```
# ============================================================
# 1. IMPORT LIBRARIES
# ============================================================

import tensorflow as tf
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.optimizers import Adam
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
```

```
# Set random seed for reproducibility
tf.random.set_seed(42)
np.random.seed(42)
```

```
# ============================================================
# 2. LOAD AND PREPROCESS DATASET
# ============================================================

(X_train, y_train), (X_test, y_test) = cifar10.load_data()

# Normalize pixel values
X_train = X_train / 255.0
X_test  = X_test / 255.0

# One-hot encode labels
y_train = to_categorical(y_train, 10)
y_test  = to_categorical(y_test, 10)
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 ━━━━━━━━━━━━━━━━━━━━ 16s 0us/step
```

```
# ============================================================
# 3. CNN MODEL FUNCTION
# ============================================================

def build_cnn(kernel_size, filters):
    model = Sequential([
        Conv2D(filters, kernel_size, activation='relu', input_shape=(32, 32, 3)),
        MaxPooling2D(pool_size=(2, 2)),
        Conv2D(filters * 2, kernel_size, activation='relu'),
        MaxPooling2D(pool_size=(2, 2)),
        Flatten(),
        Dense(128, activation='relu'),
        Dense(10, activation='softmax')
    ])

    model.compile(
        optimizer=Adam(),
        loss='categorical_crossentropy',
        metrics=['accuracy']
    )

    return model
```

```
# ============================================================
# 4. EXPERIMENT CONFIGURATIONS
# ============================================================

experiments = {
    "3x3_32filters": {"kernel": (3,3), "filters": 32},
    "5x5_32filters": {"kernel": (5,5), "filters": 32},
    "3x3_64filters": {"kernel": (3,3), "filters": 64},
    "5x5_64filters": {"kernel": (5,5), "filters": 64}
}

history_dict = {}
test_results = []
```

```
# ============================================================
# PRINT MODEL SUMMARY FOR EACH CONFIGURATION
# ============================================================

for name, params in experiments.items():
