimators=600; total time=  56.7s
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=2,
n_estimators=600; total time=  55.9s
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=10,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=2, min_samples_split=10,
n_estimators=1000; total time= 1.3min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=2,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=2,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=2,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=2,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=2,
n_estimators=1000; total time= 1.4min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=5,
n_estimators=600; total time=  56.8s
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=5,
n_estimators=600; total time=  55.6s
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=5,
n_estimators=600; total time=  59.4s
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=2,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=5,
n_estimators=800; total time= 1.0min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=5,
n_estimators=800; total time= 1.0min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=5,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=5,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=5,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=10,
n_estimators=600; total time=  43.3s
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=10,
n_estimators=600; total time=  54.0s
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=10,
n_estimators=600; total time=  52.3s
```

```
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=5,
n_estimators=1000; total time= 1.2min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=10,
n_estimators=800; total time= 1.0min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=10,
n_estimators=800; total time= 1.0min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=10,
n_estimators=800; total time= 1.1min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=10,
n_estimators=1000; total time= 1.4min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=10,
n_estimators=1000; total time= 1.3min
[CV] END max_depth=10, min_samples_leaf=4, min_samples_split=10,
n_estimators=1000; total time= 1.3min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=2,
n_estimators=600; total time= 2.1min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=2,
n_estimators=600; total time= 2.1min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=2,
n_estimators=600; total time= 2.1min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=2,
n_estimators=800; total time= 2.6min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=2,
n_estimators=800; total time= 2.9min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=2,
n_estimators=800; total time= 2.9min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=5,
n_estimators=600; total time= 2.3min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=2,
n_estimators=1000; total time= 3.3min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=5,
n_estimators=600; total time= 2.0min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=2,
n_estimators=1000; total time= 3.2min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=5,
n_estimators=600; total time= 2.0min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=2,
n_estimators=1000; total time= 3.3min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=5,
n_estimators=800; total time= 2.7min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=5,
n_estimators=800; total time= 3.0min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=10,
n_estimators=600; total time= 2.3min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=5,
n_estimators=800; total time= 3.0min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=10,
n_estimators=600; total time= 2.3min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=5,
```

```
n_estimators=1000; total time= 3.1min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=10,
n_estimators=600; total time= 2.2min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=5,
n_estimators=1000; total time= 3.2min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=10,
n_estimators=800; total time= 2.9min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=5,
n_estimators=1000; total time= 3.4min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=10,
n_estimators=800; total time= 3.0min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=2,
n_estimators=600; total time= 2.2min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=10,
n_estimators=800; total time= 2.9min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=2,
n_estimators=600; total time= 2.3min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=2,
n_estimators=600; total time= 2.3min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=10,
n_estimators=1000; total time= 3.4min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=10,
n_estimators=1000; total time= 3.5min
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=10,
n_estimators=1000; total time= 3.5min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=2,
n_estimators=800; total time= 2.8min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=2,
n_estimators=800; total time= 2.9min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=2,
n_estimators=800; total time= 3.1min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=2,
n_estimators=1000; total time= 3.0min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=5,
n_estimators=600; total time= 2.8min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=2,
n_estimators=1000; total time= 3.0min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=5,
n_estimators=600; total time= 2.0min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=2,
n_estimators=1000; total time= 3.0min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=5,
n_estimators=600; total time= 2.0min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=5,
n_estimators=800; total time= 2.4min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=5,
n_estimators=800; total time= 2.8min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=5,
n_estimators=800; total time= 2.9min
```

```
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=10,
n_estimators=600; total time= 2.1min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=10,
n_estimators=600; total time= 2.1min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=10,
n_estimators=600; total time= 2.2min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=5,
n_estimators=1000; total time= 3.1min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=10,
n_estimators=800; total time= 2.5min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=5,
n_estimators=1000; total time= 2.8min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=5,
n_estimators=1000; total time= 2.8min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=10,
n_estimators=800; total time= 2.6min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=10,
n_estimators=800; total time= 3.0min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=2,
n_estimators=600; total time= 2.0min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=10,
n_estimators=1000; total time= 3.3min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=2,
n_estimators=600; total time= 2.2min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=2,
n_estimators=600; total time= 1.9min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=10,
n_estimators=1000; total time= 2.8min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=2,
n_estimators=800; total time= 2.4min
[CV] END max_depth=20, min_samples_leaf=2, min_samples_split=10,
n_estimators=1000; total time= 3.1min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=2,
n_estimators=800; total time= 2.7min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=2,
n_estimators=800; total time= 3.4min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=5,
n_estimators=600; total time= 2.2min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=5,
n_estimators=600; total time= 2.2min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=2,
n_estimators=1000; total time= 2.6min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=2,
n_estimators=1000; total time= 2.6min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=5,
n_estimators=600; total time= 1.9min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=2,
n_estimators=1000; total time= 2.6min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=5,
```

```
n_estimators=800; total time= 2.5min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=5,
n_estimators=800; total time= 2.5min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=5,
n_estimators=800; total time= 2.6min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=10,
n_estimators=600; total time= 1.8min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=10,
n_estimators=600; total time= 1.8min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=10,
n_estimators=600; total time= 1.8min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=5,
n_estimators=1000; total time= 2.5min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=5,
n_estimators=1000; total time= 2.6min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=5,
n_estimators=1000; total time= 2.7min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=10,
n_estimators=800; total time= 2.4min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=10,
n_estimators=800; total time= 2.4min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=10,
n_estimators=800; total time= 2.7min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=10,
n_estimators=1000; total time= 4.0min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=2,
n_estimators=600; total time= 3.6min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=10,
n_estimators=1000; total time= 3.8min
[CV] END max_depth=20, min_samples_leaf=4, min_samples_split=10,
n_estimators=1000; total time= 3.7min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=2,
n_estimators=600; total time= 3.6min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=2,
n_estimators=600; total time= 5.5min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=2,
n_estimators=800; total time= 5.5min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=2,
n_estimators=800; total time= 5.5min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=2,
n_estimators=800; total time= 5.1min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=5,
n_estimators=600; total time= 4.6min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=2,
n_estimators=1000; total time= 6.6min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=5,
n_estimators=600; total time= 4.3min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=5,
n_estimators=600; total time= 4.6min
```

```
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=2,
n_estimators=1000; total time= 5.3min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=2,
n_estimators=1000; total time= 5.4min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=5,
n_estimators=800; total time= 7.8min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=5,
n_estimators=800; total time= 9.9min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=5,
n_estimators=800; total time=10.0min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=10,
n_estimators=600; total time= 8.0min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=10,
n_estimators=600; total time= 8.0min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=5,
n_estimators=1000; total time=10.0min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=10,
n_estimators=600; total time=12.1min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=5,
n_estimators=1000; total time=15.1min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=10,
n_estimators=800; total time=14.3min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=5,
n_estimators=1000; total time=15.2min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=10,
n_estimators=800; total time= 9.6min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=2,
n_estimators=600; total time= 8.8min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=10,
n_estimators=800; total time= 9.1min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=2,
n_estimators=600; total time= 4.5min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=10,
n_estimators=1000; total time= 9.3min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=10,
n_estimators=1000; total time= 9.4min
[CV] END max_depth=30, min_samples_leaf=1, min_samples_split=10,
n_estimators=1000; total time= 9.6min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=2,
n_estimators=600; total time= 3.0min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=2,
n_estimators=800; total time= 5.0min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=2,
n_estimators=800; total time= 5.0min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=2,
n_estimators=800; total time= 5.0min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=5,
n_estimators=600; total time= 3.4min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=5,
```

```
n_estimators=600; total time= 3.3min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=2,
n_estimators=1000; total time= 4.6min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=5,
n_estimators=600; total time= 3.9min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=2,
n_estimators=1000; total time= 4.6min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=2,
n_estimators=1000; total time= 4.7min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=5,
n_estimators=800; total time= 5.5min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=5,
n_estimators=800; total time=11.5min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=5,
n_estimators=800; total time=19.4min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=10,
n_estimators=600; total time=18.2min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=10,
n_estimators=600; total time=18.1min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=5,
n_estimators=1000; total time=19.4min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=10,
n_estimators=600; total time=18.2min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=5,
n_estimators=1000; total time=19.3min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=5,
n_estimators=1000; total time=20.3min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=10,
n_estimators=800; total time=19.7min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=10,
n_estimators=800; total time=18.0min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=10,
n_estimators=800; total time= 9.9min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=2,
n_estimators=600; total time= 3.1min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=2,
n_estimators=600; total time= 3.5min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=2,
n_estimators=600; total time= 3.8min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=10,
n_estimators=1000; total time= 4.8min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=10,
n_estimators=1000; total time= 4.7min
[CV] END max_depth=30, min_samples_leaf=2, min_samples_split=10,
n_estimators=1000; total time= 4.7min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=2,
n_estimators=800; total time= 3.5min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=2,
n_estimators=800; total time= 5.1min
```

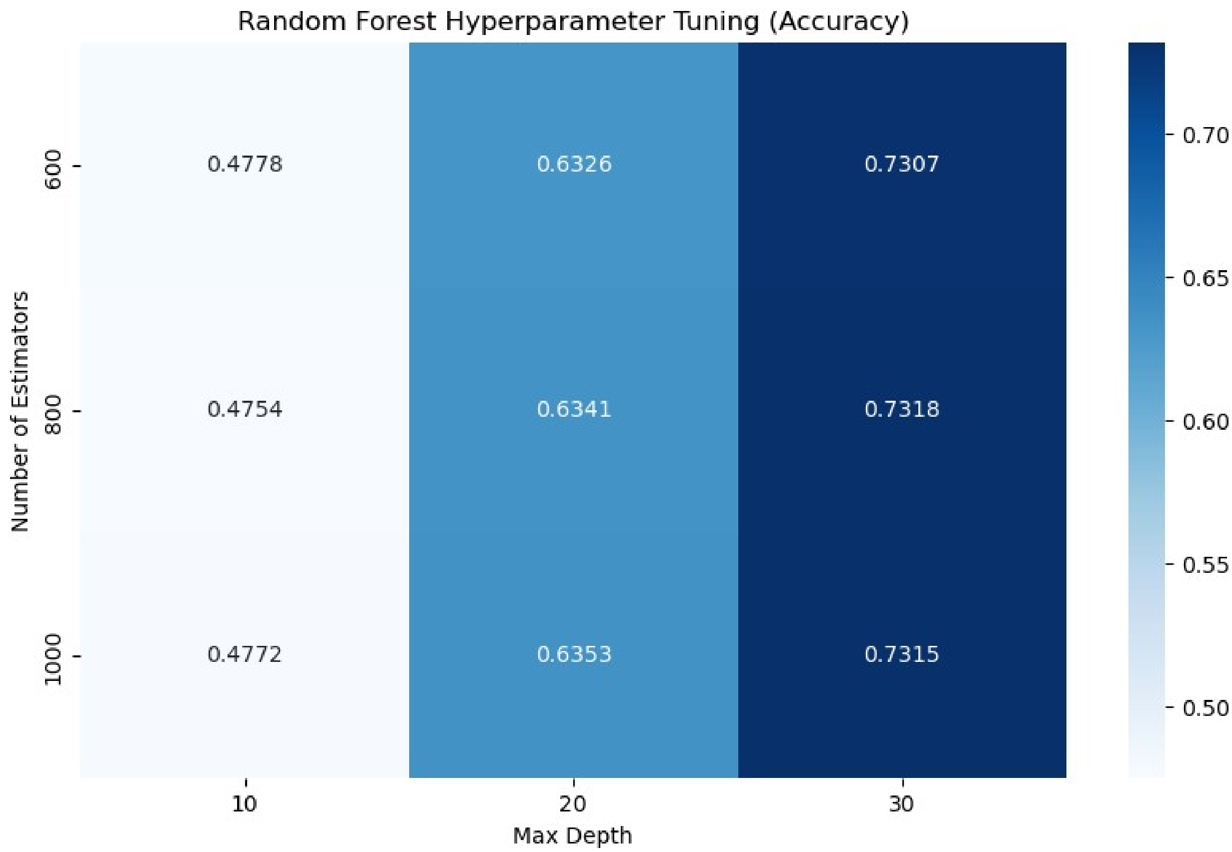
```
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=2,
n_estimators=800; total time= 6.6min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=2,
n_estimators=1000; total time= 6.9min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=5,
n_estimators=600; total time= 5.2min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=5,
n_estimators=600; total time= 4.6min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=5,
n_estimators=600; total time= 4.7min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=2,
n_estimators=1000; total time= 6.4min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=2,
n_estimators=1000; total time= 6.1min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=5,
n_estimators=800; total time= 5.7min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=5,
n_estimators=800; total time= 5.7min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=5,
n_estimators=800; total time= 4.6min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=10,
n_estimators=600; total time= 3.6min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=10,
n_estimators=600; total time= 5.3min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=5,
n_estimators=1000; total time= 6.2min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=10,
n_estimators=600; total time= 5.1min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=5,
n_estimators=1000; total time= 5.9min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=10,
n_estimators=800; total time= 5.4min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=5,
n_estimators=1000; total time= 5.8min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=10,
n_estimators=800; total time= 4.7min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=10,
n_estimators=800; total time= 4.9min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=10,
n_estimators=1000; total time= 4.4min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=10,
n_estimators=1000; total time= 2.8min
[CV] END max_depth=30, min_samples_leaf=4, min_samples_split=10,
n_estimators=1000; total time= 1.2min
Best Parameters: {'max_depth': 30, 'min_samples_leaf': 1,
'min_samples_split': 2, 'n_estimators': 800}
Best Accuracy: 0.746505020774138
```

The results indicate that setting `max_depth` to 30 **does not yield a meaningful improvement in accuracy** compared to the default configuration used in the `rf3` model, where `max_depth` is unrestricted. This suggests that the original hypothesis—that limiting tree depth would enhance generalization and reduce overfitting—was likely incorrect for this dataset.

Moreover, the grid search results show that using the **lowest values for `min_samples_leaf` (1)** and **`min_samples_split` (2)** continues to produce the best-performing models. This further supports the conclusion that **deeper trees** remain more effective for capturing the complexity of this particular classification task, and that more aggressive regularization through depth constraints may unnecessarily limit the model's learning capacity.

Hyperparameter Tuning Heatmap Visualization

```
import seaborn as sns

results = rf_grid_search.cv_results_
df_results = pd.DataFrame(results)

df_results = df_results[['param_n_estimators', 'param_max_depth',
'mean_test_score']]
df_results['param_n_estimators'] =
df_results['param_n_estimators'].astype(int)
df_results['param_max_depth'] =
df_results['param_max_depth'].astype(int)

df_results = df_results.groupby(['param_n_estimators',
'param_max_depth'])['mean_test_score'].mean().reset_index()
df_pivot = df_results.pivot(index='param_n_estimators',
columns='param_max_depth', values='mean_test_score')

plt.figure(figsize=(10, 6))
sns.heatmap(df_pivot, annot=True, fmt=".4f", cmap="Blues")
plt.xlabel("Max Depth")
plt.ylabel("Number of Estimators")
plt.title("Random Forest Hyperparameter Tuning (Accuracy)")
plt.show()
```



The results show that **increasing `max_depth` from 10 to 30 leads to a noticeable improvement in accuracy**, indicating that deeper trees are better able to capture the complexity of the data. However, **increasing the number of trees (`n_estimators`) beyond 800** appears to provide **diminishing returns**, with only marginal or negligible gains in performance. This suggests that while tree depth plays a significant role in model accuracy, simply adding more trees beyond a certain point may not be an efficient strategy for further improvement.

Conclusion

The goal of this project was to develop a machine learning classifier capable of automatically categorizing IT support tickets—a crucial step toward building an intelligent system for routing requests to the appropriate resolution teams.

Among the models evaluated, **Random Forest consistently delivered the strongest performance**, achieving an accuracy of approximately **83–84%** on the test set. This demonstrated its effectiveness in handling high-dimensional, text-based data using a Bag-of-Words representation.

To further refine the model, I conducted **hyperparameter tuning**, focusing particularly on tree depth and the number of estimators. The results showed that **increasing `max_depth` improved accuracy**, confirming that deeper trees are more effective at capturing the structure of the data. However, **adding more trees beyond 800 estimators provided minimal benefit**, with a slight decline in performance at 1,000 trees—highlighting that additional complexity does not always lead to better outcomes.

While these results are promising, they represent an early step in the development of a production-ready IT ticket classification system. There remains significant potential for further enhancement.

Future Directions

- **Explore alternative feature extraction methods**, such as TF-IDF or pre-trained word embeddings (e.g., Word2Vec, GloVe, BERT), to capture richer semantic information.
- **Experiment with more advanced models**, including Gradient Boosting algorithms (e.g., XGBoost, LightGBM) or deep learning architectures such as Recurrent Neural Networks or Transformers.
- **Perform more extensive hyperparameter optimization** using larger search spaces and more robust cross-validation techniques.
- **Implement model explainability tools**, such as SHAP or LIME, to better understand which features influence classification decisions.

Overall, this project establishes a strong baseline for IT ticket classification and opens the door for more sophisticated machine learning workflows in enterprise support systems.

#Github Repo Link https://github.com/samuelaphillips/final/tree/main