In [1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

In [2]:
```
import tensorflow as tf
from tensorflow.keras import layers, models
import os
```

In [3]:
```
# Dataset paths
train_dir = "/content/drive/MyDrive/PatchInsight - Providing insights into pat
val_dir = "/content/drive/MyDrive/PatchInsight - Providing insights into patch

# Image dimensions

batch_size = 16
```

In [4]:
```

img_height, img_width = 360, 640  # Choose the resolution of the larger images

train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    train_dir,
    image_size=(img_height, img_width),  # Resize all images to 360x640
    batch_size=batch_size
)

val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    val_dir,
    image_size=(img_height, img_width),  # Resize all images to 360x640
    batch_size=batch_size
)

# Normalize pixel values (scale to range [0, 1])
normalization_layer = tf.keras.layers.Rescaling(1./255)
train_ds = train_ds.map(lambda x, y: (normalization_layer(x), y))
val_ds = val_ds.map(lambda x, y: (normalization_layer(x), y))

# Optimize for performance
AUTOTUNE = tf.data.AUTOTUNE
train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

```
Found 200 files belonging to 2 classes.
Found 50 files belonging to 2 classes.
```

Build Model

1. EfficientNetB0

In [5]:
```
def create_efficientnet_model():
    base_model = EfficientNetB0(weights='imagenet', include_top=False, input_s
    base_model.trainable = False  # Freeze base model layers

    x = base_model.output
    x = layers.GlobalAveragePooling2D()(x)
    x = layers.Dense(128, activation='relu')(x)
    x = layers.Dropout(0.5)(x)
    output = layers.Dense(2, activation='softmax')(x)

    model = Model(inputs=base_model.input, outputs=output)
    model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', me
    return model
```

2. ResNet50

In [6]:
```
def create_resnet50_model():
    base_model = ResNet50(weights='imagenet', include_top=False, input_shape=(
    base_model.trainable = False

    x = base_model.output
    x = layers.GlobalAveragePooling2D()(x)
    x = layers.Dense(128, activation='relu')(x)
    x = layers.Dropout(0.5)(x)
    output = layers.Dense(2, activation='softmax')(x)

    model = Model(inputs=base_model.input, outputs=output)
    model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', me
    return model
```

3. InceptionV3

In [7]:
```
def create_inceptionv3_model():
    base_model = InceptionV3(weights='imagenet', include_top=False, input_shap
    base_model.trainable = False

    x = base_model.output
    x = layers.GlobalAveragePooling2D()(x)
    x = layers.Dense(128, activation='relu')(x)
    x = layers.Dropout(0.5)(x)
    output = layers.Dense(2, activation='softmax')(x)

    model = Model(inputs=base_model.input, outputs=output)
    model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', me
    return model
```

Train Each Model

In [8]:

```
from tensorflow.keras.applications import EfficientNetB0
from tensorflow.keras.models import Model


# Train EfficientNetB0
efficientnet_model = create_efficientnet_model()
efficientnet_history = efficientnet_model.fit(train_ds, validation_data=val_ds
```

```
Downloading data from https://storage.googleapis.com/keras-applications/effic
ientnetb0_notop.h5 (https://storage.googleapis.com/keras-applications/efficie
ntnetb0_notop.h5)
16705208/16705208 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Epoch 1/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 96s 3s/step - accuracy: 0.5503 - loss: 0.6966 - va
l_accuracy: 0.5000 - val_loss: 0.7210
Epoch 2/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 1s 86ms/step - accuracy: 0.5050 - loss: 0.7273 - v
al_accuracy: 0.5000 - val_loss: 0.6968
Epoch 3/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 1s 82ms/step - accuracy: 0.4264 - loss: 0.7555 - v
al_accuracy: 0.5000 - val_loss: 0.6932
Epoch 4/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 1s 90ms/step - accuracy: 0.4971 - loss: 0.7061 - v
al_accuracy: 0.5000 - val_loss: 0.6933
Epoch 5/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 1s 81ms/step - accuracy: 0.4813 - loss: 0.7006 - v
al_accuracy: 0.5000 - val_loss: 0.6933
Epoch 6/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 1s 84ms/step - accuracy: 0.4760 - loss: 0.7000 - v
al_accuracy: 0.5000 - val_loss: 0.6932
Epoch 7/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 1s 82ms/step - accuracy: 0.4949 - loss: 0.6906 - v
al_accuracy: 0.5000 - val_loss: 0.6935
Epoch 8/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 1s 81ms/step - accuracy: 0.5170 - loss: 0.6918 - v
al_accuracy: 0.5000 - val_loss: 0.6932
Epoch 9/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 1s 82ms/step - accuracy: 0.5858 - loss: 0.6873 - v
al_accuracy: 0.5000 - val_loss: 0.6939
Epoch 10/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 1s 90ms/step - accuracy: 0.5209 - loss: 0.6919 - v
al_accuracy: 0.5000 - val_loss: 0.6936
```

In [9]:

```
from tensorflow.keras.applications.resnet50 import ResNet50


# Train ResNet50
resnet50_model = create_resnet50_model()
resnet50_history = resnet50_model.fit(train_ds, validation_data=val_ds, epochs
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applica
tions/resnet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5 (https://st
orage.googleapis.com/tensorflow/keras-applications/resnet/resnet50_weights_tf
_dim_ordering_tf_kernels_notop.h5)
94765736/94765736 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Epoch 1/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 30s 1s/step - accuracy: 0.5981 - loss: 0.9933 - va
l_accuracy: 1.0000 - val_loss: 0.6012
Epoch 2/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 20s 214ms/step - accuracy: 0.5248 - loss: 0.9259 -
val_accuracy: 0.5000 - val_loss: 0.6108
Epoch 3/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 218ms/step - accuracy: 0.6040 - loss: 0.6650 -
val_accuracy: 1.0000 - val_loss: 0.5521
Epoch 4/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 5s 210ms/step - accuracy: 0.6704 - loss: 0.6085 -
val_accuracy: 0.5000 - val_loss: 0.6175
Epoch 5/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 5s 218ms/step - accuracy: 0.6376 - loss: 0.6387 -
val_accuracy: 1.0000 - val_loss: 0.5020
Epoch 6/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 214ms/step - accuracy: 0.7974 - loss: 0.5121 -
val_accuracy: 1.0000 - val_loss: 0.4845
Epoch 7/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 5s 212ms/step - accuracy: 0.7275 - loss: 0.5276 -
val_accuracy: 1.0000 - val_loss: 0.4485
Epoch 8/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 5s 216ms/step - accuracy: 0.8383 - loss: 0.4684 -
val_accuracy: 0.9800 - val_loss: 0.4262
Epoch 9/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 217ms/step - accuracy: 0.7789 - loss: 0.4560 -
val_accuracy: 1.0000 - val_loss: 0.4193
Epoch 10/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 217ms/step - accuracy: 0.7234 - loss: 0.5080 -
val_accuracy: 0.9400 - val_loss: 0.4132
```

In [10]:

```python
from tensorflow.keras.applications.inception_v3 import InceptionV3


# Train InceptionV3
inceptionv3_model = create_inceptionv3_model()
inceptionv3_history = inceptionv3_model.fit(train_ds, validation_data=val_ds,
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applica
tions/inception_v3/inception_v3_weights_tf_dim_ordering_tf_kernels_notop.h5
(https://storage.googleapis.com/tensorflow/keras-applications/inception_v3/in
ception_v3_weights_tf_dim_ordering_tf_kernels_notop.h5)
87910968/87910968 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Epoch 1/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 58s 3s/step - accuracy: 0.9142 - loss: 0.2858 - va
l_accuracy: 1.0000 - val_loss: 0.0063
Epoch 2/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 159ms/step - accuracy: 1.0000 - loss: 0.0028 -
val_accuracy: 1.0000 - val_loss: 7.3316e-04
Epoch 3/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 161ms/step - accuracy: 1.0000 - loss: 0.0015 -
val_accuracy: 1.0000 - val_loss: 5.2566e-04
Epoch 4/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 162ms/step - accuracy: 1.0000 - loss: 3.4283e-0
4 - val_accuracy: 1.0000 - val_loss: 5.2431e-04
Epoch 5/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 163ms/step - accuracy: 1.0000 - loss: 2.7655e-0
4 - val_accuracy: 1.0000 - val_loss: 4.7684e-04
Epoch 6/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 179ms/step - accuracy: 1.0000 - loss: 2.6243e-0
4 - val_accuracy: 1.0000 - val_loss: 4.2366e-04
Epoch 7/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 164ms/step - accuracy: 1.0000 - loss: 2.5787e-0
4 - val_accuracy: 1.0000 - val_loss: 3.7780e-04
Epoch 8/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 163ms/step - accuracy: 1.0000 - loss: 1.4761e-0
4 - val_accuracy: 1.0000 - val_loss: 3.5330e-04
Epoch 9/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 179ms/step - accuracy: 1.0000 - loss: 2.1566e-0
4 - val_accuracy: 1.0000 - val_loss: 3.2193e-04
Epoch 10/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 181ms/step - accuracy: 1.0000 - loss: 2.8870e-0
4 - val_accuracy: 1.0000 - val_loss: 3.0521e-04
```

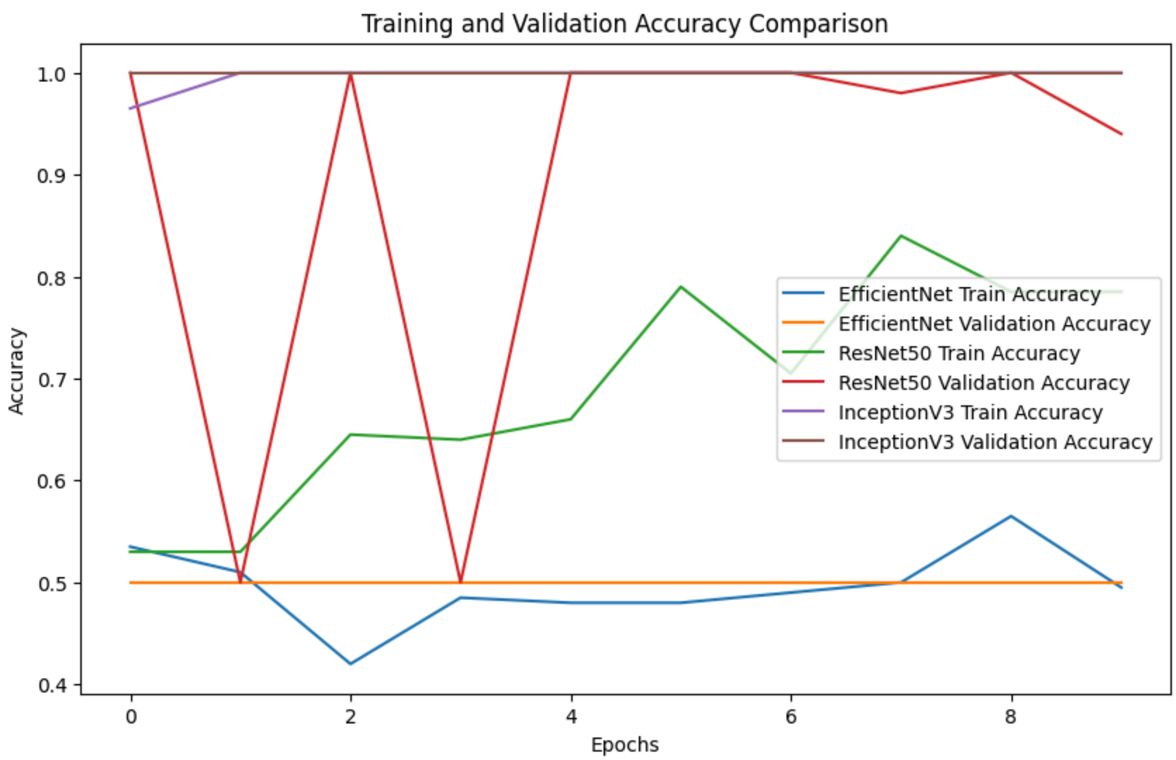
Evaluate Models Evaluate the validation accuracy for each model:

In [11]:
```
# Evaluate the validation accuracy for each model:

# Evaluate EfficientNetB0
efficientnet_loss, efficientnet_accuracy = efficientnet_model.evaluate(val_ds)
print(f"EfficientNetB0 Validation Accuracy: {efficientnet_accuracy}")

# Evaluate ResNet50
resnet50_loss, resnet50_accuracy = resnet50_model.evaluate(val_ds)
print(f"ResNet50 Validation Accuracy: {resnet50_accuracy}")

# Evaluate InceptionV3
inceptionv3_loss, inceptionv3_accuracy = inceptionv3_model.evaluate(val_ds)
print(f"InceptionV3 Validation Accuracy: {inceptionv3_accuracy}")
```

```
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 68ms/step - accuracy: 0.5146 - loss: 0.6927
EfficientNetB0 Validation Accuracy: 0.5
4/4 ━━━━━━━━━━━━━━━━━━━━ 1s 128ms/step - accuracy: 0.9448 - loss: 0.4078
ResNet50 Validation Accuracy: 0.9399999976158142
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 101ms/step - accuracy: 1.0000 - loss: 3.2687e-04
InceptionV3 Validation Accuracy: 1.0
```

In [12]:

```
import matplotlib.pyplot as plt

def plot_history(history, label):
    plt.plot(history.history['accuracy'], label=f'{label} Train Accuracy')
    plt.plot(history.history['val_accuracy'], label=f'{label} Validation Accur

plt.figure(figsize=(10, 6))
plot_history(efficientnet_history, 'EfficientNet')
plot_history(resnet50_history, 'ResNet50')
plot_history(inceptionv3_history, 'InceptionV3')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.title("Training and Validation Accuracy Comparison")
plt.show()
```



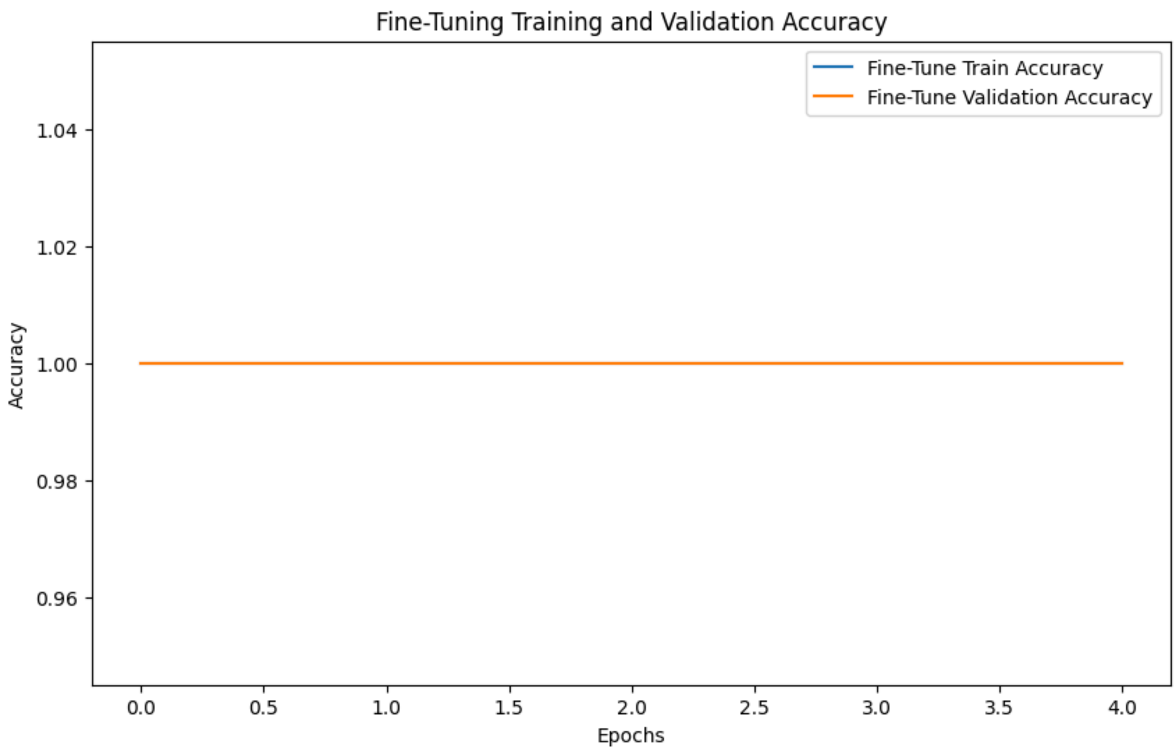
we select InceptionV3 model as future prediction.

Step 1: Fine-Tune InceptionV3

In [13]:

```
# Fine-tune the selected model by unfreezing some layers of the base model and

# Unfreeze some layers of the InceptionV3 base model
for layer in inceptionv3_model.layers[-15:]:  # Adjust the number of layers to
    layer.trainable = True

# Recompile the model with a lower learning rate for fine-tuning
inceptionv3_model.compile(optimizer=tf.keras.optimizers.Adam(1e-5),
                         loss='sparse_categorical_crossentropy',
                         metrics=['accuracy'])

# Continue training the model with the unfrozen layers
fine_tune_epochs = 5  # Adjust the number of epochs for fine-tuning
fine_tune_history = inceptionv3_model.fit(train_ds,
                                         validation_data=val_ds,
                                         epochs=fine_tune_epochs)



# Evaluate the fine-tuned model
fine_tune_loss, fine_tune_accuracy = inceptionv3_model.evaluate(val_ds)
print(f"Fine-Tuned InceptionV3 Validation Accuracy: {fine_tune_accuracy}")

# Plot training and validation accuracy for fine-tuned model
plt.figure(figsize=(10, 6))
plt.plot(fine_tune_history.history['accuracy'], label='Fine-Tune Train Accurac
plt.plot(fine_tune_history.history['val_accuracy'], label='Fine-Tune Validatio
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.title("Fine-Tuning Training and Validation Accuracy")
plt.show()
```

```
Epoch 1/5
13/13 ━━━━━━━━━━━━━━━━━━━━ 34s 2s/step - accuracy: 1.0000 - loss: 1.0063e-04
- val_accuracy: 1.0000 - val_loss: 2.8467e-04
Epoch 2/5
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 161ms/step - accuracy: 1.0000 - loss: 2.9796e-0
4 - val_accuracy: 1.0000 - val_loss: 2.5237e-04
Epoch 3/5
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 163ms/step - accuracy: 1.0000 - loss: 1.5150e-0
4 - val_accuracy: 1.0000 - val_loss: 2.3988e-04
Epoch 4/5
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 182ms/step - accuracy: 1.0000 - loss: 3.2689e-0
4 - val_accuracy: 1.0000 - val_loss: 2.1664e-04
Epoch 5/5
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 165ms/step - accuracy: 1.0000 - loss: 8.4117e-0
5 - val_accuracy: 1.0000 - val_loss: 1.9772e-04
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 99ms/step - accuracy: 1.0000 - loss: 2.1385e-04
Fine-Tuned InceptionV3 Validation Accuracy: 1.0
```



In [14]:
```
# 2. Hyperparameter Tuning
# Use Keras Tuner to find the optimal hyperparameters for your model, includin

!pip install keras-tuner

import keras_tuner as kt

def build_model(hp):
    """Builds a model with hyperparameters to be tuned."""
    base_model = InceptionV3(weights='imagenet', include_top=False, input_shap
    base_model.trainable = False

    x = base_model.output
    x = layers.GlobalAveragePooling2D()(x)
    x = layers.Dense(
        units=hp.Int('units', min_value=32, max_value=256, step=32),
        activation='relu'
    )(x)
    x = layers.Dropout(
        rate=hp.Float('dropout', min_value=0.1, max_value=0.5, step=0.1)
    )(x)
    output = layers.Dense(2, activation='softmax')(x)

    model = Model(inputs=base_model.input, outputs=output)
    model.compile(
        optimizer=tf.keras.optimizers.Adam(
            hp.Float('learning_rate', min_value=1e-4, max_value=1e-2, sampling
        ),
        loss='sparse_categorical_crossentropy',
        metrics=['accuracy']
    )
    return model


tuner = kt.Hyperband(
    build_model,
    objective='val_accuracy',
    max_epochs=10,
    factor=3,
    directory='my_dir',
    project_name='inceptionv3_tuning'
)


tuner.search(train_ds, validation_data=val_ds, epochs=10)

# Get the best hyperparameters
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]

print(f"""
The hyperparameter search is complete. The optimal number of units in the dens
the optimal dropout rate is {best_hps.get('dropout')}, and the optimal learnin
""")

# Build the model with the optimal hyperparameters and train it on the data fo
model = tuner.hypermodel.build(best_hps)
history = model.fit(train_ds, validation_data=val_ds, epochs=20)
```

```
Trial 5 Complete [00h 00m 41s]
val_accuracy: 1.0

Best val_accuracy So Far: 1.0
Total elapsed time: 00h 03m 46s

Search: Running Trial #6

Value             |Best Value So Far |Hyperparameter
256               |32                |units
0.3               |0.4               |dropout
0.0062539         |0.00049429        |learning_rate
2                 |2                 |tuner/epochs
0                 |0                 |tuner/initial_epoch
2                 |2                 |tuner/bracket
0                 |0                 |tuner/round

Epoch 1/2
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 670ms/step - accuracy: 0.7859 - loss: 0.5961
```

In [15]:

```
# Get the best hyperparameters
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]

print(f"Best Learning Rate: {best_hps.get('learning_rate')}")
print(f"Best Units: {best_hps.get('units')}")
print(f"Best Dropout: {best_hps.get('dropout')}")
```

```
Best Learning Rate: 0.000494289254485023
Best Units: 32
Best Dropout: 0.4
```

In [16]:
```
best_model = tuner.hypermodel.build(best_hps)
best_model.fit(train_ds, validation_data=val_ds, epochs=10)
```

```
Epoch 1/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 37s 2s/step - accuracy: 0.7423 - loss: 0.5381 - va
l_accuracy: 1.0000 - val_loss: 0.2148
Epoch 2/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 158ms/step - accuracy: 1.0000 - loss: 0.1276 -
val_accuracy: 1.0000 - val_loss: 0.0631
Epoch 3/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 160ms/step - accuracy: 1.0000 - loss: 0.0520 -
val_accuracy: 1.0000 - val_loss: 0.0343
Epoch 4/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 162ms/step - accuracy: 0.9989 - loss: 0.0434 -
val_accuracy: 1.0000 - val_loss: 0.0253
Epoch 5/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 166ms/step - accuracy: 1.0000 - loss: 0.0147 -
val_accuracy: 1.0000 - val_loss: 0.0161
Epoch 6/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 183ms/step - accuracy: 1.0000 - loss: 0.0159 -
val_accuracy: 1.0000 - val_loss: 0.0137
Epoch 7/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 167ms/step - accuracy: 1.0000 - loss: 0.0234 -
val_accuracy: 1.0000 - val_loss: 0.0115
Epoch 8/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 164ms/step - accuracy: 1.0000 - loss: 0.0103 -
val_accuracy: 1.0000 - val_loss: 0.0087
Epoch 9/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 166ms/step - accuracy: 1.0000 - loss: 0.0139 -
val_accuracy: 1.0000 - val_loss: 0.0091
Epoch 10/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 167ms/step - accuracy: 0.9980 - loss: 0.0125 -
val_accuracy: 1.0000 - val_loss: 0.0074
```

Out[16]:
```
<keras.src.callbacks.history.History at 0x7bcdc563fe50>
```

In [17]:
```


val_loss, val_accuracy = best_model.evaluate(val_ds)
print(f"Final Validation Accuracy: {val_accuracy * 100:.2f}%")

# Save the model for deployment
best_model.save('/content/drive/MyDrive/PatchInsight - Providing insights into
```

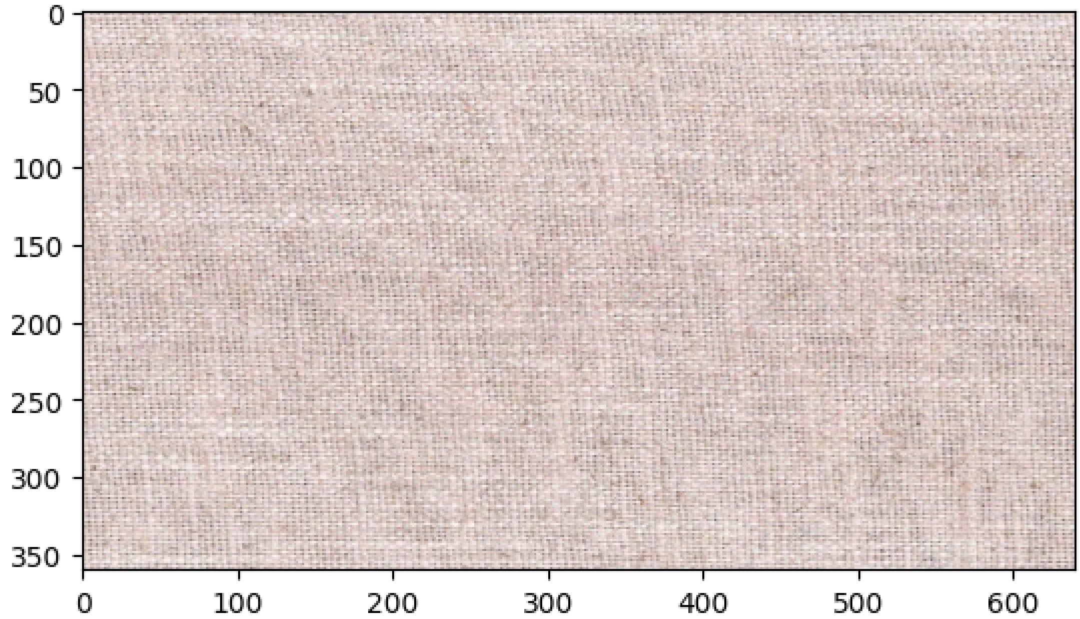
```
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 99ms/step - accuracy: 1.0000 - loss: 0.0074

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We r
ecommend using instead the native Keras format, e.g. `model.save('my_model.ke
ras')` or `keras.saving.save_model(model, 'my_model.keras')`.

Final Validation Accuracy: 100.00%
```

In [22]:
```
# prompt: clasify image using abve model
# upload image then detect patch or not

from google.colab import files
from tensorflow.keras.preprocessing import image
import numpy as np
import matplotlib.pyplot as plt

uploaded = files.upload()

for fn in uploaded.keys():
  # predicting images
  path = '/content/' + fn
  img = image.load_img(path, target_size=(img_height, img_width))
  x = image.img_to_array(img)
  x = np.expand_dims(x, axis=0)
  x /= 255.0  # Normalize the image

  images = np.vstack([x])
  classes = best_model.predict(images, batch_size=10)
  print(classes[0])

  if classes[0][0] > classes[0][1]:
    print(fn + " is not Patch")
  else:
    print(fn + " is  Patch")

  plt.imshow(img)
  plt.show()
```

Choose Files No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving Ian-Mankin-The-Forfar-and-Newbury-Collection-Newbury-Plain-Podwer-Fabr
ic-FA150-218-Swatch-768x768.jpg to Ian-Mankin-The-Forfar-and-Newbury-Collecti
on-Newbury-Plain-Podwer-Fabric-FA150-218-Swatch-768x768.jpg
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
[0.8857597  0.11424026]
Ian-Mankin-The-Forfar-and-Newbury-Collection-Newbury-Plain-Podwer-Fabric-FA15
0-218-Swatch-768x768.jpg is not Patch
```


0
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