    print("\n" + "="*60)
    print(f"Model Summary: {name}")
    print(f"Kernel Size: {params['kernel']} | Filters: {params['filters']}")
    print("="*60)

    model = build_cnn(params["kernel"], params["filters"])
    model.summary()
```

```
============================================================
Model Summary: 3x3_32filters
Kernel Size: (3, 3) | Filters: 32
============================================================
/usr/local/lib/python3.12/dist-packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Seque
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_1 (Conv2D)	(None, 13, 13, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 64)	0
flatten (Flatten)	(None, 2304)	0
dense (Dense)	(None, 128)	295,040
dense_1 (Dense)	(None, 10)	1,290

Total params: 315,722 (1.20 MB)
Trainable params: 315,722 (1.20 MB)
Non-trainable params: 0 (0.00 B)

```
============================================================
Model Summary: 5x5_32filters
Kernel Size: (5, 5) | Filters: 32
============================================================
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_2 (Conv2D)	(None, 28, 28, 32)	2,432
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 32)	0
conv2d_3 (Conv2D)	(None, 10, 10, 64)	51,264
max_pooling2d_3 (MaxPooling2D)	(None, 5, 5, 64)	0
flatten_1 (Flatten)	(None, 1600)	0
dense_2 (Dense)	(None, 128)	204,928
dense_3 (Dense)	(None, 10)	1,290

Total params: 259,914 (1015.29 KB)
Trainable params: 259,914 (1015.29 KB)
Non-trainable params: 0 (0.00 B)

```
============================================================
Model Summary: 3x3_64filters
Kernel Size: (3, 3) | Filters: 64
============================================================
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 30, 30, 64)	1,792
max_pooling2d_4 (MaxPooling2D)	(None, 15, 15, 64)	0
conv2d_5 (Conv2D)	(None, 13, 13, 128)	73,856
max_pooling2d_5 (MaxPooling2D)	(None, 6, 6, 128)	0
flatten_2 (Flatten)	(None, 4608)	0
dense_4 (Dense)	(None, 128)	589,952
dense_5 (Dense)	(None, 10)	1,290

Total params: 666,890 (2.54 MB)
Trainable params: 666,890 (2.54 MB)
Non-trainable params: 0 (0.00 B)

```
============================================================
Model Summary: 5x5_64filters
Kernel Size: (5, 5) | Filters: 64
============================================================
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 28, 28, 64)	4,864
max_pooling2d_6 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_7 (Conv2D)	(None, 10, 10, 128)	204,928
max_pooling2d_7 (MaxPooling2D)	(None, 5, 5, 128)	0
flatten_3 (Flatten)	(None, 3200)	0
dense_6 (Dense)	(None, 128)	409,728
dense_7 (Dense)	(None, 10)	1,290

```
# ============================================================
# 5. TRAIN MODELS
# ============================================================

for name, params in experiments.items():
    print(f"\nTraining Model: {name}")

    model = build_cnn(params["kernel"], params["filters"])

    history = model.fit(
        X_train, y_train,
        epochs=15,
        batch_size=64,
        validation_split=0.2,
        verbose=1
    )

    test_loss, test_acc = model.evaluate(X_test, y_test, verbose=0)

    history_dict[name] = history
```

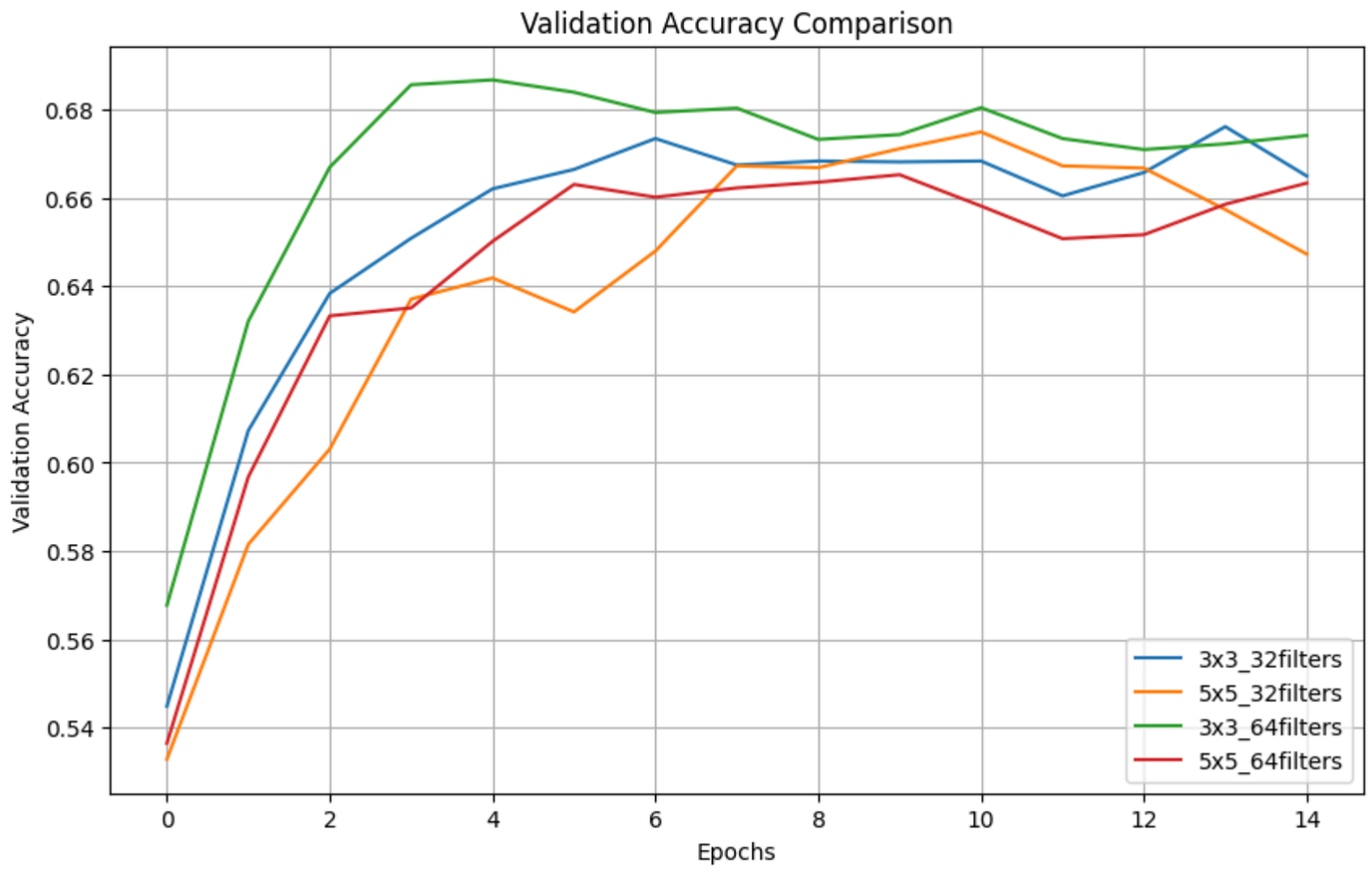
```
    test_results.append([name, test_acc])

    print(f"Test Accuracy for {name}: {test_acc:.4f}")
```

```
Training Model: 3x3_32filters
Epoch 1/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy: 0.3580 - loss: 1.7606 - val_accuracy: 0.5448 - val_loss: 1.2761
Epoch 2/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.5686 - loss: 1.2222 - val_accuracy: 0.6073 - val_loss: 1.1141
Epoch 3/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.6301 - loss: 1.0534 - val_accuracy: 0.6384 - val_loss: 1.0459
Epoch 4/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.6652 - loss: 0.9513 - val_accuracy: 0.6509 - val_loss: 1.0100
Epoch 5/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.6923 - loss: 0.8736 - val_accuracy: 0.6621 - val_loss: 0.9957
Epoch 6/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7195 - loss: 0.8048 - val_accuracy: 0.6665 - val_loss: 0.9955
Epoch 7/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7419 - loss: 0.7395 - val_accuracy: 0.6735 - val_loss: 0.9968
Epoch 8/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7630 - loss: 0.6792 - val_accuracy: 0.6675 - val_loss: 1.0347
Epoch 9/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7838 - loss: 0.6254 - val_accuracy: 0.6684 - val_loss: 1.0556
Epoch 10/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.8028 - loss: 0.5734 - val_accuracy: 0.6682 - val_loss: 1.0934
Epoch 11/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.8215 - loss: 0.5241 - val_accuracy: 0.6684 - val_loss: 1.1256
Epoch 12/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.8362 - loss: 0.4790 - val_accuracy: 0.6605 - val_loss: 1.1934
Epoch 13/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.8469 - loss: 0.4467 - val_accuracy: 0.6658 - val_loss: 1.2215
Epoch 14/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.8624 - loss: 0.4027 - val_accuracy: 0.6762 - val_loss: 1.2558
Epoch 15/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.8741 - loss: 0.3643 - val_accuracy: 0.6650 - val_loss: 1.3556
Test Accuracy for 3x3_32filters: 0.6634

Training Model: 5x5_32filters
Epoch 1/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 6s 5ms/step - accuracy: 0.3440 - loss: 1.8005 - val_accuracy: 0.5328 - val_loss: 1.3513
Epoch 2/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.5379 - loss: 1.2986 - val_accuracy: 0.5815 - val_loss: 1.1849
Epoch 3/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.6076 - loss: 1.1107 - val_accuracy: 0.6031 - val_loss: 1.1368
Epoch 4/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.6487 - loss: 0.9984 - val_accuracy: 0.6371 - val_loss: 1.0478
Epoch 5/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.6815 - loss: 0.9166 - val_accuracy: 0.6419 - val_loss: 1.0421
Epoch 6/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7053 - loss: 0.8511 - val_accuracy: 0.6342 - val_loss: 1.0868
Epoch 7/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7227 - loss: 0.7899 - val_accuracy: 0.6480 - val_loss: 1.0625
Epoch 8/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7445 - loss: 0.7335 - val_accuracy: 0.6673 - val_loss: 1.0248
Epoch 9/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7645 - loss: 0.6803 - val_accuracy: 0.6669 - val_loss: 1.0381
Epoch 10/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7789 - loss: 0.6360 - val_accuracy: 0.6712 - val_loss: 1.0535
Epoch 11/15
625/625 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7889 - loss: 0.6035 - val_accuracy: 0.6750 - val_loss: 1.0834
Epoch 12/15
```

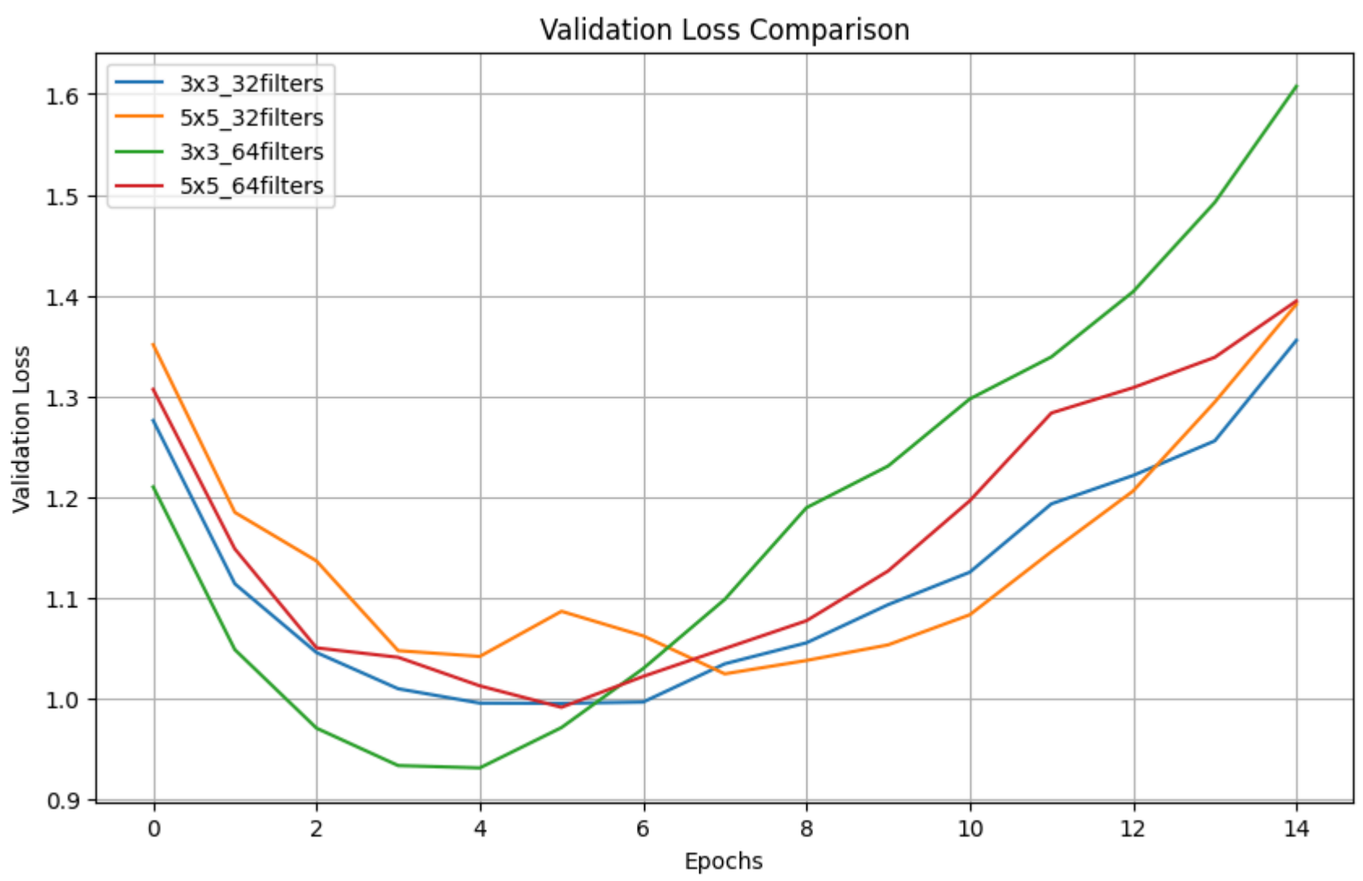
```
# ============================================================
# 6. CONVERT RESULTS TO DATAFRAME
# ============================================================

results_df = pd.DataFrame(test_results, columns=["Model", "Test Accuracy"])
print("\nFinal Test Accuracy Comparison:\n")
print(results_df)
```

```
Final Test Accuracy Comparison:

           Model  Test Accuracy
0  3x3_32filters         0.6634
1  5x5_32filters         0.6308
2  3x3_64filters         0.6686
3  5x5_64filters         0.6544
```

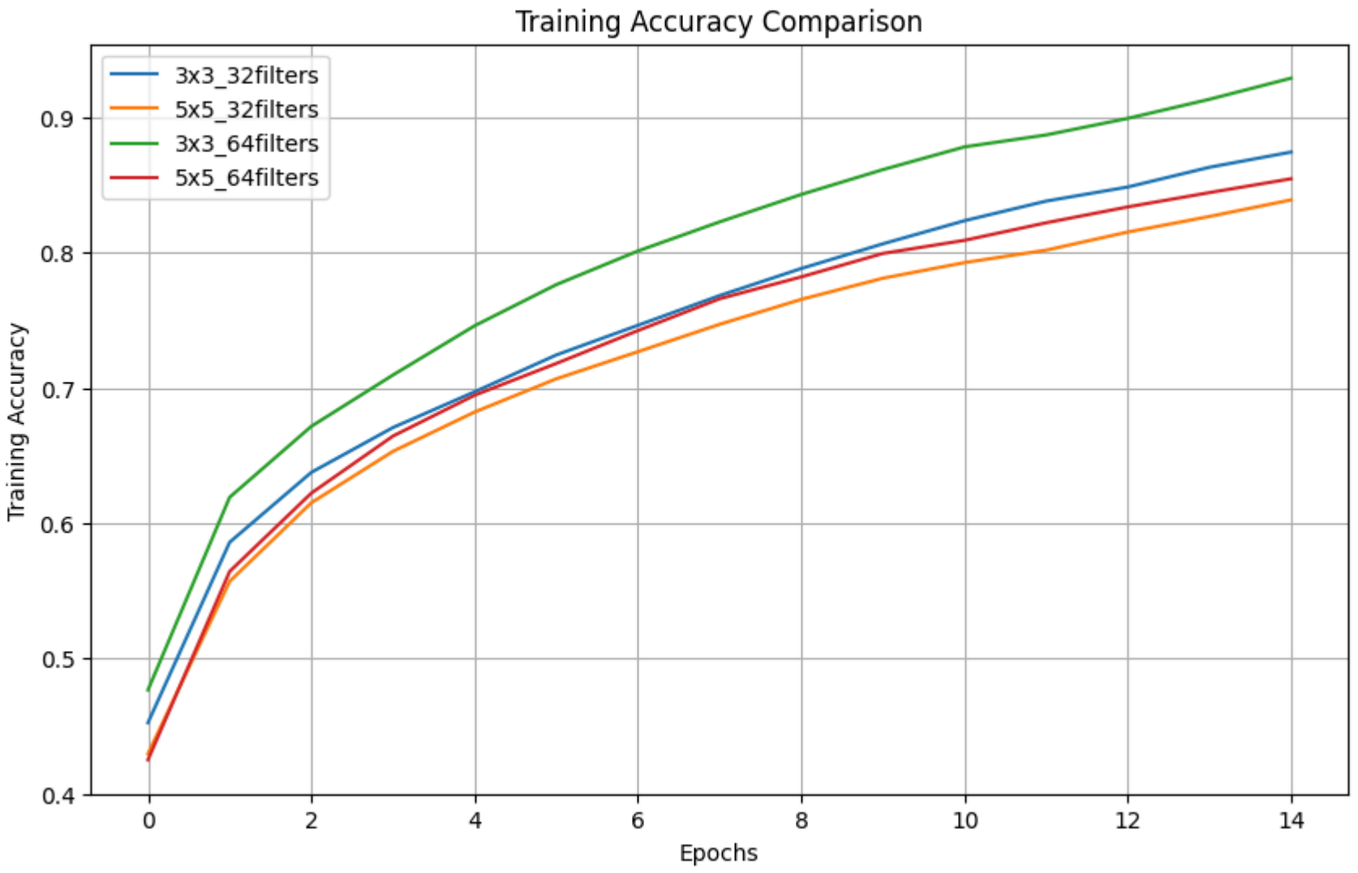
```
# ============================================================
# 7. PLOT ACCURACY CURVES
# ============================================================

plt.figure(figsize=(10,6))

for name, history in history_dict.items():
    plt.plot(history.history['val_accuracy'], label=name)

plt.title("Validation Accuracy Comparison")
plt.xlabel("Epochs")
plt.ylabel("Validation Accuracy")
plt.legend()
plt.grid(True)
plt.show()
```




```
# ============================================================
# 8. PLOT LOSS CURVES
# ============================================================

plt.figure(figsize=(10,6))

for name, history in history_dict.items():
    plt.plot(history.history['val_loss'], label=name)

plt.title("Validation Loss Comparison")
plt.xlabel("Epochs")
plt.ylabel("Validation Loss")
plt.legend()
plt.grid(True)
plt.show()
```




```
# ============================================================
# PLOT TRAINING ACCURACY COMPARISON
# ============================================================

import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))

for name, history in history_dict.items():
    plt.plot(history.history['accuracy'], label=name)

plt.title("Training Accuracy Comparison")
plt.xlabel("Epochs")
plt.ylabel("Training Accuracy")
plt.legend()
plt.grid(True)
plt.show()
```


Training Accuracy Comparison
3x3_32filters
5x5_32filters
3x3_64filters
5x5_64filters
Training Accuracy
Epochs
0.4
0.5
0.6
0.7
0.8
0.9
0
2
4
6
8
10
12
14

```
# ------------------------------------------------------------
```