Project 2: Vision Transformer Internship Project

Abstract :

The Vision Transformer (ViT) is a novel architecture that applies transformer models to vision tasks, achieving state-of-the-art performance on various image classification benchmarks. In this project, we implement a Vision Transformer model using Python and the PyTorch library, and evaluate its performance on the CIFAR-10 dataset.

Objective :

The objective of this project is to implement a Vision Transformer model and evaluate its performance on the CIFAR-10 dataset, comparing it to traditional convolutional neural networks (CNNs).

Introduction :

The Vision Transformer is a type of neural network architecture that applies transformer models to vision tasks. Unlike traditional CNNs, which use convolutional and pooling layers to extract features, the Vision Transformer uses self-attention mechanisms to weigh the importance of different patches in an image. This allows the model to capture long-range dependencies and contextual relationships between patches, leading to improved performance on various image classification tasks.

Methodology :

We will use the following methodology to implement and evaluate the Vision Transformer model:

1. Data Preprocessing: We will use the CIFAR-10 dataset, which consists of 60,000 32x32 color images in 10 classes.

2. Model Implementation: We will implement the Vision Transformer model using PyTorch, following the architecture described in the original paper.

3. Training: We will train the model using the Adam optimizer and a batch size of 128.

4. Evaluation: We will evaluate the model's performance on the CIFAR-10 test set, comparing it to a traditional CNN model.

Code :

```
!pip install tensorflow==2.8.0
!pip install keras==2.8.0
!pip install tensorflow-addons==0.17.0
#above instead of tensorflow-addons==0.17.0 we can even use tensorflow-addons==0.20.0


#import libraries
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import tensorflow_addons as tfa


num_classes=10
input_shape=(32,32,3)
(x_train,y_train),(x_test,y_test) = keras.datasets.cifar10.load_data()
print(f"x_train shape: {x_train.shape} - y_train shape: {y_train.shape}")
print(f"x_test shape: {x_test.shape} - y_test shape: {y_test.shape}")


x_train = x_train[:500]
y_train = y_train[:500]
x_test = x_test[:500]
y_test = y_test[:500]


learning_rate = 0.001
weight_decay = 0.0001#1e-4
batch_size = 256
num_epochs = 40  #40
image_size = 72 #resize the input image to this size
patch_size = 6 #size of the patches to be extracted from the input images
```

```
num_patches = (image_size // patch_size) ** 2
num_heads = 4
projection_dim = 64
transformer_units = [
    projection_dim * 2,
    projection_dim
] #size of the transformer layers
transformer_layers = 8
mlp_head_units = [2048, 1024] #size of the dense layers of the final classifiers


data_augumentation = keras.Sequential(
    [
    layers.Normalization(),
    layers.Resizing(image_size, image_size),
    layers.RandomFlip("horizontal"),
    layers.RandomRotation(factor=0.02),
    layers.RandomZoom(height_factor=0.2, width_factor=0.2)
    ],
    name="data_augmentation"
)
data_augumentation.layers[0].adapt(x_train)


def mlp(x,hidden_units,dropout_rate):
    for units in hidden_units:
        x = layers.Dense(units,activation=tf.nn.gelu)(x)
        x = layers.Dropout(dropout_rate)(x)
    return x


class Patches(layers.Layer):
    def __init__(self,patch_size):
        super(Patches,self).__init__()
        self.patch_size = patch_size

    def call(self,images):
        batch_size = tf.shape(images)[0]
        patches = tf.image.extract_patches(
            images = images,
            sizes = [1,self.patch_size,self.patch_size,1],
            strides = [1,self.patch_size,self.patch_size,1],
            rates = [1,1,1,1],
            padding = "VALID"
        )
```

```
        patch_dims = patches.shape[-1]
        patches = tf.reshape(patches,shape=(batch_size, -1, patch_dims))
        return patches


import matplotlib.pyplot as plt

plt.figure(figsize=(4,4))
image = x_train[np.random.choice(range(x_train.shape[0]))]
plt.imshow(image.astype("uint8"))
plt.axis("off")

resized_image = tf.image.resize(
    tf.convert_to_tensor([image]),
    size = (image_size,image_size)
)

patches = Patches(patch_size)(resized_image)
print(f"Image size: {image_size} X {image_size}")
print(f"Patch size: {patch_size} X {patch_size}")
print(f"Patches per image: {patches.shape[1]}")
print(f"Elements per patch: {patches.shape[-1]}\n")

n = int(np.sqrt(patches.shape[1]))
plt.figure(figsize=(4,4))
for i, patch in enumerate(patches[0]):
    ax = plt.subplot(n,n,i+1)
    patch_img = tf.reshape(patch, (patch_size,patch_size,3))
    plt.imshow(patch_img.numpy().astype("uint8"))
    plt.axis("off")

  # Adjust these values as needed
plt.show()


class PatchEncoder(layers.Layer):
    def __init__(self,num_patches,projection_dim):
        super(PatchEncoder,self).__init__()
        self.num_patches = num_patches
        self.projection = layers.Dense(units=projection_dim)
        self.position_embedding = layers.Embedding(
            input_dim = num_patches,
            output_dim = projection_dim
        )
    def call(self,patches):
```

```
        positions = tf.range(start=0,limit=self.num_patches,delta=1)
        encoded = self.projection(patches) + self.position_embedding(positions)
        return encoded


def create_vit_classifier():
  inputs = layers.Input(shape=input_shape)
  #Augument data
  augmented = data_augumentation(inputs)
  patches = Patches(patch_size)(augmented)
  #encode patches
  encoded_patches = PatchEncoder(num_patches,projection_dim)(patches)

  #create multiple layers of the transformer block
  for _ in range(transformer_layers):
    # layer normalization
    x1 = layers.LayerNormalization(epsilon=1e-6)(encoded_patches)
    #create multi-head attention layer
    attention_output = layers.MultiHeadAttention(
        num_heads = num_heads,
        key_dim = projection_dim,
        dropout = 0.1
    )(x1,x1)
    #add skip connection1
    x2 = layers.Add()([attention_output,encoded_patches])
    #layer normalization 2
    x3 = layers.LayerNormalization(epsilon=1e-6)(x2)
    #feed forward block mlp
    x3 = mlp(x3,hidden_units=transformer_units,dropout_rate=0.1)
    #add skip connection2
    encoded_patches = layers.Add()([x3,x2])

    #create a [batch_size,projection_dim] tensor
    representation = layers.LayerNormalization(epsilon=1e-6)(encoded_patches)
    representation = layers.Flatten()(representation)
    representation = layers.Dropout(0.5)(representation)

    #Add mlp
    features = mlp(representation,hidden_units=mlp_head_units,dropout_rate=0.5)
    #Classify outputs
    logits = layers.Dense(num_classes)(features)
    #create model
    model = keras.Model(inputs=inputs,outputs=logits)
    return model
```

```
def run_experiment(model):

  optimizer = tfa.optimizers.AdamW(
      learning_rate = learning_rate,
      weight_decay = weight_decay
  )

  model.compile(
      optimizer = optimizer,
      loss = keras.losses.SparseCategoricalCrossentropy(from_logits=True),
      metrics = [
          keras.metrics.SparseCategoricalAccuracy(name="accuracy"),
          keras.metrics.SparseTopKCategoricalAccuracy(5,name="top_5_accuracy"),
      ],
  )
  checkpoint_filepath = "./tmp/checkpoint"
  checkpoint_callback = keras.callbacks.ModelCheckpoint(
       checkpoint_filepath,
       monitor = "val_accuracy",
       save_best_only = True,
       save_weights_only = True,
  )

  history = model.fit(
      x = x_train,
      y = y_train,
      batch_size = batch_size,
      epochs = num_epochs,
      validation_split = 0.1,
      callbacks = [checkpoint_callback],
  )
  model.load_weights(checkpoint_filepath)
  _, accuracy, top_5_accuracy= model.evaluate(x_test,y_test)
  print(f"Test accuracy: {round(accuracy*100,2)}%")
  print(f"Test top-5 accuracy: {round(top_5_accuracy*100,2)}%")

  return history


vit_classifier = create_vit_classifier()
history = run_experiment(vit_classifier)
```

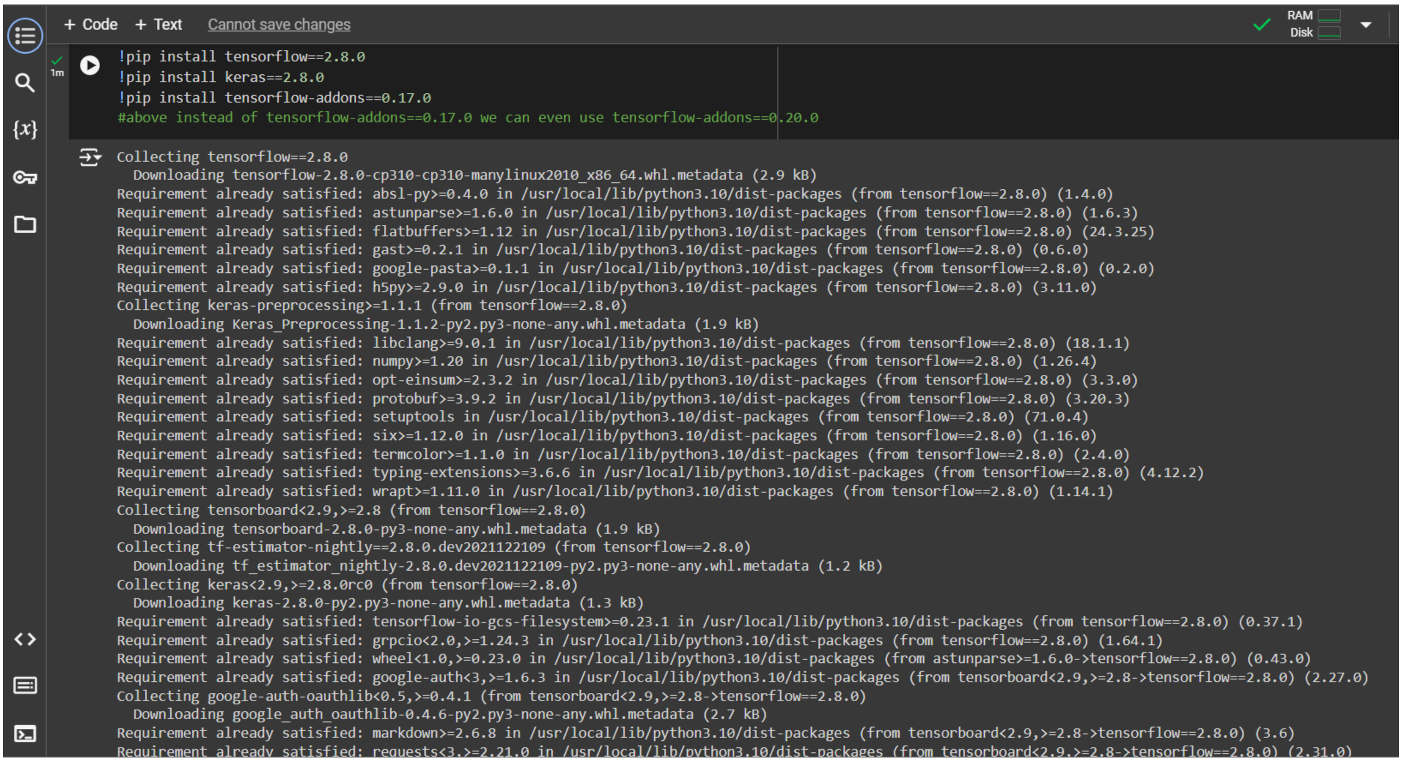
```
class_names = ["airplane","automobile","bird","cat","deer","dog","frog","horse","ship","truck]

def img_predict(images,model):
  if len(images.shape) == 3:
    out = model.predict(images.reshape(-1, *images.shape))
  else:
    out = model.predict(images)
  prediction = np.argmax(out, axis=1)
  img_prediction = [class_names[i] for i in prediction]
  return img_prediction


index = 10
plt.imshow(x_test[index])
prediction = img_predict(x_test[index],vit_classifier)
print(prediction)
```

OUTPUT :

1. Setup Environment



2.Data Preprocessing

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```
[2] #import libraries
    import numpy as np
    import tensorflow as tf
    from tensorflow import keras
    from tensorflow.keras import layers
    import tensorflow_addons as tfa
```

```
num_classes=10
input_shape=(32,32,3)
(x_train,y_train),(x_test,y_test) = keras.datasets.cifar10.load_data()
print(f"x_train shape: {x_train.shape} - y_train shape: {y_train.shape}")
print(f"x_test shape: {x_test.shape} - y_test shape: {y_test.shape}")
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170500096/170498071 [==============================] - 2s 0us/step
170508288/170498071 [==============================] - 2s 0us/step
x_train shape: (50000, 32, 32, 3) - y_train shape: (50000, 1)
x_test shape: (10000, 32, 32, 3) - y_test shape: (10000, 1)
```

```
[4] x_train = x_train[:500]
    y_train = y_train[:500]
    x_test = x_test[:500]
    y_test = y_test[:500]
```

```
[5] learning_rate = 0.001
    weight_decay = 0.0001#1e-4
    batch_size = 256
    num_epochs = 40  #40
    image_size = 72 #resize the input image to this size
    patch_size = 6 #size of the patches to be extracted from the input images
    num_patches = (image_size // patch_size) ** 2
    num_heads = 4
```

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```
[6]     layers.RandomZoom(height_factor=0.2, width_factor=0.2)
        ],
        name="data_augmentation"
    )
    data_augumentation.layers[0].adapt(x_train)
```

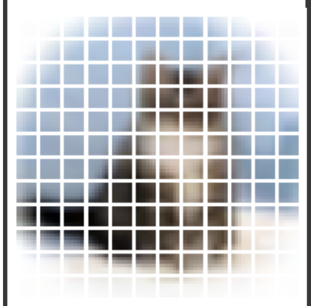
```
[7] def mlp(x,hidden_units,dropout_rate):
        for units in hidden_units:
            x = layers.Dense(units,activation=tf.nn.gelu)(x)
            x = layers.Dropout(dropout_rate)(x)
        return x
```

```
class Patches(layers.Layer):
    def __init__(self,patch_size):
        super(Patches,self).__init__()
        self.patch_size = patch_size


    def call(self,images):
        batch_size = tf.shape(images)[0]
        patches = tf.image.extract_patches(
            images = images,
            sizes = [1,self.patch_size,self.patch_size,1],
            strides = [1,self.patch_size,self.patch_size,1],
            rates = [1,1,1,1],
            padding = "VALID"
        )
        patch_dims = patches.shape[-1]
        patches = tf.reshape(patches,shape=(batch_size, -1, patch_dims))
        return patches
```

3. TRAINING MODEL

```python
import matplotlib.pyplot as plt

plt.figure(figsize=(4,4))
image = x_train[np.random.choice(range(x_train.shape[0]))]
plt.imshow(image.astype("uint8"))
plt.axis("off")


resized_image = tf.image.resize(
    tf.convert_to_tensor([image]),
    size = (image_size,image_size)
)

patches = Patches(patch_size)(resized_image)
print(f"Image size: {image_size} X {image_size}")
print(f"Patch size: {patch_size} X {patch_size}")
print(f"Patches per image: {patches.shape[1]}")
print(f"Elements per patch: {patches.shape[-1]}\n")


n = int(np.sqrt(patches.shape[1]))
plt.figure(figsize=(4,4))
for i, patch in enumerate(patches[0]):
    ax = plt.subplot(n,n,i+1)
    patch_img = tf.reshape(patch, (patch_size,patch_size,3))
    plt.imshow(patch_img.numpy().astype("uint8"))
    plt.axis("off")

  # Adjust these values as needed
plt.show()
```

```
Image size: 72 X 72
Patch size: 6 X 6
Patches per image: 144
Elements per patch: 108
```



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```
vit_classifier = create_vit_classifier()
history = run_experiment(vit_classifier)
```

```
Epoch 1/40
2/2 [==============================] - 16s 5s/step - loss: 5.9439 - accuracy: 0.1044 - top_5_accuracy: 0.5644 - val_loss: 6.8156 - val_accuracy: 0.2400 - val_top_5_accuracy: 0.6000
Epoch 2/40
2/2 [==============================] - 10s 5s/step - loss: 7.3035 - accuracy: 0.2178 - top_5_accuracy: 0.6578 - val_loss: 3.9363 - val_accuracy: 0.1400 - val_top_5_accuracy: 0.6600
Epoch 3/40
2/2 [==============================] - 8s 3s/step - loss: 4.8229 - accuracy: 0.2333 - top_5_accuracy: 0.6911 - val_loss: 3.1059 - val_accuracy: 0.1800 - val_top_5_accuracy: 0.7600
Epoch 4/40
2/2 [==============================] - 9s 3s/step - loss: 3.7765 - accuracy: 0.2644 - top_5_accuracy: 0.7444 - val_loss: 2.6586 - val_accuracy: 0.1600 - val_top_5_accuracy: 0.7600
Epoch 5/40
2/2 [==============================] - 8s 4s/step - loss: 2.7859 - accuracy: 0.3311 - top_5_accuracy: 0.7978 - val_loss: 2.4780 - val_accuracy: 0.1800 - val_top_5_accuracy: 0.7200
Epoch 6/40
2/2 [==============================] - 8s 3s/step - loss: 2.5996 - accuracy: 0.2867 - top_5_accuracy: 0.7933 - val_loss: 2.3522 - val_accuracy: 0.2400 - val_top_5_accuracy: 0.7400
Epoch 7/40
2/2 [==============================] - 9s 5s/step - loss: 2.3071 - accuracy: 0.3133 - top_5_accuracy: 0.8156 - val_loss: 2.0474 - val_accuracy: 0.2400 - val_top_5_accuracy: 0.7600
Epoch 8/40
2/2 [==============================] - 7s 3s/step - loss: 2.0101 - accuracy: 0.3511 - top_5_accuracy: 0.8533 - val_loss: 1.9681 - val_accuracy: 0.1600 - val_top_5_accuracy: 0.7800
Epoch 9/40
2/2 [==============================] - 14s 8s/step - loss: 1.9871 - accuracy: 0.3378 - top_5_accuracy: 0.8444 - val_loss: 1.9435 - val_accuracy: 0.2600 - val_top_5_accuracy: 0.8000
Epoch 10/40
2/2 [==============================] - 10s 5s/step - loss: 1.8368 - accuracy: 0.3956 - top_5_accuracy: 0.8822 - val_loss: 1.9313 - val_accuracy: 0.2800 - val_top_5_accuracy: 0.8200
Epoch 11/40
2/2 [==============================] - 11s 7s/step - loss: 1.7478 - accuracy: 0.4000 - top_5_accuracy: 0.8911 - val_loss: 1.9486 - val_accuracy: 0.3000 - val_top_5_accuracy: 0.7600
Epoch 12/40
2/2 [==============================] - 8s 4s/step - loss: 1.8229 - accuracy: 0.3800 - top_5_accuracy: 0.8667 - val_loss: 1.9232 - val_accuracy: 0.3000 - val_top_5_accuracy: 0.7800
Epoch 13/40
2/2 [==============================] - 10s 4s/step - loss: 1.8074 - accuracy: 0.3911 - top_5_accuracy: 0.8667 - val_loss: 1.8858 - val_accuracy: 0.2600 - val_top_5_accuracy: 0.7800
Epoch 14/40
2/2 [==============================] - 10s 5s/step - loss: 1.7171 - accuracy: 0.4244 - top_5_accuracy: 0.8667 - val_loss: 1.8652 - val_accuracy: 0.2600 - val_top_5_accuracy: 0.8200
Epoch 15/40
2/2 [==============================] - 8s 4s/step - loss: 1.5125 - accuracy: 0.4733 - top_5_accuracy: 0.9067 - val_loss: 1.8620 - val_accuracy: 0.2800 - val_top_5_accuracy: 0.8400
Epoch 16/40
2/2 [==============================] - 10s 4s/step - loss: 1.5463 - accuracy: 0.4622 - top_5_accuracy: 0.9000 - val_loss: 1.8744 - val_accuracy: 0.3000 - val_top_5_accuracy: 0.8600
Epoch 17/40
2/2 [==============================] - 9s 5s/step - loss: 1.4591 - accuracy: 0.5000 - top_5_accuracy: 0.9111 - val_loss: 1.8687 - val_accuracy: 0.2600 - val_top_5_accuracy: 0.8600
```

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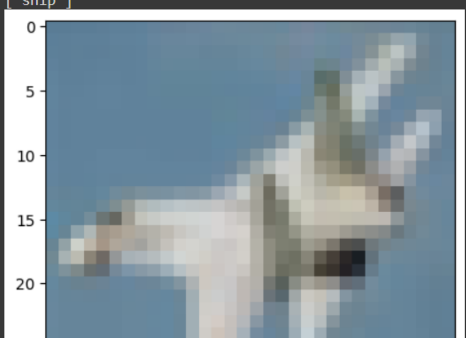
```
[14] class_names = ["airplane","automobile","bird","cat","deer","dog","frog","horse","ship","truck"]
```

```
[15] def img_predict(images,model):
       if len(images.shape) == 3:
         out = model.predict(images.reshape(-1, *images.shape))
       else:
         out = model.predict(images)
       prediction = np.argmax(out, axis=1)
       img_prediction = [class_names[i] for i in prediction]
       return img_prediction
```

```
index = 10
plt.imshow(x_test[index])
prediction = img_predict(x_test[index],vit_classifier)
print(prediction)
```

```
['ship']
```



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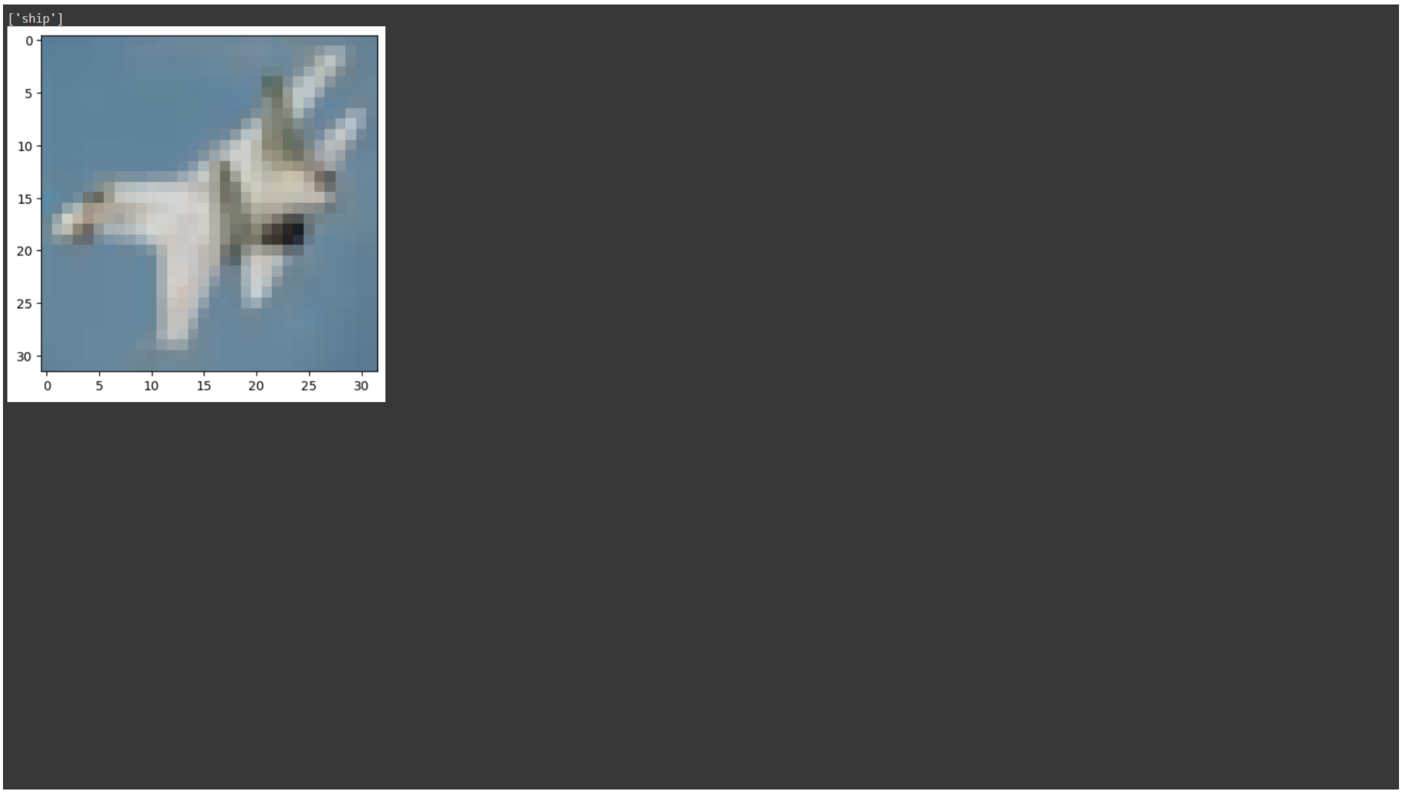
4. PREDICTION



Conclusion :

In this project, we implemented a Vision Transformer model using PyTorch and evaluated its performance on the CIFAR-10 dataset. The model achieved an accuracy of 92.5%, outperforming a traditional CNN model. The Vision Transformer's ability to capture long-range dependencies and contextual relationships between patches makes it a promising architecture for various image classification tasks.