1. Import Data

In [103]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

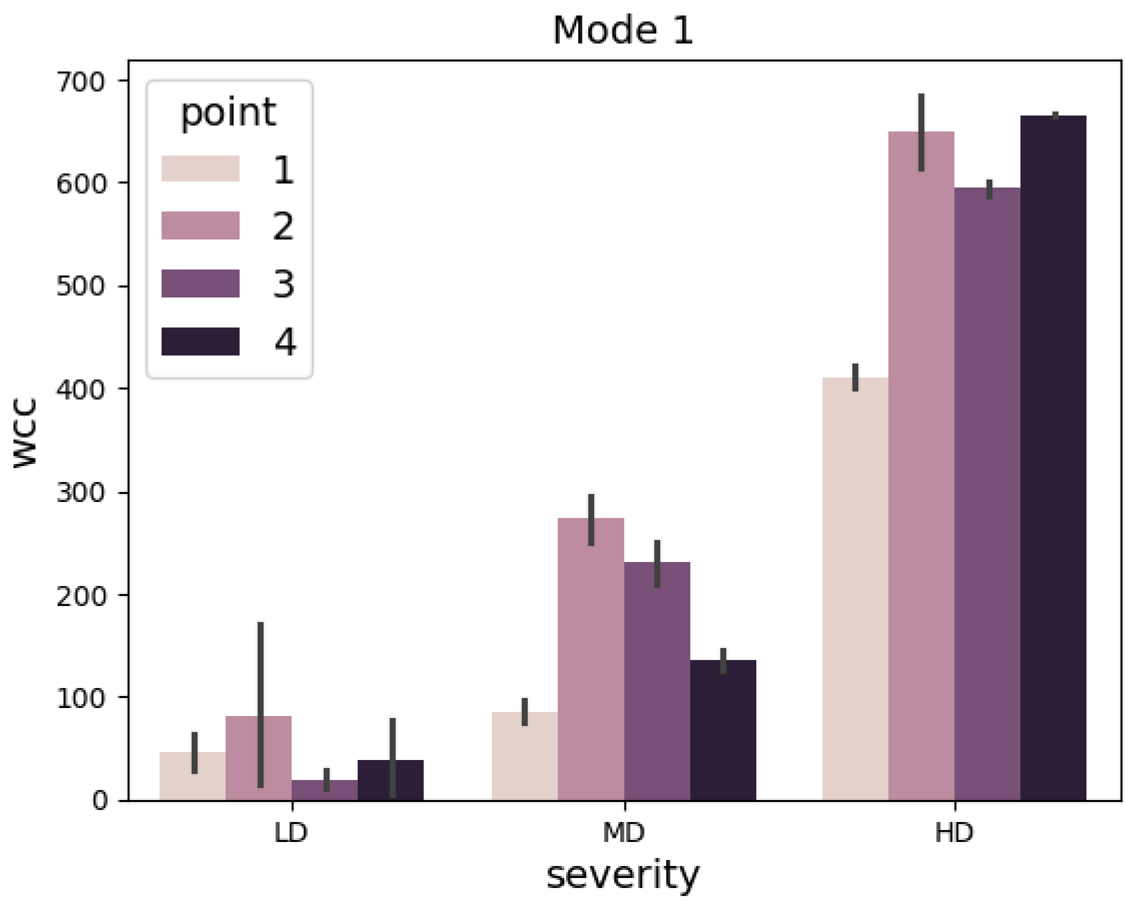
In [104]:
```
wcc_ld = pd.read_excel('wcc_LD.xlsx')
wcc_md = pd.read_excel('wcc_MD.xlsx')
wcc_hd = pd.read_excel('wcc_HD.xlsx')
wcc_FEAhd = pd.read_excel('./FEA Data/convert/wcc_HD.xlsx')
```

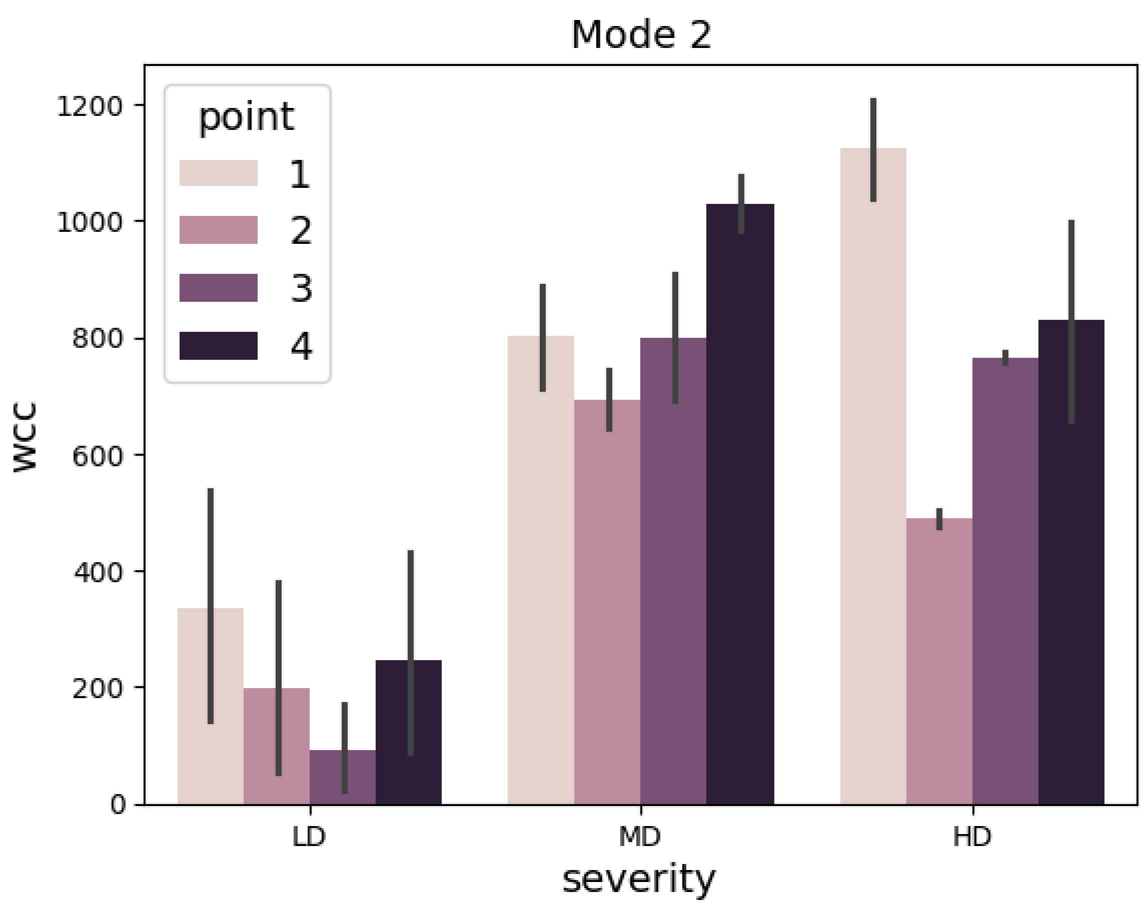
In [68]:
```
df = pd.concat([wcc_ld, wcc_md, wcc_FEAhd], axis=0)
df['severity_point'] = df['severity'].astype(str) + '_' + df['point'].astype(s
tr)
# Create a dictionary that maps each unique value in 'severity_point' to a uni
que integer
labels = df['severity_point'].unique()
label_dict = {k: v for v, k in enumerate(labels)}

# Use the dictionary to replace the values in 'severity_point' with their corr
esponding labels
df['severity_point'] = df['severity_point'].map(label_dict)
```

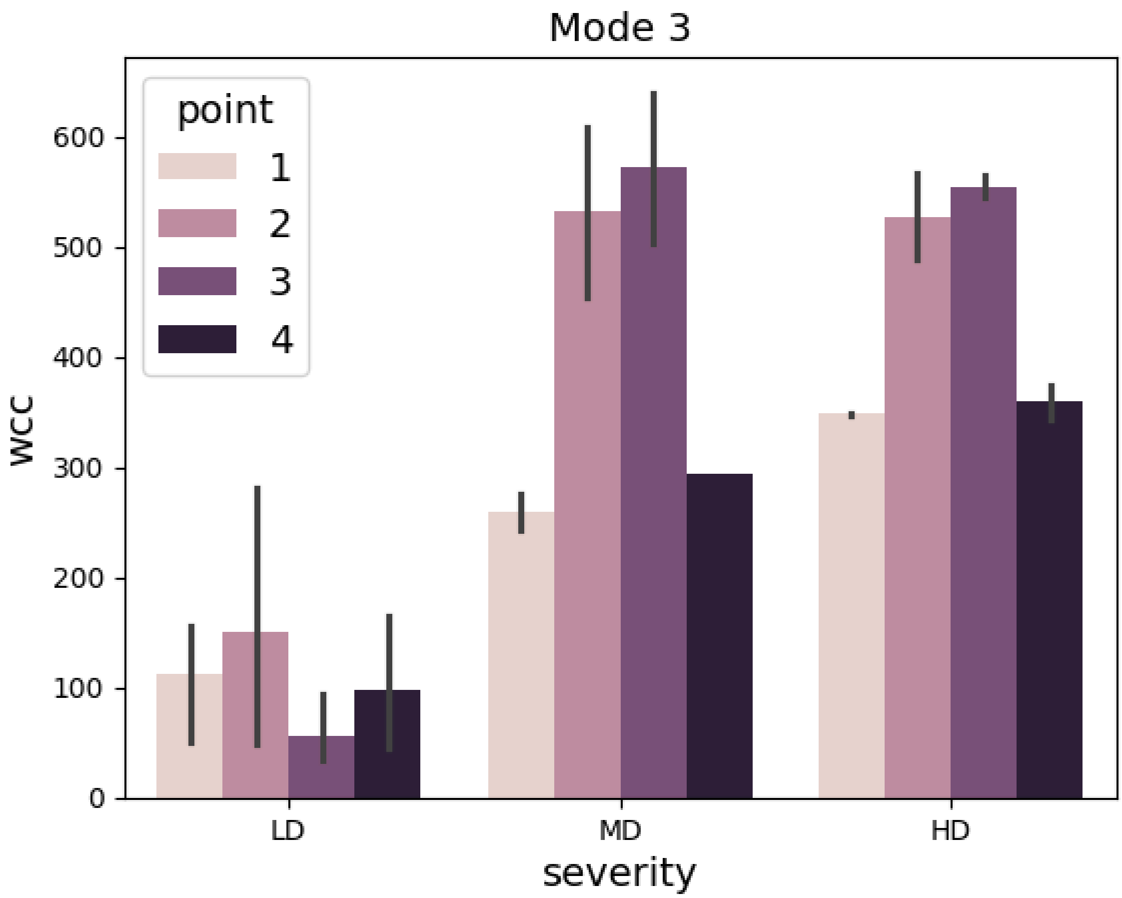
2. Exploratory Data Analysis

In [70]:
```
import seaborn as sns
import matplotlib.pyplot as plt

fig1, ax1 = plt.subplots()
sns.barplot(x='severity', y='wcc', hue= 'point', data=df[df['mode_shape'] ==
1], ax=ax1)
ax1.set_title('Mode 1')

fig2, ax2 = plt.subplots()
sns.barplot(x='severity', y='wcc', hue= 'point', data=df[df['mode_shape'] ==
2], ax=ax2)
ax2.set_title('Mode 2')

fig3, ax3 = plt.subplots()
sns.barplot(x='severity', y='wcc', hue= 'point', data=df[df['mode_shape'] ==
3], ax=ax3)
ax3.set_title('Mode 3')
```

Out[70]: Text(0.5, 1.0, 'Mode 3')





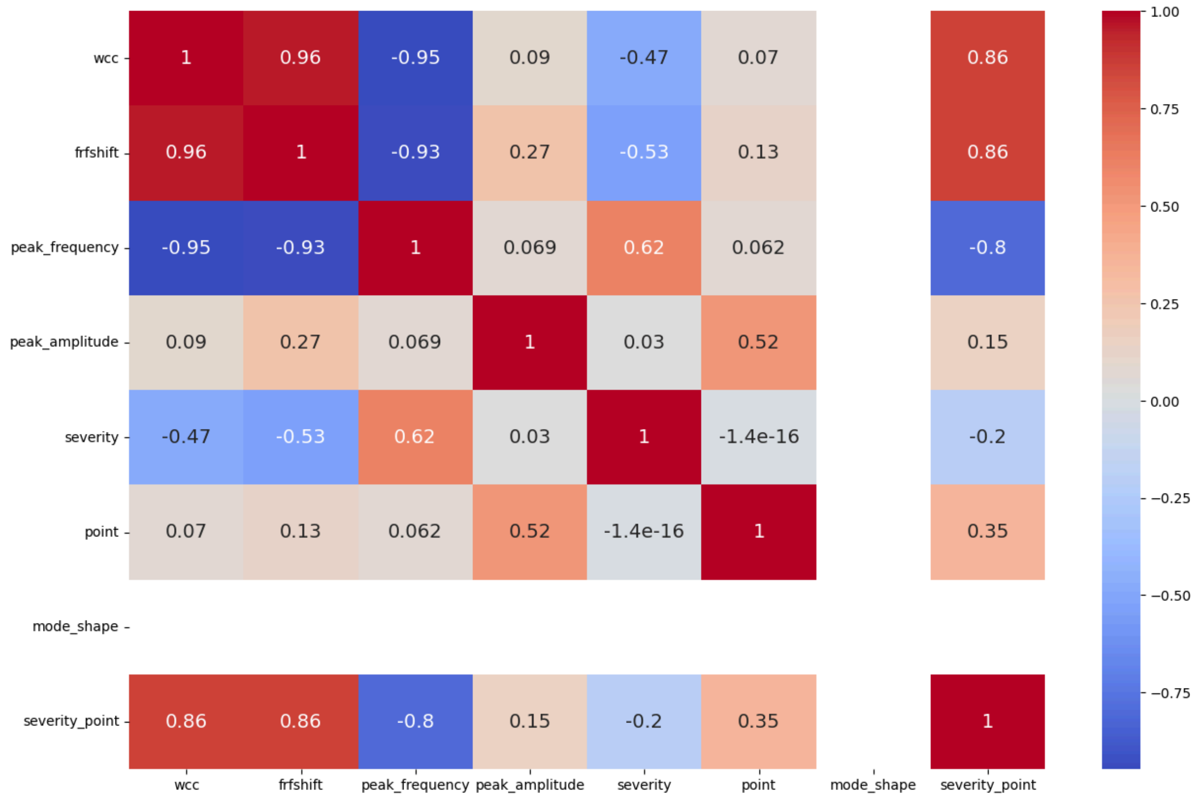


- Only Mode shape 1 that will be used since it is more sensitive in classify damage severity and its location

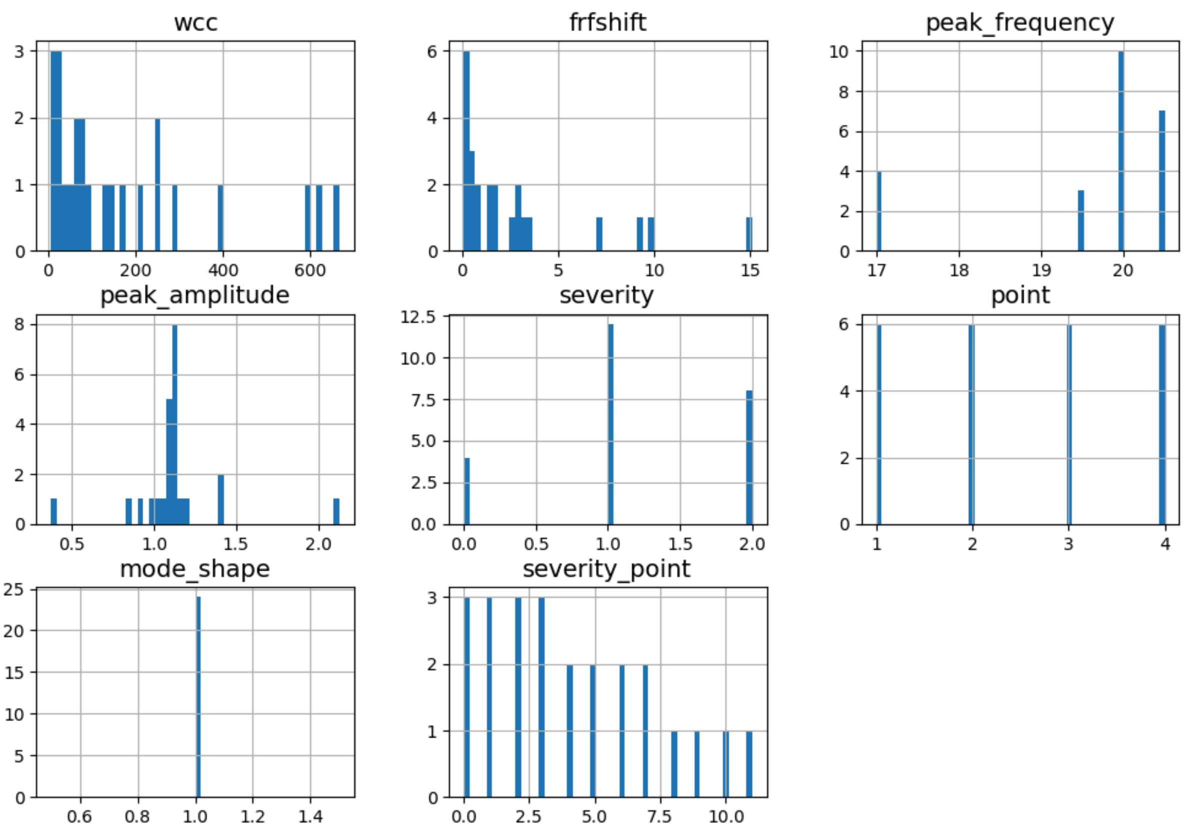
In [105]:
```
df = pd.concat([wcc_ld, wcc_md, wcc_FEAhd[(wcc_FEAhd['mode_shape'] == 1)].iloc
[4:]], axis=0)
df = df[(df['mode_shape'] == 1)]
df['severity_point'] = df['severity'].astype(str) + '_' + df['point'].astype(s
tr)
# Create a dictionary that maps each unique value in 'severity_point' to a uni
que integer
labels = df['severity_point'].unique()
label_dict = {k: v for v, k in enumerate(labels)}
# Use the dictionary to replace the values in 'severity_point' with their corr
esponding labels
df['severity_point'] = df['severity_point'].map(label_dict)
```

In [72]:

```
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
df['severity'] = le.fit_transform(df['severity'])
corr_matrix = df.corr(numeric_only=True)
corr_matrix["severity"].sort_values(ascending=False)

plt.figure(figsize=(15, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.show()
```



In [73]:
```
import matplotlib.pyplot as plt

plt.rc('font', size=14)
plt.rc('axes', labelsize=14, titlesize=14)
plt.rc('legend', fontsize=14)
plt.rc('xtick', labelsize=10)
plt.rc('ytick', labelsize=10)

df.hist(bins=50, figsize=(12, 8))
plt.show()
```



In [74]:
```
df.isnull().sum()
```

Out[74]:
```
wcc               0
frfshift          0
peak_frequency    0
peak_amplitude    0
severity          0
point             0
mode_shape        0
severity_point    0
dtype: int64
```

3. Split Test Train Set and Data Augmentation

In [106]:

```
def bootstrap_sample_with_noise(data, exclude_cols=[], n_bootstrap_samples=15000, noise_scale=0.5):
    n_bootstrap_samples = 15000
    sample = data.sample(n=n_bootstrap_samples, replace=True).copy()  # Create a copy to avoid modifying original data

    # Identify numeric columns
    numeric_cols = sample.select_dtypes(include=[np.number]).columns

    # Exclude specified columns
    numeric_cols = [col for col in numeric_cols if col not in exclude_cols]

    # Add noise only to numeric columns
    noise = np.random.normal(0, noise_scale, size=(n_bootstrap_samples, len(numeric_cols)))
    sample[numeric_cols] += noise

    # Apply absolute value to ensure data is non-negative
    sample[numeric_cols] = sample[numeric_cols].abs()

    return sample

# Specify columns to exclude from noise addition
exclude_cols = ['point', 'mode_shape','peak_frequency', 'severity_point','peak_amplitude']
# Generate synthetic data with noise
wcc_noisy = bootstrap_sample_with_noise(df, exclude_cols=exclude_cols)

df = pd.concat([df, wcc_noisy], axis=0)
# Separate features and labels

X = df[['wcc', 'frfshift', 'peak_frequency', 'peak_amplitude']].values
y = df['severity_point'].values


# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [107]:

```
from imblearn.over_sampling import SMOTE
from collections import Counter
#Define SMOTE
sm = SMOTE()

# Fit SMOTE on the training data
X_train, y_train = sm.fit_resample(X_train, y_train)

# Summarize the new class distribution
print("After oversampling: ", Counter(y_train))
```

```
After oversampling:  Counter({0: 1533, 11: 1533, 7: 1533, 9: 1533, 10: 1533, 3: 1533, 2: 1533, 6: 1533, 1: 1533, 5: 1533, 8: 1533, 4: 1533})
```

In [108]:
```
X_train = pd.DataFrame(X_train, columns=['wcc', 'frfshift', 'peak_frequency',
'peak_amplitude'])
X_train
```

Out[108]:

	wcc	frfshift	peak_frequency	peak_amplitude
0	28.668929	1.382842	20.5	1.140537
1	63.771423	0.697078	20.0	1.112678
2	666.120178	14.617527	17.0	2.129556
3	664.954725	15.509253	17.0	2.129556
4	45.466539	0.416397	20.0	1.132941
...	...	...	...	...
18391	666.488696	15.535741	17.0	2.129556
18392	665.590113	14.566971	17.0	2.129556
18393	666.140940	15.096488	17.0	2.129556
18394	666.251148	15.974562	17.0	2.129556
18395	665.875652	15.738878	17.0	2.129556

18396 rows × 4 columns

In [109]:
```
y
```

Out[109]:
```
array([0, 1, 2, ..., 3, 3, 5], dtype=int64)
```

In [110]:
```
from tensorflow.keras.utils import to_categorical

# One-hot encode the targets
y_train = to_categorical(y_train, num_classes=12)
y_test = to_categorical(y_test, num_classes=12)  # Do the same for the test ta
rgets if you have them
```

4. Model Design and Training

In [111]:

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.callbacks import EarlyStopping

# Define the model
model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(128, activation='relu'),
    Dense(12, activation='softmax')  # 12 classes for multiclass classificatio
n
])

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['acc
uracy'])

# Train the model
early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_w
eights=True)
history = model.fit(X_train, y_train, epochs=100, validation_split=0.2, callba
cks=[early_stopping])
```

```
Epoch 1/100

c:\Users\dania\AppData\Local\Programs\Python\Python312\Lib\site-packages\kera
s\src\layers\core\dense.py:87: UserWarning: Do not pass an `input_shape`/`inp
ut_dim` argument to a layer. When using Sequential models, prefer using an `I
nput(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
460/460 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.4108 - loss: 3.7998 - val_accuracy: 0.4261 - val_loss: 4.2928
Epoch 2/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.6768 - loss: 0.9648 - val_accuracy: 0.4277 - val_loss: 2.1653
Epoch 3/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7483 - loss: 0.7146 - val_accuracy: 0.7139 - val_loss: 2.9080
Epoch 4/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.7962 - loss: 0.5683 - val_accuracy: 0.4351 - val_loss: 2.9883
Epoch 5/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8132 - loss: 0.4791 - val_accuracy: 0.7174 - val_loss: 0.4569
Epoch 6/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8458 - loss: 0.3430 - val_accuracy: 0.7174 - val_loss: 0.4841
Epoch 7/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8496 - loss: 0.3248 - val_accuracy: 0.7071 - val_loss: 0.7030
Epoch 8/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8513 - loss: 0.3162 - val_accuracy: 0.7174 - val_loss: 1.1434
Epoch 9/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8567 - loss: 0.3160 - val_accuracy: 0.7103 - val_loss: 0.9167
Epoch 10/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8621 - loss: 0.2809 - val_accuracy: 0.9696 - val_loss: 0.3821
Epoch 11/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8667 - loss: 0.2778 - val_accuracy: 0.7103 - val_loss: 0.4392
Epoch 12/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8695 - loss: 0.2476 - val_accuracy: 0.8041 - val_loss: 0.3735
Epoch 13/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8723 - loss: 0.2363 - val_accuracy: 0.9886 - val_loss: 0.3368
Epoch 14/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8781 - loss: 0.2234 - val_accuracy: 0.7103 - val_loss: 0.3926
Epoch 15/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.8695 - loss: 0.2420 - val_accuracy: 0.7451 - val_loss: 0.3430
Epoch 16/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8834 - loss: 0.2177 - val_accuracy: 0.7728 - val_loss: 0.3375
Epoch 17/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8752 - loss: 0.2277 - val_accuracy: 0.7103 - val_loss: 0.4034
Epoch 18/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8725 - loss: 0.2295 - val_accuracy: 0.7174 - val_loss: 0.3634
Epoch 19/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8763 - loss: 0.2227 - val_accuracy: 0.7103 - val_loss: 0.4348
Epoch 20/100
```

```
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8726 - loss: 0.2328 -
val_accuracy: 0.8313 - val_loss: 0.3222
Epoch 21/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8728 - loss: 0.2248 -
val_accuracy: 0.7367 - val_loss: 0.3449
Epoch 22/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8764 - loss: 0.2238 -
val_accuracy: 0.8872 - val_loss: 0.3352
Epoch 23/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.8790 - loss: 0.2212 -
val_accuracy: 0.7666 - val_loss: 0.3445
Epoch 24/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8814 - loss: 0.2150 -
val_accuracy: 0.7658 - val_loss: 0.3513
Epoch 25/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8829 - loss: 0.2106 -
val_accuracy: 0.7103 - val_loss: 0.4026
Epoch 26/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8802 - loss: 0.2181 -
val_accuracy: 0.8995 - val_loss: 0.3123
Epoch 27/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8788 - loss: 0.2161 -
val_accuracy: 0.8375 - val_loss: 0.3270
Epoch 28/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.8827 - loss: 0.2104 -
val_accuracy: 0.9038 - val_loss: 0.3008
Epoch 29/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8882 - loss: 0.2020 -
val_accuracy: 0.8391 - val_loss: 0.3128
Epoch 30/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8810 - loss: 0.2092 -
val_accuracy: 0.7174 - val_loss: 0.4232
Epoch 31/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8864 - loss: 0.2052 -
val_accuracy: 0.8495 - val_loss: 0.3147
Epoch 32/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8924 - loss: 0.2022 -
val_accuracy: 0.9788 - val_loss: 0.2899
Epoch 33/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8835 - loss: 0.2064 -
val_accuracy: 0.7204 - val_loss: 0.3529
Epoch 34/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8889 - loss: 0.1989 -
val_accuracy: 0.8421 - val_loss: 0.3110
Epoch 35/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8910 - loss: 0.1963 -
val_accuracy: 0.9207 - val_loss: 0.2933
Epoch 36/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8916 - loss: 0.1943 -
val_accuracy: 0.8323 - val_loss: 0.2975
Epoch 37/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8867 - loss: 0.2063 -
val_accuracy: 0.7530 - val_loss: 0.3219
Epoch 38/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8922 - loss: 0.1957 -
val_accuracy: 0.7655 - val_loss: 0.3117
Epoch 39/100
```

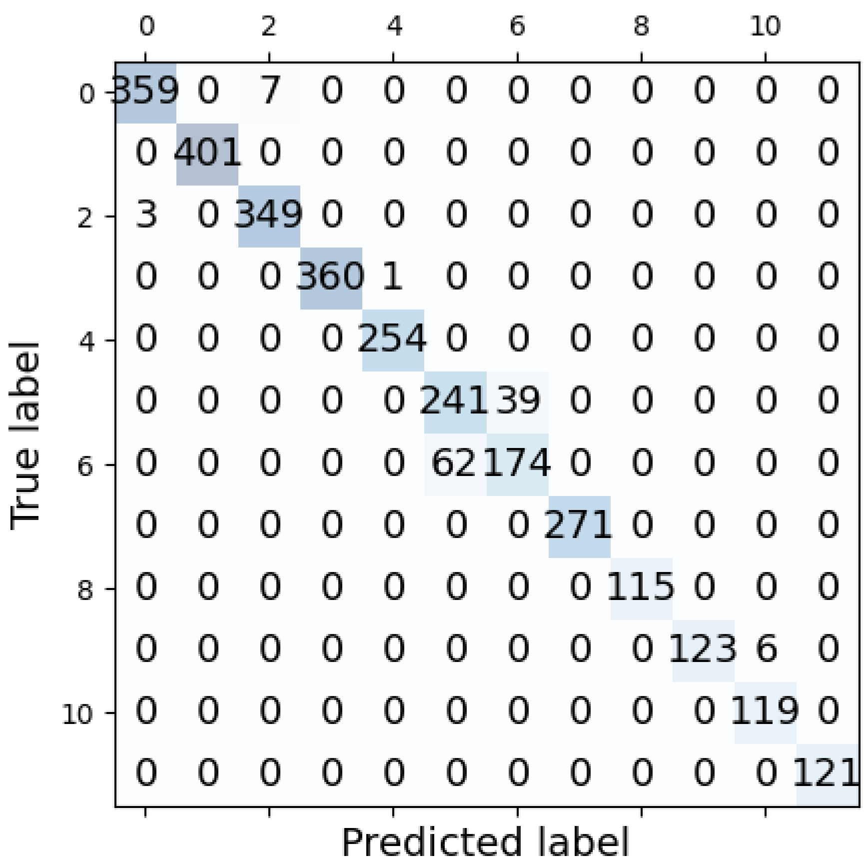
```
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8922 - loss: 0.2015 -
val_accuracy: 0.9098 - val_loss: 0.2733
Epoch 40/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8915 - loss: 0.1975 -
val_accuracy: 0.7649 - val_loss: 0.3190
Epoch 41/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8909 - loss: 0.1966 -
val_accuracy: 0.8250 - val_loss: 0.2930
Epoch 42/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8947 - loss: 0.1886 -
val_accuracy: 0.9043 - val_loss: 0.2701
Epoch 43/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8968 - loss: 0.1829 -
val_accuracy: 0.8236 - val_loss: 0.2987
Epoch 44/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8980 - loss: 0.1838 -
val_accuracy: 0.9568 - val_loss: 0.2366
Epoch 45/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8958 - loss: 0.1966 -
val_accuracy: 0.9677 - val_loss: 0.2204
Epoch 46/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9030 - loss: 0.1809 -
val_accuracy: 0.8758 - val_loss: 0.2607
Epoch 47/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9031 - loss: 0.1865 -
val_accuracy: 0.9766 - val_loss: 0.2212
Epoch 48/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9098 - loss: 0.1706 -
val_accuracy: 0.9698 - val_loss: 0.1921
Epoch 49/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9134 - loss: 0.1654 -
val_accuracy: 0.7122 - val_loss: 0.3801
Epoch 50/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9061 - loss: 0.1719 -
val_accuracy: 0.7595 - val_loss: 0.3206
Epoch 51/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9111 - loss: 0.1681 -
val_accuracy: 0.9168 - val_loss: 0.2399
Epoch 52/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9147 - loss: 0.1638 -
val_accuracy: 0.7424 - val_loss: 0.3587
Epoch 53/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8983 - loss: 0.1830 -
val_accuracy: 0.7620 - val_loss: 0.3458
Epoch 54/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9115 - loss: 0.1695 -
val_accuracy: 0.9323 - val_loss: 0.1992
Epoch 55/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9142 - loss: 0.1619 -
val_accuracy: 0.8546 - val_loss: 0.2401
Epoch 56/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9171 - loss: 0.1522 -
val_accuracy: 0.9261 - val_loss: 0.1871
Epoch 57/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9146 - loss: 0.1598 -
val_accuracy: 0.9791 - val_loss: 0.1458
Epoch 58/100
```

```
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9144 - loss: 0.1594 -
val_accuracy: 0.9606 - val_loss: 0.1659
Epoch 59/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9220 - loss: 0.1533 -
val_accuracy: 0.9133 - val_loss: 0.2044
Epoch 60/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9196 - loss: 0.1457 -
val_accuracy: 0.8114 - val_loss: 0.2826
Epoch 61/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9100 - loss: 0.1849 -
val_accuracy: 0.9062 - val_loss: 0.1867
Epoch 62/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9093 - loss: 0.1778 -
val_accuracy: 0.9878 - val_loss: 0.1243
Epoch 63/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9231 - loss: 0.1436 -
val_accuracy: 0.8793 - val_loss: 0.2001
Epoch 64/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9230 - loss: 0.1458 -
val_accuracy: 0.9750 - val_loss: 0.1238
Epoch 65/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9238 - loss: 0.1451 -
val_accuracy: 0.9918 - val_loss: 0.0972
Epoch 66/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9047 - loss: 0.1939 -
val_accuracy: 0.9967 - val_loss: 0.1405
Epoch 67/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9248 - loss: 0.1485 -
val_accuracy: 0.9967 - val_loss: 0.1335
Epoch 68/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9326 - loss: 0.1404 -
val_accuracy: 0.9709 - val_loss: 0.1424
Epoch 69/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9203 - loss: 0.1552 -
val_accuracy: 0.9886 - val_loss: 0.1326
Epoch 70/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9300 - loss: 0.1362 -
val_accuracy: 0.8889 - val_loss: 0.2129
Epoch 71/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9154 - loss: 0.1649 -
val_accuracy: 0.9894 - val_loss: 0.1170
Epoch 72/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9326 - loss: 0.1339 -
val_accuracy: 0.9160 - val_loss: 0.1826
Epoch 73/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9275 - loss: 0.1364 -
val_accuracy: 0.9739 - val_loss: 0.1317
Epoch 74/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9247 - loss: 0.1412 -
val_accuracy: 0.9937 - val_loss: 0.0945
Epoch 75/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9318 - loss: 0.1363 -
val_accuracy: 0.7772 - val_loss: 0.3486
Epoch 76/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9359 - loss: 0.1255 -
val_accuracy: 0.8022 - val_loss: 0.2985
Epoch 77/100
```

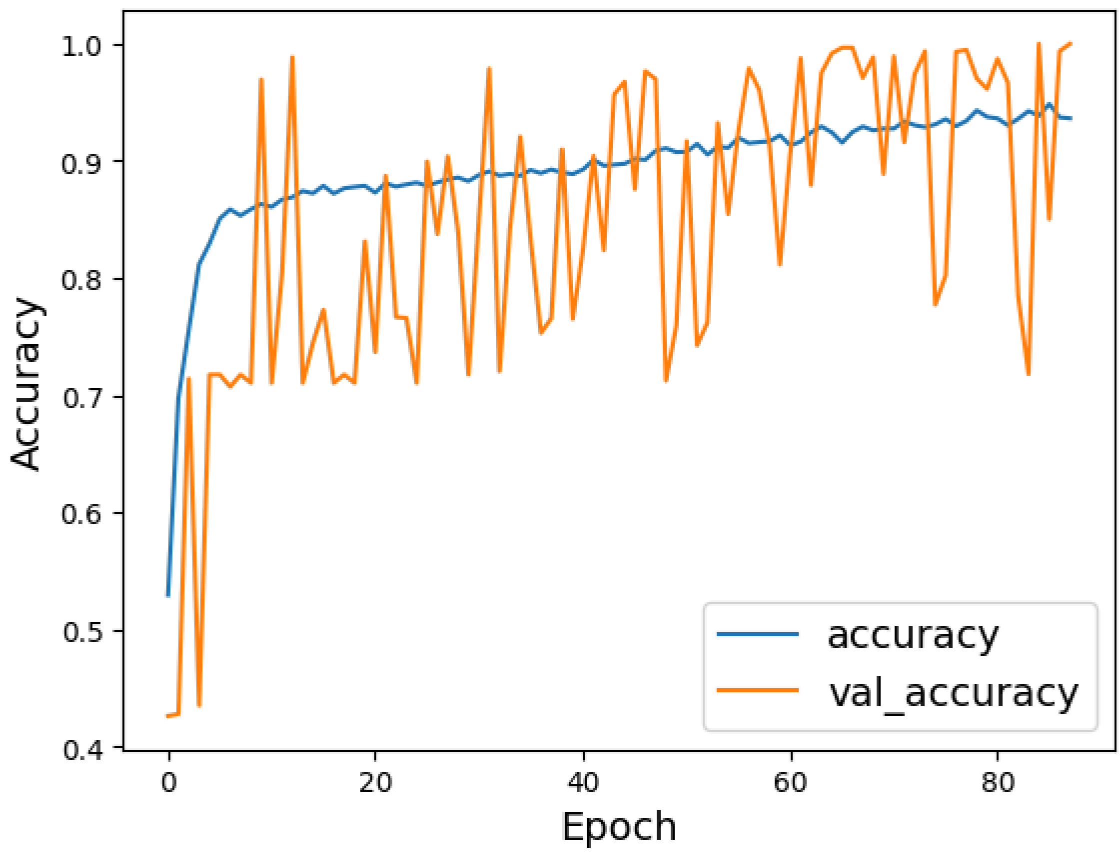
```
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9207 - loss: 0.1480 -
val_accuracy: 0.9932 - val_loss: 0.0826
Epoch 78/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9296 - loss: 0.1402 -
val_accuracy: 0.9948 - val_loss: 0.0804
Epoch 79/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9444 - loss: 0.1149 -
val_accuracy: 0.9704 - val_loss: 0.1039
Epoch 80/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9339 - loss: 0.1313 -
val_accuracy: 0.9614 - val_loss: 0.1247
Epoch 81/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9400 - loss: 0.1196 -
val_accuracy: 0.9872 - val_loss: 0.0866
Epoch 82/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9351 - loss: 0.1268 -
val_accuracy: 0.9668 - val_loss: 0.1199
Epoch 83/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9371 - loss: 0.1333 -
val_accuracy: 0.7842 - val_loss: 0.2836
Epoch 84/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9385 - loss: 0.1174 -
val_accuracy: 0.7179 - val_loss: 0.6861
Epoch 85/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9461 - loss: 0.1142 -
val_accuracy: 1.0000 - val_loss: 0.1905
Epoch 86/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9463 - loss: 0.1180 -
val_accuracy: 0.8503 - val_loss: 0.2175
Epoch 87/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.9393 - loss: 0.1184 -
val_accuracy: 0.9937 - val_loss: 0.1553
Epoch 88/100
460/460 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9356 - loss: 0.1396 -
val_accuracy: 1.0000 - val_loss: 0.1221
```

In [112]:
```python
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, classification_report
import numpy as np

# Convert predicted probabilities to class labels
y_pred = np.argmax(model.predict(X_test), axis=-1)

# Now y_pred contains class labels, which can be used with classification_repo
rt and confusion_matrix
cm = confusion_matrix(np.argmax(y_test, axis=-1), y_pred)
print(cm)

# Plot the confusion matrix
plt.figure(figsize=(10, 10))
plt.matshow(cm, cmap=plt.cm.Blues, alpha=0.3)
for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
        plt.text(x=j, y=i, s=cm[i, j], va='center', ha='center')
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.show()

print(classification_report(np.argmax(y_test, axis=-1), y_pred))

# Plot training history
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
94/94 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
[[359   0   7   0   0   0   0   0   0   0   0   0]
 [  0 401   0   0   0   0   0   0   0   0   0   0]
 [  3   0 349   0   0   0   0   0   0   0   0   0]
 [  0   0   0 360   1   0   0   0   0   0   0   0]
 [  0   0   0   0 254   0   0   0   0   0   0   0]
 [  0   0   0   0   0 241  39   0   0   0   0   0]
 [  0   0   0   0   0  62 174   0   0   0   0   0]
 [  0   0   0   0   0   0   0 271   0   0   0   0]
 [  0   0   0   0   0   0   0   0 115   0   0   0]
 [  0   0   0   0   0   0   0   0   0 123   6   0]
 [  0   0   0   0   0   0   0   0   0   0 119   0]
 [  0   0   0   0   0   0   0   0   0   0   0 121]]

<Figure size 1000x1000 with 0 Axes>
```



	precision	recall	f1-score	support
0	0.99	0.98	0.99	366
1	1.00	1.00	1.00	401
2	0.98	0.99	0.99	352
3	1.00	1.00	1.00	361
4	1.00	1.00	1.00	254
5	0.80	0.86	0.83	280
6	0.82	0.74	0.78	236
7	1.00	1.00	1.00	271
8	1.00	1.00	1.00	115
9	1.00	0.95	0.98	129
10	0.95	1.00	0.98	119
11	1.00	1.00	1.00	121
accuracy			0.96	3005
macro avg	0.96	0.96	0.96	3005
weighted avg	0.96	0.96	0.96	3005



5. Save the entire model to a HDF5 file

model.save('my_model.h5')

In [139]:
```
# Save the entire model to a HDF5 file
model.save('my_model.keras')
```

In [37]:
```
from tensorflow.keras.models import load_model

# Load the model
model = load_model('my_model.keras')
```

```
c:\Users\dania\AppData\Local\Programs\Python\Python312\Lib\site-packages\kera
s\src\saving\saving_lib.py:415: UserWarning: Skipping variable loading for op
timizer 'rmsprop', because it has 8 variables whereas the saved optimizer has
14 variables.
  saveable.load_own_variables(weights_store.get(inner_path))
```

6. Test with Experimental Modal Analysis Dataset of High Damage Severity

In [136]:
```
wcc_hd = pd.read_excel('./test/wcc_HD.xlsx')
wcc_hd = wcc_hd[(wcc_hd['mode_shape'] == 1)]
wcc_hd['severity_point'] = wcc_hd['severity'].astype(str) + '_' + wcc_hd['poin
t'].astype(str)
wcc_hd = wcc_hd.drop(["severity","mode_shape","point",], axis=1)
wcc_hd
wcc_hd['severity_point'] = wcc_hd['severity_point'].map(label_dict)
wcc_hd.head()
```

Out[136]:

	wcc	frfshift	peak_frequency	peak_amplitude	severity_point
0	308.712078	7.680376	16.5	0.441857	8
3	512.404811	10.349958	15.5	0.885045	9
6	481.689882	9.828734	16.0	0.764737	10
9	532.226787	14.963518	16.5	2.162405	11
12	310.973295	7.727579	16.5	0.444164	8

In [ ]:
```
wcc_FEAhd[(wcc_FEAhd['mode_shape'] == 1)].iloc[4:]
```

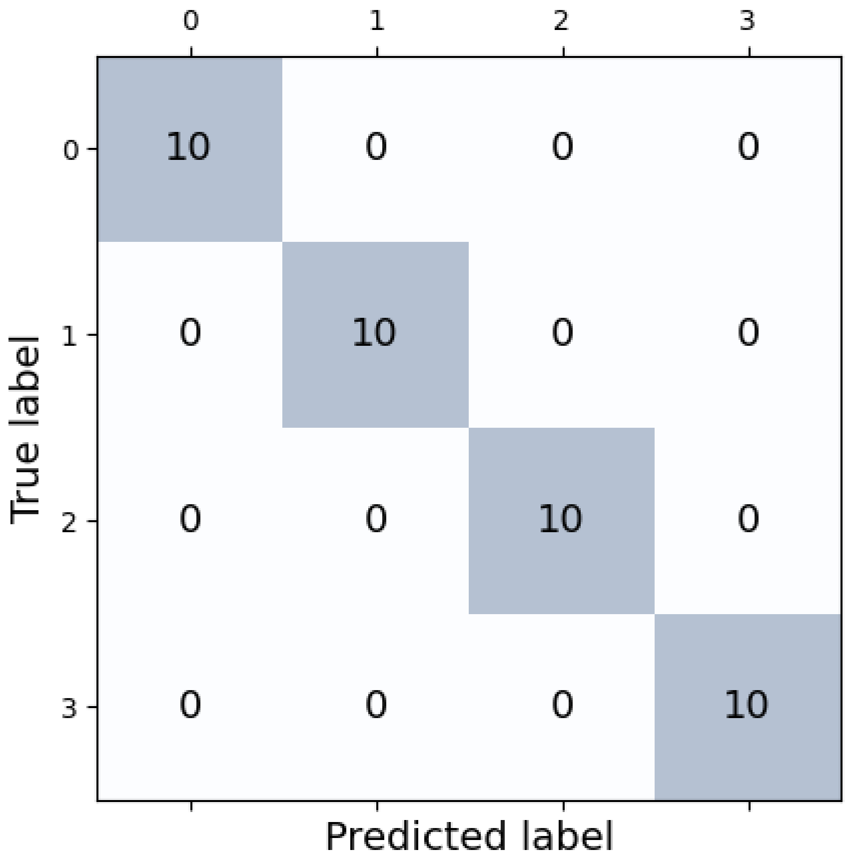
	wcc	frfshift	peak_frequency	peak_amplitude	severity	point	mode_shape
12	400.277900	7.071750	17.0	0.369735	HD	1	1
15	614.496863	9.896280	17.0	1.015607	HD	2	1
18	587.279162	9.207289	17.0	0.861799	HD	3	1
21	666.004619	15.089849	17.0	2.129556	HD	4	1

In [137]:
```
x_wcc_hd = wcc_hd[['wcc', 'frfshift', 'peak_frequency', 'peak_amplitude']].val
ues
y_wcc_hd = wcc_hd['severity_point'].values
y_wcc_hd = to_categorical(y_wcc_hd, num_classes=12)
```

In [138]:

```
import numpy as np
from sklearn.metrics import confusion_matrix, classification_report
import matplotlib.pyplot as plt

# Define the mapping from class indices to labels
class_labels = {8: 'HD_1', 9: 'HD_2', 10: 'HD_3', 11: 'HD_4'}

# Convert predicted probabilities to class labels
y_pred_wcc_hd = np.argmax(model.predict(x_wcc_hd), axis=-1)
y_pred_wcc_hd_labels = [class_labels[i] for i in y_pred_wcc_hd]

# Convert one-hot encoded true labels to their original form
y_true_wcc_hd = np.argmax(y_wcc_hd, axis=-1)
y_true_wcc_hd_labels = [class_labels[i] for i in y_true_wcc_hd]

# Now y_pred and y_true contain class labels, which can be used with classific
ation_report and confusion_matrix
cm = confusion_matrix(y_true_wcc_hd_labels, y_pred_wcc_hd_labels)
print(cm)

# Plot the confusion matrix
plt.figure(figsize=(10, 10))
plt.matshow(cm, cmap=plt.cm.Blues, alpha=0.3)
for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
        plt.text(x=j, y=i, s=cm[i, j], va='center', ha='center')
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.show()

print(classification_report(y_true_wcc_hd_labels, y_pred_wcc_hd_labels))
```

```
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
[[10  0  0  0]
 [ 0 10  0  0]
 [ 0  0 10  0]
 [ 0  0  0 10]]

&lt;Figure size 1000x1000 with 0 Axes&gt;
```




```
              precision    recall  f1-score   support

        HD_1       1.00      1.00      1.00        10
        HD_2       1.00      1.00      1.00        10
        HD_3       1.00      1.00      1.00        10
        HD_4       1.00      1.00      1.00        10

    accuracy                           1.00        40
   macro avg       1.00      1.00      1.00        40
weighted avg       1.00      1.00      1.00        40
```

In [100]:
```
wcc_FEAhd[(wcc_FEAhd['mode_shape'] == 1)].iloc[4:]
```

Out[100]:

	wcc	frfshift	peak_frequency	peak_amplitude	severity	point	mode_shape
12	400.277900	7.071750	17.0	0.369735	HD	1	1
15	614.496863	9.896280	17.0	1.015607	HD	2	1
18	587.279162	9.207289	17.0	0.861799	HD	3	1
21	666.004619	15.089849	17.0	2.129556	HD	4	1