In [29]:
```
# Import required libraries for this project.
import string

import nltk
from nltk.corpus import stopwords
nltk.download('stopwords')
from nltk.stem import PorterStemmer, WordNetLemmatizer
nltk.download('wordnet')

from sklearn.feature_extraction.text import CountVectorizer

from skmultilearn.problem_transform import ClassifierChain
from skmultilearn.problem_transform import LabelPowerset
from skmultilearn.problem_transform import BinaryRelevance

from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB

from sklearn.svm import SVC

from skmultilearn.adapt import MLkNN

from keras.models import Sequential
from keras.layers import Dense, Activation, Dropout
from keras.callbacks import ModelCheckpoint

from sklearn.metrics import hamming_loss
from sklearn.metrics import accuracy_score
from sklearn.metrics import log_loss

import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\shais\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\shais\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

In [41]:
```
# Load data into pandas dataframes.
TRAIN_DATA_PATH = '../data/train.csv'
TEST_DATA_PATH = '../data/test.csv'
TEST_LABELS_PATH = '../data/test_labels.csv'

df_train = pd.read_csv(TRAIN_DATA_PATH)
df_test = pd.read_csv(TEST_DATA_PATH)
df_test_labels = pd.read_csv(TEST_LABELS_PATH)
```

In [42]:
```
# Printing first 5 rows of training data.
df_train.head()
```

Out[42]:

| | id | comment_text | toxic | severe_toxic | obscene | threat | insult | identity_hate |
|---|---|---|---|---|---|---|---|---|
| **0** | 0000997932d777bf | Explanation\nWhy the edits made under my usern... | 0 | 0 | 0 | 0 | 0 | 0 |
| **1** | 000103f0d9cfb60f | D'aww! He matches this background colour I'm s... | 0 | 0 | 0 | 0 | 0 | 0 |
| **2** | 000113f07ec002fd | Hey man, I'm really not trying to edit war. It... | 0 | 0 | 0 | 0 | 0 | 0 |
| **3** | 0001b41b1c6bb37e | "\nMore\nI can't make any real suggestions on ... | 0 | 0 | 0 | 0 | 0 | 0 |
| **4** | 0001d958c54c6e35 | You, sir, are my hero. Any chance you remember... | 0 | 0 | 0 | 0 | 0 | 0 |

In [43]:
```
# Getting all the ids having label value as -1 and removing them from the test data.
ids_to_remove = (df_test_labels[df_test_labels.toxic == -1]).id
df_test = df_test[~df_test['id'].isin(ids_to_remove)]
df_test_labels = df_test_labels[~df_test_labels['id'].isin(ids_to_remove)]
```

In [44]:
```
df_test.head()
```

Out[44]:

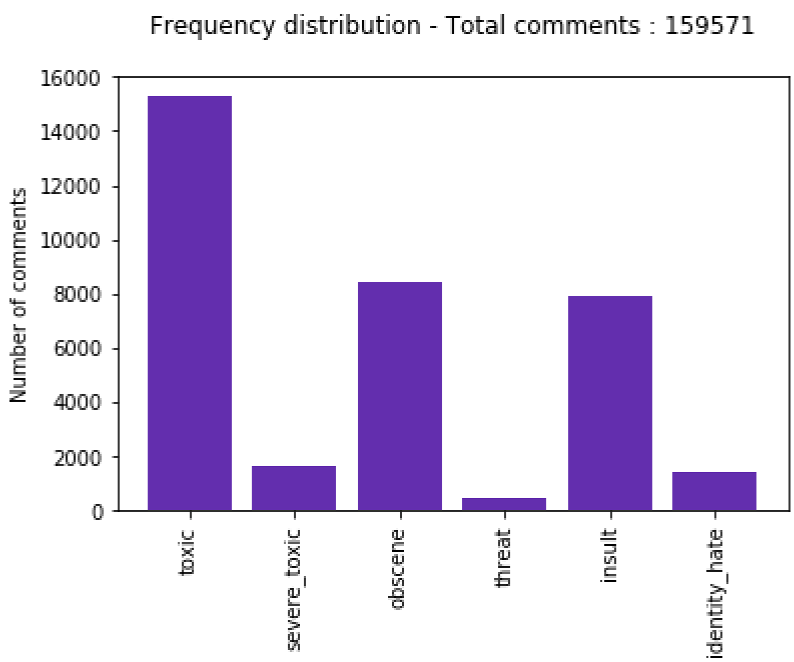
| | id | comment_text |
|---|---|---|
| **5** | 0001ea8717f6de06 | Thank you for understanding. I think very high... |
| **7** | 000247e83dcc1211 | :Dear god this site is horrible. |
| **11** | 0002f87b16116a7f | "::: Somebody will invariably try to add Relig... |
| **13** | 0003e1cccfd5a40a | " \n\n It says it right there that it IS a typ... |
| **14** | 00059ace3e3e9a53 | " \n\n == Before adding a new product to the l... |

In [45]:
```
df_test_labels.head()
```

Out[45]:

| | id | toxic | severe_toxic | obscene | threat | insult | identity_hate |
|---|---|---|---|---|---|---|---|
| **5** | 0001ea8717f6de06 | 0 | 0 | 0 | 0 | 0 | 0 |
| **7** | 000247e83dcc1211 | 0 | 0 | 0 | 0 | 0 | 0 |
| **11** | 0002f87b16116a7f | 0 | 0 | 0 | 0 | 0 | 0 |
| **13** | 0003e1cccfd5a40a | 0 | 0 | 0 | 0 | 0 | 0 |
| **14** | 00059ace3e3e9a53 | 0 | 0 | 0 | 0 | 0 | 0 |

In [46]:
```
# Plotting a frequency distribution graph.

total = len(df_train)
toxic_count = (df_train.toxic.values == 1).sum()
severe_toxic_count = (df_train.severe_toxic.values == 1).sum()
obscene_count = (df_train.obscene.values == 1).sum()
threat_count = (df_train.threat.values == 1).sum()
insult_count = (df_train.insult.values == 1).sum()
identity_hate_count = (df_train.identity_hate.values == 1).sum()

comment_classes = ('toxic', 'severe_toxic', 'obscene', 'threat', 'insult', 'id
entity_hate')
y_pos = np.arange(len(comment_classes))

plt.title(f'Frequency distribution - Total comments : {total}\n')
plt.ylabel('Number of comments')

freq = [toxic_count,severe_toxic_count,obscene_count,threat_count,insult_count
,identity_hate_count]

plt.bar(y_pos, freq, align='center', color='#632EAE')
plt.xticks(y_pos, comment_classes, rotation=90)

plt.grid(False)
plt.show()
```

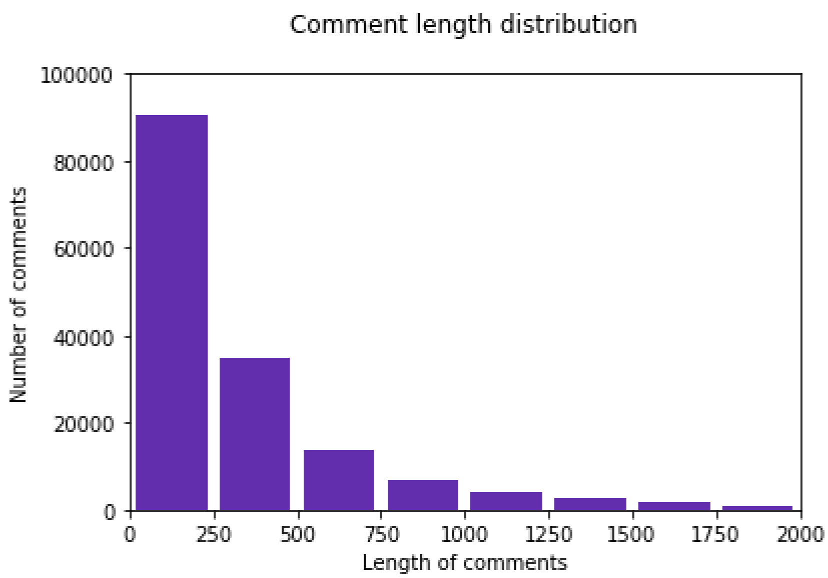


In [47]:
```
# Getting info about the number of comments which are toxic and/or belongs to
 more than one toxicity level.
c1,c2 = 0,0
temp = df_train.loc[:, ['toxic', 'severe_toxic', 'obscene', 'threat', 'insult'
, 'identity_hate']]

for tup in temp.itertuples(index=False):
    c = np.count_nonzero(tup)
    if c:
        c1 = c1 + 1
    if c > 1:
        c2 = c2 + 1

print(f'Number of comments which belongs to one of the toxic class : {c1}')
print(f'Number of comments which belongs to more than one toxic classes : {c2}
')
```

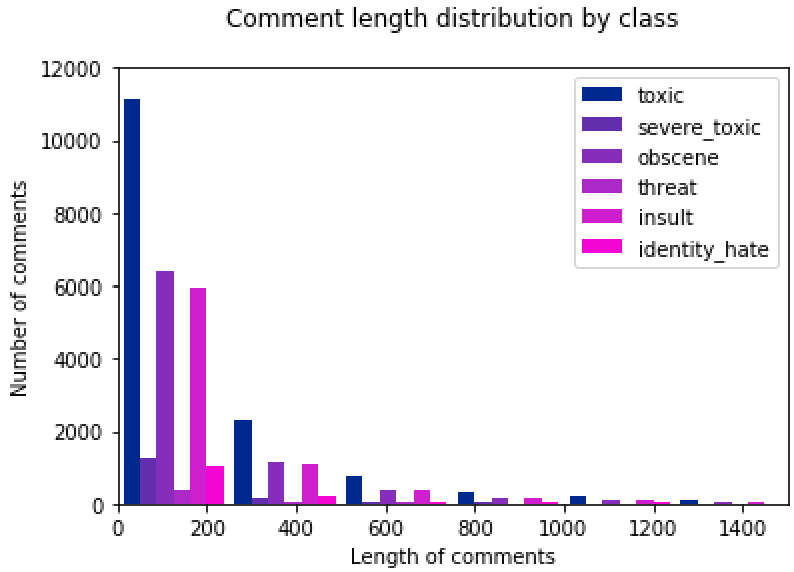
```
Number of comments which belongs to one of the toxic class : 16225
Number of comments which belongs to more than one toxic classes : 9865
```

In [48]:
```
# Plotting a graph of comment length distribution.
comments = df_train.loc[:, 'comment_text']

len_arr = [len(comments[i]) for i in range(comments.shape[0])]

avg_len = sum(len_arr) / len(len_arr)
print(f'Average length of a comment : {avg_len}')

bins = [1,250,500,750,1000,1250,1500,1750,2000]
plt.hist(len_arr, bins=bins, rwidth=0.85, color='#632EAE')

plt.title(f'Comment length distribution\n')
plt.xlabel('Length of comments')
plt.ylabel('Number of comments')

plt.axis([0, 2000, 0, 100000])

plt.grid(False)
plt.show()
```

```
Average length of a comment : 394.0732213246768
```



In [49]:
```
# Plotting a graph of comment length distribution by class.
temp = df_train.loc[:, ['toxic', 'severe_toxic', 'obscene', 'threat', 'insult'
, 'identity_hate']]
temp = temp.to_numpy()

y = np.zeros(temp.shape)

for i in range(comments.shape[0]):
    cmt_len = len(comments[i])
    # If toxic
    if temp[i][0]:
        y[i][0] = cmt_len

    # If severe_toxic
    if temp[i][1]:
        y[i][1] = cmt_len

    # If obscene
    if temp[i][2]:
        y[i][2] = cmt_len

    # If threat
    if temp[i][3]:
        y[i][3] = cmt_len

    # If insult
    if temp[i][4]:
        y[i][4] = cmt_len

    # If identity_hate
    if temp[i][5]:
        y[i][5] = cmt_len

bins = [1,250,500,750,1000,1250,1500]
colors = ['#00298F','#632EAE','#872DBB','#AB29C6','#CF1ECE','#F305D3']
plt.hist(y, bins=bins, rwidth=0.9, label=comment_classes, color=colors)

plt.title(f'Comment length distribution by class\n')
plt.xlabel('Length of comments')
plt.ylabel('Number of comments')

plt.legend()

plt.axis([0, 1500, 0, 12000])

plt.grid(False)
plt.show()
```




In [50]:
```
# Remove rows having length more than 500.
df_train = df_train[df_train['comment_text'].map(len) <= 500]
```

In [51]:
```
# Prepare for special characters removal.
special_chars = string.punctuation.replace('\'','') + "0123456789"
space = "                                         "
trans_table = str.maketrans(special_chars, space)
```

In [52]:
```
# Prepare for stop words removal.
stop_words = stopwords.words('english')
stop_words.append('')

for letter in range(ord('b'), ord('z') + 1):
    stop_words.append(chr(letter))
```

In [53]:
```
# Prepare for Stemming and Lemmatising
stemmer = PorterStemmer()
lemmatiser = WordNetLemmatizer()
```

In [60]:
```
# Apply above prepared preprocessors.
comments = df_train.loc[:, 'comment_text'].values

for i in range(len(comments)):
    comments[i] = comments[i].lower().translate(trans_table)
    comment = []
    for word in comments[i].split():
        comment.append(stemmer.stem(lemmatiser.lemmatize(word, pos="v")))
    comments[i] = " ".join(comment)
```

In [ ]:
```
# Applying count vectorizer using the stop words created.
cv = CountVectorizer(lowercase=False, stop_words=stop_words)

# Convert comments into bag of words format
tf = cv.fit_transform(comments).toarray()
```

In [ ]:
```
# Labels
labels = []

temp_labels = df_train.loc[:, ['toxic', 'severe_toxic', 'obscene', 'threat', 
'insult', 'identity_hate']]
temp_labels = temp_labels.to_numpy()

for i in range(comments.shape[0]):
    labels.append(temp_labels[i])

labels = np.asarray(labels)
```

In [ ]:
```
# Splitting the dataset into training and testing.
def shuffle(mat, target, propotion):
    ratio = int(mat.shape[0] / propotion)

    X_train = mat[ratio:, :]
    X_test =  mat[:ratio, :]

    Y_train = target[ratio:, :]
    Y_test =  target[:ratio, :]

    return X_train, X_test, Y_train, Y_test

X_train, X_test, Y_train, Y_test = shuffle(tf, labels, 3)

print(X_train.shape)
print(X_test.shape)
```

In [ ]:
```
# Evaluation.
def evaluate(Y_test, predict):
    h_loss = hamming_loss(Y_test, predict)
    acc = accuracy_score(Y_test, predict)
    try:
        l_loss = log_loss(Y_test, predict)
    except:
        l_loss = log_loss(Y_test, predict.toarray())

    print("Hamming Loss = {}".format(h_loss*100))
    print("Log Loss = {}".format(l_loss))
    print("Accuracy = {}".format(acc*100))
```

In [ ]:
```
# Binary Relevance with Multinomial Naive Bayes.
classifier = BinaryRelevance(classifier = MultinomialNB(), require_dense = [Fa
lse, True])
classifier.fit(X_train, Y_train)
```

In [ ]:
```
# Prediction list.
predictions = classifier.predict(X_test)
```

In [27]:
```
# Results for Binary Relevance with Multinomial Naive Bayes.
evaluate(Y_test, predictions)
```

```
Hamming Loss = 3.27
Log Loss = 1.92
Accuracy = 88.291235214
```

In [ ]:
```
# Binary Relevance with support vector machine classifier.
classifier = BinaryRelevance(classifier = SVC(), require_dense = [False, True
])
classifier.fit(X_train, Y_train)
```

In [ ]:
```
# Prediction list.
predictions = classifier.predict(X_test)
```

In [26]:
```
# Results for Binary Relevance with support vector machine classifier.
evaluate(Y_test, predictions)
```

```
Hamming Loss = 4.26
Log Loss = 0.46
Accuracy = 88.276325974
```

In [ ]:
```
# Binary Relevance with Gaussean Naive Bayes.
classifiers = []
for i in range(6):
    classifiers.append(GaussianNB())
    classifiers[i].fit(X_train, Y_train[:, i])
```

In [ ]:
```
# Prediction list.
predictions = []
for i in range(6):
    predictions.append(classifiers[i].predict(X_test))

predictions = np.asarray(np.transpose(predictions))
```

In [24]:
```
# Results for Binary Relevance with Gaussean Naive Bayes.
evaluate(Y_test, predictions)
```

```
Hamming Loss = 20.74
Log Loss = 1.422
Accuracy = 52.19
```

In [ ]:
```
# Classifier chain with Multinomial Naive Bayes.
classifier = ClassifierChain(MultinomialNB())
classifier.fit(X_train, Y_train)
```

In [ ]:
```
# Prediction list.
predictions = classifier.predict(X_test)
```

In [23]:
```
# Results for Classifier chain with Multinomial Naive Bayes.
evaluate(Y_test, predictions)
```

```
Hamming Loss = 3.56
Log Loss = 1.5
Accuracy = 88.25951231
```

In [ ]:
```
# Label Powerset with Multinomial Naive Bayes.
classifier = LabelPowerset(MultinomialNB())
classifier.fit(X_train, Y_train)
```

In [ ]:
```
# Prediction list.
predictions = classifier.predict(X_test)
```

In [21]:
```
# Results for Label Powerset with Multinomial Naive Bayes.
evaluate(Y_test, predictions)
```

```
Hamming Loss = 3.17
Log Loss = 1.47
Accuracy = 88.802365412
```

In [ ]:
```
# ML-KNN
classifier = MLkNN(k=2)
classifier.fit(X_train, Y_train)
```

In [ ]:
```
# Prediction list.
predictions = classifier.predict(X_test)
```

In [ ]:
```
# Results for Label Powerset with Multinomial Naive Bayes.
evaluate(Y_test, predictions)
```

In [ ]:
```
# BP-MLL Neural Networks

# Define model architecture
model = Sequential()
model.add(Dense(4, activation='relu', input_dim = X_train.shape[1]))
model.add(Dropout(0.3))
model.add(Dense(6, activation='softmax'))
model.summary()
```

In [ ]:
```
# Compile model
model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=[
'accuracy'])
```

In [ ]:
```
# Train model using ModelCheckpoint.
checkpoint = ModelCheckpoint(filepath='saved_models/weights.best.myneural.h5p
y',
                                verbose=1, save_best_only=True)
model.fit(X_train, Y_train, epochs=10, batch_size=32)
```

In [ ]:

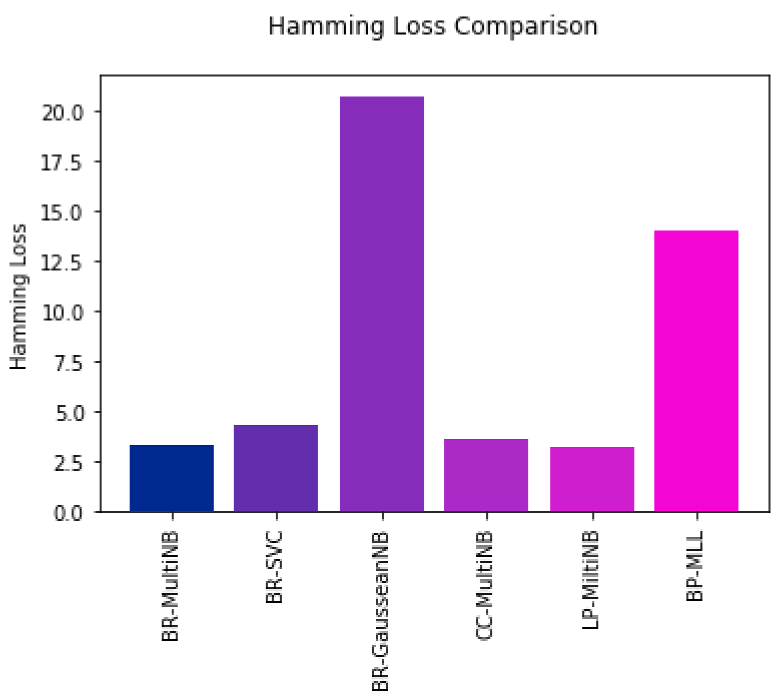
```
# Prediction list.
predictions = model.predict(X_test)
```

In [19]:

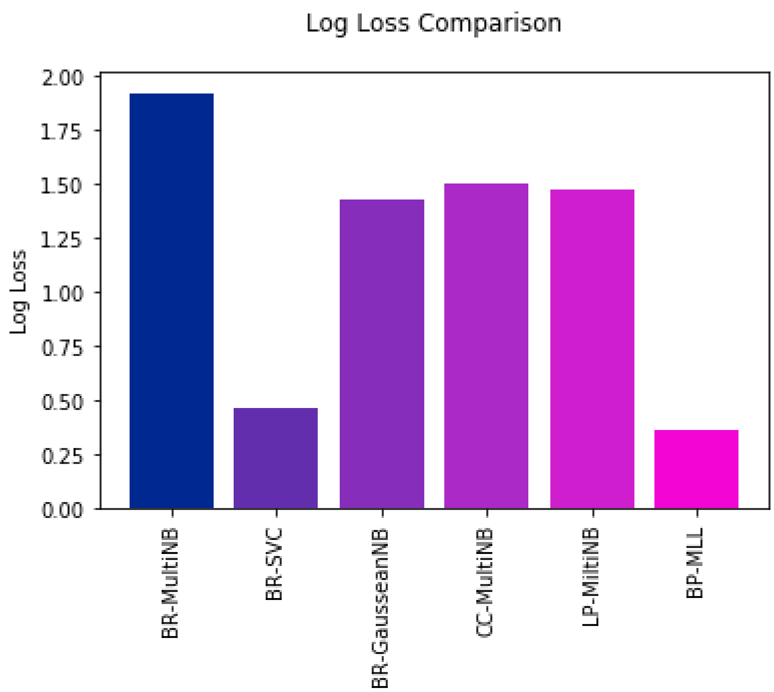
```
# Results
l_loss = log_loss(Y_test, predictions)

predictions = np.round(predictions)
h_loss = hamming_loss(Y_test, predictions)

acc = accuracy_score(Y_test, predictions)

print("Hamming Loss = {}".format(h_loss*100))
print("Log Loss = {}".format(l_loss))
print("Accuracy = {}".format(acc*100))
```

```
Hamming Loss = 13.96
Log Loss = 0.36
Accuracy = 29.52
```

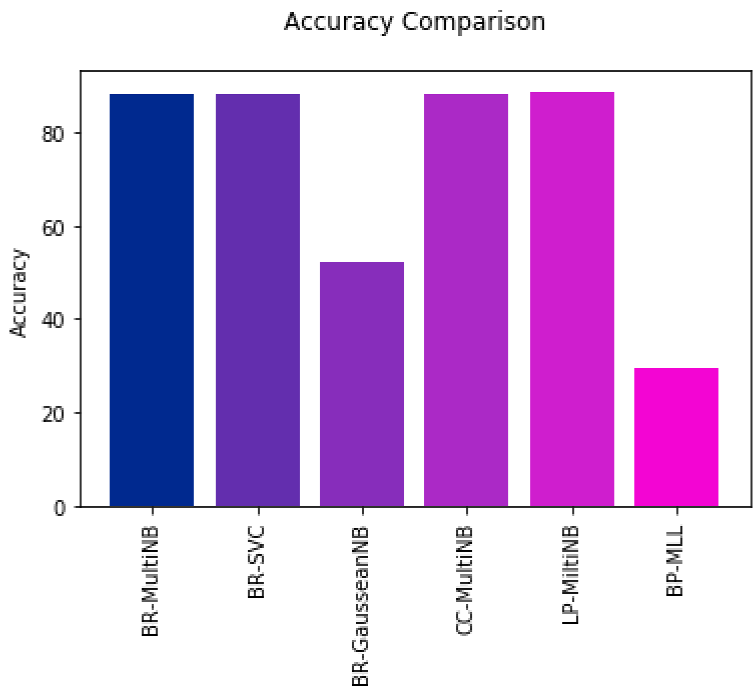
In [12]:
```
# Hamming Loss Comparison.
models = ['BR-MultiNB', 'BR-SVC', 'BR-GausseanNB', 'CC-MultiNB', 'LP-MiltiNB',
'BP-MLL']
h_loss_arr = [3.27, 4.26, 20.74, 3.56, 3.17, 13.96]

col = ['#00298F','#632EAE','#872DBB','#AB29C6','#CF1ECE','#F305D3']

plt.title(f'Hamming Loss Comparison\n')
plt.ylabel('Hamming Loss')
# plt.xlabel('Models')

plt.xticks(rotation=90)

for i in range(len(h_loss_arr)):
    plt.bar(models[i], h_loss_arr[i], color=col[i])

plt.show()
```



In [13]:
```
# Log Loss Comparison.
models = ['BR-MultiNB', 'BR-SVC', 'BR-GausseanNB', 'CC-MultiNB', 'LP-MiltiNB',
'BP-MLL']
h_loss_arr = [1.92, 0.46, 1.422, 1.5, 1.47, 0.36]

col = ['#00298F','#632EAE','#872DBB','#AB29C6','#CF1ECE','#F305D3']

plt.title(f'Log Loss Comparison\n')
plt.ylabel('Log Loss')
# plt.xlabel('Models')

plt.xticks(rotation=90)

for i in range(len(h_loss_arr)):
    plt.bar(models[i], h_loss_arr[i], color=col[i])

plt.show()
```



In [15]:
```
# Accuracy Comparison.
models = ['BR-MultiNB', 'BR-SVC', 'BR-GausseanNB', 'CC-MultiNB', 'LP-MiltiNB',
'BP-MLL']
h_loss_arr = [88.29, 88.27, 52.19, 88.25, 88.80, 29.52]

col = ['#00298F','#632EAE','#872DBB','#AB29C6','#CF1ECE','#F305D3']

plt.title(f'Accuracy Comparison\n')
plt.ylabel('Accuracy')
# plt.xlabel('Models')

plt.xticks(rotation=90)

for i in range(len(h_loss_arr)):
    plt.bar(models[i], h_loss_arr[i], color=col[i])

plt.show()
```




In [ ]: