In [26]:
```
import h5py
import numpy as np
import pandas as pd
import numpy as np

file_path = '/Users/rizq/projects/roaddata/ROAD_dataset.h5'
```

In [2]:
```
train = 'train_data/data'
test = 'test_data/data'

train_indices = 0
test_indices = 0
anomalyGroups = []
```

In [3]:
```
with h5py.File(file_path, 'r') as hf:
  train_indices = len(hf[train])
  test_indices = len(hf[test])

  for k in hf['anomaly_data'].keys():
    anomalyGroups.append(k)
  print(anomalyGroups)
```

```
['first_order_data_loss', 'first_order_high_noise', 'galactic_plane', '
lightning', 'oscillating_tile', 'rfi_ionosphere_reflect', 'solar_stor
m', 'source_in_sidelobes', 'third_order_data_loss']
```

In [4]:
```
print(train_indices)
print(test_indices)
```

```
3687
1000
```

In [5]:
```
anomalyTrainGroupDict = {}
anomalyTestGroupDict = {}
```

In [6]:
```
import torch
from torch.utils.data import random_split

with h5py.File(file_path, 'r') as hf:

  for k in hf['anomaly_data'].keys():
    dataset = hf['anomaly_data'][k]['data']
    #print(k)

    # Define the sizes of the splits
    train_size = int(0.8 * len(dataset))
    test_size = len(dataset) - train_size

    # Split the dataset into training and testing sets
    train_dataset, test_dataset = random_split(dataset, [train_size, t
```

```
    anomalyTrainGroupDict[k] = train_dataset.indices
    anomalyTestGroupDict[k] = test_dataset.indices

    #print(test_dataset.indices)
```

In [8]:
```
trainPaths = []
testPaths = []
for i in range(train_indices):
  tup = ('train_data', i)
  trainPaths.append(tup)

for i in range(test_indices):
  tup = ('test_data', i)
  testPaths.append(tup)

for k in anomalyTrainGroupDict.keys():
  for idx in anomalyTrainGroupDict[k]:
    tup = (f'anomaly_data/{k}', idx)
    trainPaths.append(tup)

for k in anomalyTestGroupDict.keys():
  for idx in anomalyTestGroupDict[k]:
    tup = (f'anomaly_data/{k}', idx)
    testPaths.append(tup)
```

In [9]:
```
print(len(trainPaths))
print(len(testPaths))
```

```
5575
1478
```

In [11]:
```
import random

random.shuffle(trainPaths)
random.shuffle(testPaths)
#print(trainPaths)
```

In [12]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim

# Set device to GPU if available, otherwise use CPU
#device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
# Set device to MPS (Apple Silicon) if available, otherwise use CPU
device = torch.device("mps" if torch.backends.mps.is_available() else
```

In [23]:
```
from torch.utils.data import Dataset, DataLoader

class H5Dataset(Dataset):
    def __init__(self, paths, hf, transform=None):
        """
```

```
        paths: A list of tuples (path, index)
        transform: Optional transform to be applied on a sample.
        """
        self.paths = paths
        self.transform = transform
        self.hf = hf

        self.anomaly_mapping = {
            "first_order_data_loss": 1,
            "first_order_high_noise": 2,
            "galactic_plane": 3,
            "lightning": 4,
            "oscillating_tile": 5,
            "rfi_ionosphere_reflect": 6,
            "solar_storm": 7,
            "source_in_sidelobes": 8,
            "third_order_data_loss": 9
        }

    def __len__(self):
        return len(self.paths)

    def __getitem__(self, i):
        path, index = self.paths[i]
        #print(path)

        # Open the file and retrieve the sample and label on the fly
        #with h5py.File(file_path, 'r') as hf:
            # Extract the data sample and label using the index
        data = hf[f'{path}/data'][index]
        label = hf[f'{path}/labels'][index]

        # Optionally apply a transformation to the data sample
        if self.transform:
            data = self.transform(data)

        # Convert sample to a tensor
        data = torch.tensor(data, dtype=torch.float32)

        data = data.permute(2, 0, 1)

        if isinstance(label, (np.bytes_, bytes)):
            label = label.decode('utf-8')

        if label == '':
            label_int = 0
            #print('normal')
        else:
            label = path.split("/")[-1]
            if label in self.anomaly_mapping:
                label_int = self.anomaly_mapping[label]
                #print(f"label = {label}")
```

```
            else:
                raise ValueError(f"Label {label} not found in mapping


        label_int = torch.tensor(label_int, dtype=torch.long)

        return data, label_int
```

In [25]:
```
import os
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
from tqdm import tqdm
import itertools
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Set the device
#device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
device = torch.device("mps" if torch.backends.mps.is_available() else

# =====================================================================
# Define the CNN Model that accepts hyperparameters
# =====================================================================
class CNNClassifier(nn.Module):
    def __init__(self, num_classes=10, base_filters=16, kernel_size=3,
        """
        num_classes: Total number of classes (0 for normal and 1-9 for
        base_filters: Number of filters for the first convolution laye
        kernel_size: Convolution kernel size (assumed square).
        dropout_rate: Dropout probability.
        """
        super(CNNClassifier, self).__init__()
        padding = kernel_size // 2  # this keeps the spatial dimension
        # First conv block
        self.conv1 = nn.Conv2d(in_channels=4, out_channels=base_filter
        self.bn1 = nn.BatchNorm2d(base_filters)
        self.pool = nn.MaxPool2d(2)

        # Second conv block (doubling filters)
        self.conv2 = nn.Conv2d(in_channels=base_filters, out_channels=
        self.bn2 = nn.BatchNorm2d(base_filters * 2)

        # Third conv block (doubling again)
        self.conv3 = nn.Conv2d(in_channels=base_filters * 2, out_chann
        self.bn3 = nn.BatchNorm2d(base_filters * 4)

        # Dropout layer
        self.dropout = nn.Dropout(dropout_rate)
```

```
        # Global average pooling layer
        self.gap = nn.AdaptiveAvgPool2d((1, 1))

        # Fully connected layer
        self.fc = nn.Linear(base_filters * 4, num_classes)

    def forward(self, x):
        x = torch.relu(self.bn1(self.conv1(x)))
        x = self.pool(x)
        x = torch.relu(self.bn2(self.conv2(x)))
        x = self.pool(x)
        x = torch.relu(self.bn3(self.conv3(x)))
        x = self.pool(x)
        x = self.dropout(x)
        x = self.gap(x)
        x = x.view(x.size(0), -1)
        x = self.fc(x)
        return x

# ======================================================================
# Data Preparation Helpers
# ======================================================================
# Assuming train_dataset and test_dataset are already defined.
# Example:
# train_dataset = YourCustomH5Dataset(trainPaths, transform=your_trans
# test_dataset  = YourCustomH5Dataset(testPaths, transform=your_transf
hf = h5py.File(file_path, 'r')
train_dataset = H5Dataset(paths=trainPaths, hf=hf)
test_dataset = H5Dataset(paths=testPaths, hf=hf)

def get_data_loaders(batch_size):
    train_loader = DataLoader(train_dataset, batch_size=batch_size, sh
    test_loader = DataLoader(test_dataset, batch_size=batch_size, shuf
    return train_loader, test_loader

# ======================================================================
# Training and Evaluation Function
# ======================================================================
def train_and_evaluate(lr, batch_size, base_filters, kernel_size, drop
    """
    Trains a model with the specified hyperparameters for num_epochs (
    Returns a tuple of (test_accuracy, model_state_dict).
    """
    train_loader, test_loader = get_data_loaders(batch_size)

    # Initialize the model with provided hyperparameters
    model = CNNClassifier(num_classes=10, base_filters=base_filters, k
    model.to(device)

    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=lr)
```

```
    # Training loop
    model.train()
    for epoch in range(num_epochs):
        running_loss = 0.0
        progress_bar = tqdm(train_loader, desc=f"Epoch {epoch+1}/{num_
        for inputs, labels in progress_bar:
            inputs, labels = inputs.to(device), labels.to(device)
            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            running_loss += loss.item() * inputs.size(0)
            progress_bar.set_postfix(loss=loss.item())

    # Evaluation loop
    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for inputs, labels in test_loader:
            inputs, labels = inputs.to(device), labels.to(device)
            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
            total += labels.size(0)
            correct += (preds == labels).sum().item()
    accuracy = correct / total
    return accuracy, model.state_dict()

# ======================================================================
# Hyperparameter Tuning Loop with Periodic Checkpointing
# ======================================================================
# Hyperparameter grid
learning_rates = [1e-3, 5e-4]
batch_sizes = [16, 32]
base_filters_list = [16, 32]
kernel_sizes = [3, 5]
dropout_rates = [0.0, 0.5]

# All hyperparameter combinations
hyperparam_combinations = list(itertools.product(learning_rates, batch

# Create directory for model checkpoints
checkpoint_dir = "checkpoints"
if not os.path.exists(checkpoint_dir):
    os.makedirs(checkpoint_dir)

results = []
print("Starting hyperparameter tuning...")

# Loop over hyperparameter combinations
for idx, (lr, batch_size, base_filters, kernel_size, dropout_rate) in
```

```python
    print(f"\nExperiment {idx+1}/{len(hyperparam_combinations)}: lr={l

    test_acc, model_state = train_and_evaluate(lr, batch_size, base_fi

    # Save model checkpoint with filename encoding hyperparameters.
    model_filename = f"model_lr{lr}_bs{batch_size}_f{base_filters}_k{k
    model_save_path = os.path.join(checkpoint_dir, model_filename)
    torch.save(model_state, model_save_path)

    # Record results along with the model checkpoint path.
    results.append({
        "lr": lr,
        "batch_size": batch_size,
        "base_filters": base_filters,
        "kernel_size": kernel_size,
        "dropout_rate": dropout_rate,
        "test_accuracy": test_acc,
        "model_path": model_save_path
    })

    print(f"Test Accuracy: {test_acc:.4f} -- Model saved as {model_sav

    # Save intermediate results to CSV after each experiment.
    results_df = pd.DataFrame(results)
    results_df.to_csv("hyperparam_tuning_results.csv", index=False)

# ========================================================================
# Final Results Table and Plot
# ========================================================================
results_df = pd.DataFrame(results)
print("\nHyperparameter Tuning Results:")
print(results_df)

results_df_sorted = results_df.sort_values(by="test_accuracy", ascendi
print("\nBest Hyperparameters:")
print(results_df_sorted.head())

plt.figure(figsize=(10,6))
plt.barh(results_df_sorted.index.astype(str), results_df_sorted['test_
plt.xlabel("Test Accuracy")
plt.title("Hyperparameter Tuning Results")
plt.gca().invert_yaxis()
plt.show()


# close the file
hf.close()
```

```
Starting hyperparameter tuning...

Experiment 1/32: lr=0.001, batch_size=16, filters=16, kernel_size=3, dr
opout=0.0
```

```
Test Accuracy: 0.7077 -- Model saved as checkpoints/model_lr0.001_bs16_
f16_k3_d0.0.pth

Experiment 2/32: lr=0.001, batch_size=16, filters=16, kernel_size=3, dr
opout=0.5

Test Accuracy: 0.7057 -- Model saved as checkpoints/model_lr0.001_bs16_
f16_k3_d0.5.pth

Experiment 3/32: lr=0.001, batch_size=16, filters=16, kernel_size=5, dr
opout=0.0

Test Accuracy: 0.6982 -- Model saved as checkpoints/model_lr0.001_bs16_
f16_k5_d0.0.pth

Experiment 4/32: lr=0.001, batch_size=16, filters=16, kernel_size=5, dr
opout=0.5

Test Accuracy: 0.7341 -- Model saved as checkpoints/model_lr0.001_bs16_
f16_k5_d0.5.pth

Experiment 5/32: lr=0.001, batch_size=16, filters=32, kernel_size=3, dr
opout=0.0

Test Accuracy: 0.3484 -- Model saved as checkpoints/model_lr0.001_bs16_
f32_k3_d0.0.pth

Experiment 6/32: lr=0.001, batch_size=16, filters=32, kernel_size=3, dr
opout=0.5

Test Accuracy: 0.7192 -- Model saved as checkpoints/model_lr0.001_bs16_
f32_k3_d0.5.pth

Experiment 7/32: lr=0.001, batch_size=16, filters=32, kernel_size=5, dr
opout=0.0

Test Accuracy: 0.7388 -- Model saved as checkpoints/model_lr0.001_bs16_
f32_k5_d0.0.pth

Experiment 8/32: lr=0.001, batch_size=16, filters=32, kernel_size=5, dr
opout=0.5

Test Accuracy: 0.7395 -- Model saved as checkpoints/model_lr0.001_bs16_
f32_k5_d0.5.pth

Experiment 9/32: lr=0.001, batch_size=32, filters=16, kernel_size=3, dr
opout=0.0
```

```
Test Accuracy: 0.6800 -- Model saved as checkpoints/model_lr0.001_bs32_
f16_k3_d0.0.pth

Experiment 10/32: lr=0.001, batch_size=32, filters=16, kernel_size=3, d
ropout=0.5

Test Accuracy: 0.7023 -- Model saved as checkpoints/model_lr0.001_bs32_
f16_k3_d0.5.pth

Experiment 11/32: lr=0.001, batch_size=32, filters=16, kernel_size=5, d
ropout=0.0

Test Accuracy: 0.6827 -- Model saved as checkpoints/model_lr0.001_bs32_
f16_k5_d0.0.pth

Experiment 12/32: lr=0.001, batch_size=32, filters=16, kernel_size=5, d
ropout=0.5

Test Accuracy: 0.7476 -- Model saved as checkpoints/model_lr0.001_bs32_
f16_k5_d0.5.pth

Experiment 13/32: lr=0.001, batch_size=32, filters=32, kernel_size=3, d
ropout=0.0

Test Accuracy: 0.7192 -- Model saved as checkpoints/model_lr0.001_bs32_
f32_k3_d0.0.pth

Experiment 14/32: lr=0.001, batch_size=32, filters=32, kernel_size=3, d
ropout=0.5

Test Accuracy: 0.6915 -- Model saved as checkpoints/model_lr0.001_bs32_
f32_k3_d0.5.pth

Experiment 15/32: lr=0.001, batch_size=32, filters=32, kernel_size=5, d
ropout=0.0

Test Accuracy: 0.6103 -- Model saved as checkpoints/model_lr0.001_bs32_
f32_k5_d0.0.pth

Experiment 16/32: lr=0.001, batch_size=32, filters=32, kernel_size=5, d
ropout=0.5

Test Accuracy: 0.1590 -- Model saved as checkpoints/model_lr0.001_bs32_
f32_k5_d0.5.pth

Experiment 17/32: lr=0.0005, batch_size=16, filters=16, kernel_size=3,
dropout=0.0
```

```
Test Accuracy: 0.6861 -- Model saved as checkpoints/model_lr0.0005_bs16
_f16_k3_d0.0.pth

Experiment 18/32: lr=0.0005, batch_size=16, filters=16, kernel_size=3,
dropout=0.5

Test Accuracy: 0.6982 -- Model saved as checkpoints/model_lr0.0005_bs16
_f16_k3_d0.5.pth

Experiment 19/32: lr=0.0005, batch_size=16, filters=16, kernel_size=5,
dropout=0.0

Test Accuracy: 0.7300 -- Model saved as checkpoints/model_lr0.0005_bs16
_f16_k5_d0.0.pth

Experiment 20/32: lr=0.0005, batch_size=16, filters=16, kernel_size=5,
dropout=0.5

Test Accuracy: 0.7145 -- Model saved as checkpoints/model_lr0.0005_bs16
_f16_k5_d0.5.pth

Experiment 21/32: lr=0.0005, batch_size=16, filters=32, kernel_size=3,
dropout=0.0

Test Accuracy: 0.7307 -- Model saved as checkpoints/model_lr0.0005_bs16
_f32_k3_d0.0.pth

Experiment 22/32: lr=0.0005, batch_size=16, filters=32, kernel_size=3,
dropout=0.5

Test Accuracy: 0.7158 -- Model saved as checkpoints/model_lr0.0005_bs16
_f32_k3_d0.5.pth

Experiment 23/32: lr=0.0005, batch_size=16, filters=32, kernel_size=5,
dropout=0.0

Test Accuracy: 0.7327 -- Model saved as checkpoints/model_lr0.0005_bs16
_f32_k5_d0.0.pth

Experiment 24/32: lr=0.0005, batch_size=16, filters=32, kernel_size=5,
dropout=0.5

Test Accuracy: 0.7158 -- Model saved as checkpoints/model_lr0.0005_bs16
_f32_k5_d0.5.pth

Experiment 25/32: lr=0.0005, batch_size=32, filters=16, kernel_size=3,
dropout=0.0
```

```
Test Accuracy: 0.6834 -- Model saved as checkpoints/model_lr0.0005_bs32
_f16_k3_d0.0.pth

Experiment 26/32: lr=0.0005, batch_size=32, filters=16, kernel_size=3,
dropout=0.5

Test Accuracy: 0.6766 -- Model saved as checkpoints/model_lr0.0005_bs32
_f16_k3_d0.5.pth

Experiment 27/32: lr=0.0005, batch_size=32, filters=16, kernel_size=5,
dropout=0.0

Test Accuracy: 0.4655 -- Model saved as checkpoints/model_lr0.0005_bs32
_f16_k5_d0.0.pth

Experiment 28/32: lr=0.0005, batch_size=32, filters=16, kernel_size=5,
dropout=0.5

Test Accuracy: 0.6982 -- Model saved as checkpoints/model_lr0.0005_bs32
_f16_k5_d0.5.pth

Experiment 29/32: lr=0.0005, batch_size=32, filters=32, kernel_size=3,
dropout=0.0

Test Accuracy: 0.6976 -- Model saved as checkpoints/model_lr0.0005_bs32
_f32_k3_d0.0.pth

Experiment 30/32: lr=0.0005, batch_size=32, filters=32, kernel_size=3,
dropout=0.5

Test Accuracy: 0.7050 -- Model saved as checkpoints/model_lr0.0005_bs32
_f32_k3_d0.5.pth

Experiment 31/32: lr=0.0005, batch_size=32, filters=32, kernel_size=5,
dropout=0.0

Test Accuracy: 0.4046 -- Model saved as checkpoints/model_lr0.0005_bs32
_f32_k5_d0.0.pth

Experiment 32/32: lr=0.0005, batch_size=32, filters=32, kernel_size=5,
dropout=0.5

Test Accuracy: 0.7145 -- Model saved as checkpoints/model_lr0.0005_bs32
_f32_k5_d0.5.pth

Hyperparameter Tuning Results:
        lr  batch_size  base_filters  kernel_size  dropout_rate  \
0   0.0010          16            16            3           0.0
1   0.0010          16            16            3           0.5
2   0.0010          16            16            5           0.0
```

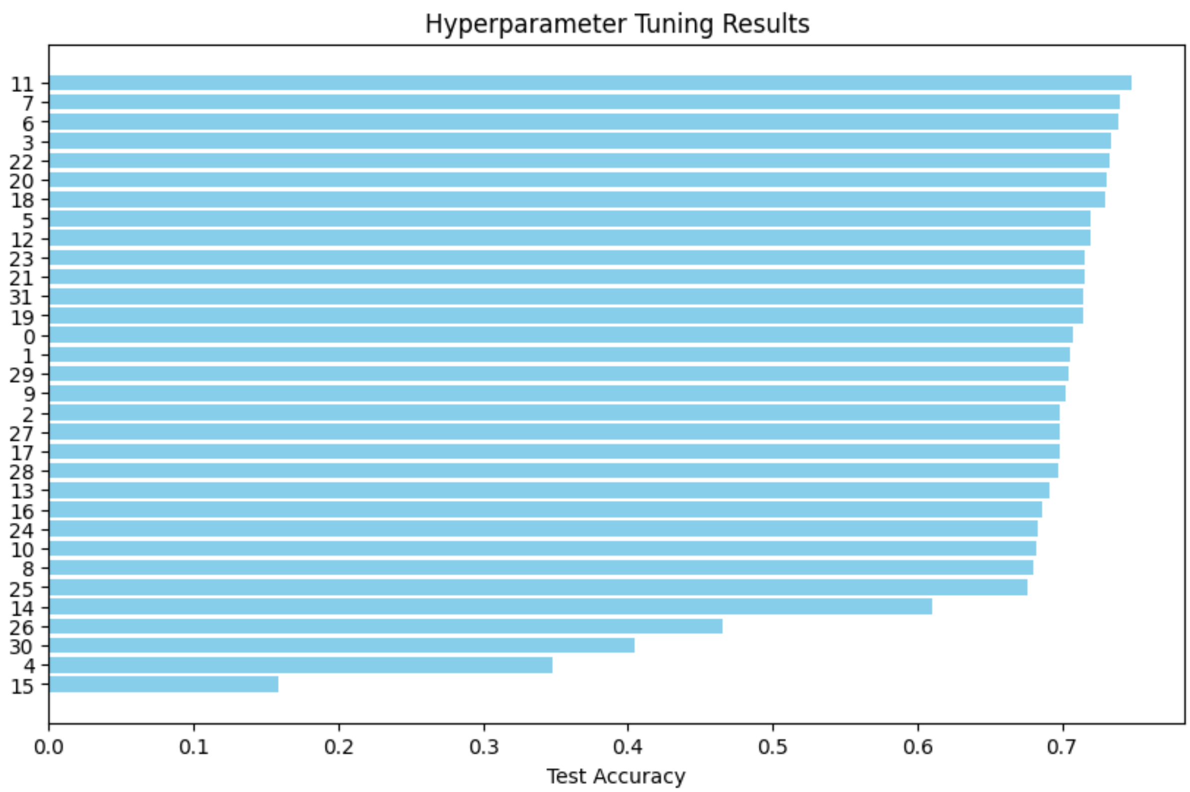
3	0.0010	16	16	5	0.5
4	0.0010	16	32	3	0.0
5	0.0010	16	32	3	0.5
6	0.0010	16	32	5	0.0
7	0.0010	16	32	5	0.5
8	0.0010	32	16	3	0.0
9	0.0010	32	16	3	0.5
10	0.0010	32	16	5	0.0
11	0.0010	32	16	5	0.5
12	0.0010	32	32	3	0.0
13	0.0010	32	32	3	0.5
14	0.0010	32	32	5	0.0
15	0.0010	32	32	5	0.5
16	0.0005	16	16	3	0.0
17	0.0005	16	16	3	0.5
18	0.0005	16	16	5	0.0
19	0.0005	16	16	5	0.5
20	0.0005	16	32	3	0.0
21	0.0005	16	32	3	0.5
22	0.0005	16	32	5	0.0
23	0.0005	16	32	5	0.5
24	0.0005	32	16	3	0.0
25	0.0005	32	16	3	0.5
26	0.0005	32	16	5	0.0
27	0.0005	32	16	5	0.5
28	0.0005	32	32	3	0.0
29	0.0005	32	32	3	0.5
30	0.0005	32	32	5	0.0
31	0.0005	32	32	5	0.5

	test_accuracy	model_path
0	0.707713	checkpoints/model_lr0.001_bs16_f16_k3_d0.0.pth
1	0.705683	checkpoints/model_lr0.001_bs16_f16_k3_d0.5.pth
2	0.698241	checkpoints/model_lr0.001_bs16_f16_k5_d0.0.pth
3	0.734100	checkpoints/model_lr0.001_bs16_f16_k5_d0.5.pth
4	0.348444	checkpoints/model_lr0.001_bs16_f32_k3_d0.0.pth
5	0.719215	checkpoints/model_lr0.001_bs16_f32_k3_d0.5.pth
6	0.738836	checkpoints/model_lr0.001_bs16_f32_k5_d0.0.pth
7	0.739513	checkpoints/model_lr0.001_bs16_f32_k5_d0.5.pth
8	0.679973	checkpoints/model_lr0.001_bs32_f16_k3_d0.0.pth
9	0.702300	checkpoints/model_lr0.001_bs32_f16_k3_d0.5.pth
10	0.682679	checkpoints/model_lr0.001_bs32_f16_k5_d0.0.pth
11	0.747632	checkpoints/model_lr0.001_bs32_f16_k5_d0.5.pth
12	0.719215	checkpoints/model_lr0.001_bs32_f32_k3_d0.0.pth
13	0.691475	checkpoints/model_lr0.001_bs32_f32_k3_d0.5.pth
14	0.610284	checkpoints/model_lr0.001_bs32_f32_k5_d0.0.pth
15	0.158999	checkpoints/model_lr0.001_bs32_f32_k5_d0.5.pth
16	0.686062	checkpoints/model_lr0.0005_bs16_f16_k3_d0.0.pth
17	0.698241	checkpoints/model_lr0.0005_bs16_f16_k3_d0.5.pth
18	0.730041	checkpoints/model_lr0.0005_bs16_f16_k5_d0.0.pth
19	0.714479	checkpoints/model_lr0.0005_bs16_f16_k5_d0.5.pth
20	0.730717	checkpoints/model_lr0.0005_bs16_f32_k3_d0.0.pth

```
21        0.715832  checkpoints/model_lr0.0005_bs16_f32_k3_d0.5.pth
22        0.732747  checkpoints/model_lr0.0005_bs16_f32_k5_d0.0.pth
23        0.715832  checkpoints/model_lr0.0005_bs16_f32_k5_d0.5.pth
24        0.683356  checkpoints/model_lr0.0005_bs32_f16_k3_d0.0.pth
25        0.676590  checkpoints/model_lr0.0005_bs32_f16_k3_d0.5.pth
26        0.465494  checkpoints/model_lr0.0005_bs32_f16_k5_d0.0.pth
27        0.698241  checkpoints/model_lr0.0005_bs32_f16_k5_d0.5.pth
28        0.697564  checkpoints/model_lr0.0005_bs32_f32_k3_d0.0.pth
29        0.705007  checkpoints/model_lr0.0005_bs32_f32_k3_d0.5.pth
30        0.404601  checkpoints/model_lr0.0005_bs32_f32_k5_d0.0.pth
31        0.714479  checkpoints/model_lr0.0005_bs32_f32_k5_d0.5.pth

Best Hyperparameters:
        lr  batch_size  base_filters  kernel_size  dropout_rate  \
11  0.0010          32            16            5           0.5
7   0.0010          16            32            5           0.5
6   0.0010          16            32            5           0.0
3   0.0010          16            16            5           0.5
22  0.0005          16            32            5           0.0

    test_accuracy                                        model_path
11       0.747632   checkpoints/model_lr0.001_bs32_f16_k5_d0.5.pth
7        0.739513   checkpoints/model_lr0.001_bs16_f32_k5_d0.5.pth
6        0.738836   checkpoints/model_lr0.001_bs16_f32_k5_d0.0.pth
3        0.734100   checkpoints/model_lr0.001_bs16_f16_k5_d0.5.pth
22       0.732747  checkpoints/model_lr0.0005_bs16_f32_k5_d0.0.pth
```



In [ ]: