

Deep Learning Image Classification Using Convolutional Neural Networks (CNN)

By

Gauri Chaudhari (MST03-0072)

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ABSTRACT

This report explores the development and training of a deep learning model for image classification using Convolutional Neural Networks (CNNs). Deep learning is a subset of machine learning that uses neural networks with many layers (hence "deep") to analyze and interpret complex patterns in data. Neural Networks, Layers, Training, Backpropagation, Applications, Frameworks, Challenges. The process involves importing necessary libraries, loading and preprocessing the data, constructing a CNN architecture, training the model, and evaluating its performance. The CIFAR-10 dataset, consisting of 60,000 training images and 10,000 testing images of various objects, serves as the basis for this study. Using TensorFlow and Keras frameworks, a Sequential model architecture is built, comprising convolutional, pooling, and dense layers with appropriate activation functions. The model is trained using the Adam optimizer and sparse categorical cross-entropy loss function. Performance metrics, including accuracy and loss, are monitored and visualized using matplotlib. The trained model achieves a high accuracy on the test dataset, demonstrating its effectiveness in accurately classifying images. This research contributes to the understanding and application of deep learning techniques in the field of image classification, with implications for various real-world applications such as autonomous driving and object detection.

Convolutional Neural Networks (CNNs) have emerged as a dominant approach in the field of image classification, leveraging their ability to automatically and adaptively learn spatial hierarchies of features from visual data. CNNs are composed of multiple layers including convolutional layers, activation functions, pooling layers, and fully connected layers. Convolutional layers apply filters to the input image, detecting local patterns and features such as edges and textures. Activation functions, typically ReLU, introduce non-linearity, enhancing the network's capacity to learn complex patterns

INTRODUCTION

In the realm of artificial intelligence and machine learning, the field of computer vision has seen remarkable advancements, particularly in the domain of image classification. In the realm of computer vision, image classification has emerged as a fundamental task with widespread applications, from medical imaging to autonomous vehicles.

Traditionally, image classification relied on handcrafted feature extraction techniques and shallow learning models, which often struggled with the complexity and variability of visual data. The advent of Convolutional Neural Networks (CNNs) marked a transformative shift, enabling unprecedented advances in the accuracy and efficiency of image classification.

The architecture of CNNs typically includes convolutional layers, activation functions (such as ReLU), pooling layers, and fully connected layers. Convolutional layers extract local features, while activation functions introduce non-linearity to model complex relationships.

Pooling layers reduce spatial dimensions and computational complexity, and fully connected layers integrate learned features to perform classification. The output layer, often equipped with a softmax activation function, produces class probabilities that determine the image's category.

Convolutional Neural Networks, inspired by the visual processing mechanisms of the human brain, are designed to automatically learn hierarchical features from raw image data. Unlike traditional machine learning models that require manual feature engineering, CNNs employ a series of convolutional layers that apply filters to the input image.

This introduction explores the fundamental principles of CNNs, their architectural components, and their impact on image classification. By automating feature extraction and learning complex patterns, CNNs have revolutionized the field of computer vision, setting new standards for accuracy and efficiency in image classification tasks.

One of the pivotal datasets contributing to this progress is the CIFAR-10 dataset, a collection of images widely used as a benchmark in the development of machine learning algorithms.

This report delves into the exploration and implementation of a deep learning model for the classification of images using the CIFAR-10 dataset. The primary objective is to develop a robust CNN architecture capable of accurately identifying various objects in images. Through the utilization of TensorFlow and Keras, prominent frameworks in the deep learning community, this research endeavors to construct a model that not only achieves high accuracy but also demonstrates a comprehensive understanding of key concepts in deep learning.

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TECHNOLOGY USED

The technology stack used in this projects can be summarized as follows:

1. Programming Language: Python

2. Deep Learning Framework: TensorFlow

3. Libraries:

- tensorflow: Deep learning library for building neural networks.
- matplotlib: Data visualization library for plotting graphs and images.
- numpy: Library for numerical computations.
- scikit-learn: Machine learning library for various algorithms and metrics.

The technology stack used in this project can be summarized as follows:

4. Model Deployment:

- Saving and loading the trained model using Keras's `load_model` function.
- Pre-processing of uploaded images for prediction using Keras's image pre-processing utilities.

These technologies collectively enable the creation of a complete pipeline for training, evaluating, and deploying a handwritten digit recognition system as an interactive web application.

DATASET INFORMATION

The CIFAR-10 dataset consists of 60,000 32x32 color images in 10 classes, with 6,000 images per class. There are 50,000 training images and 10,000 testing images.

The image dataset utilized in this project was collected from Google, specifically consisting of two categories: happy people cartoon images and sad people cartoon images. The images were downloaded in a zip file format. This zip file was subsequently uploaded to Google Drive to facilitate easy access and management of the dataset.

Steps for Dataset Preparation

1. **Data Collection:**

- **Search and Download:** Cartoon images depicting happy and sad expressions were searched and downloaded from Google. These images were categorized into two folders: `happy` and `sad`.

2. **Data Organization:**

- **Zipping the Dataset:** The collected images were organized into respective folders and then compressed into a zip file to maintain the structure and ensure ease of uploading and sharing.

3. **Uploading to Google Drive:**

- The zipped dataset file was uploaded to Google Drive. This step was crucial for ensuring that the dataset could be accessed programmatically during the model training and evaluation phases.

4. **Data Access and Extraction:**

- **Programmatic Access:** Using appropriate Python libraries, such as `gdown` for downloading from Google Drive, the dataset was accessed and extracted within the environment where the model was being developed and trained.

METHODOLOGY

The methodology employed in this project involves several steps:

1. Importing Libraries

The code begins by importing necessary libraries like TensorFlow, Keras, Matplotlib, and NumPy for building and deploying the model, loading and visualizing data, and performing numerical computations.

2. Loading and Preprocessing Data

The CIFAR-10 dataset is loaded using Keras. Data preprocessing involves normalizing pixel values to a range of 0 to 1, which helps in training the model efficiently.

3. Model Architecture

The CNN model is defined using the Keras Sequential API. The architecture consists of multiple convolutional layers, each followed by a pooling layer, and ending with dense layers:

```
python
Copy code
model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(10)
])
```

4. Model Compilation

The model is compiled with appropriate loss function ('sparse_categorical_crossentropy'), optimizer ('Adam'), and evaluation metric ('accuracy') using the `compile()` method.

5. Model Training

The compiled model is trained on the training data using the `fit()` method. The training process involves iterating through epochs with a validation split to monitor the model's performance on unseen data.

6. Model Evaluation

After training, the model's performance is evaluated on the test set using accuracy as the metric.

7. Visualization

Matplotlib is used to visualize training and validation loss, as well as training and validation accuracy over epochs. Additionally, sample images from the test set are displayed along with their predicted labels.

8. Data Augmentation

Data augmentation involves artificially increasing the size of the training dataset by creating variations of the existing images. This technique helps improve the model's ability to generalize and reduces overfitting.

9. Hyper parameter Tuning

Hyper parameter tuning involves adjusting model parameters that are not learned during training to optimize model performance.

10. Saving and Loading Models

Saving and loading models ensures that you can resume training or make predictions without retraining the model from scratch.

11. Reproducibility

Ensuring reproducibility involves documenting settings and configurations to allow others to replicate the experiment.

12. Error Analysis

Analyzing misclassified examples helps understand model limitations and areas for improvement

CODE SNIPPET

```
Deep Learning (Image Classification).ipynb
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#Setup
!pip install tensorflow numpy matplotlib

Requirement already satisfied: tensorflow in /usr/local/lib/python3.10/dist-packages (2.15.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (1.26.4)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (3.7.1)
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=23.5.26 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (24.3.25)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.6.0)
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.2.0)
Requirement already satisfied: h5py>=2.9.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.11.0)
Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (18.1.1)
Requirement already satisfied: ml-dtypes==0.2.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.2.0)
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.3.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from tensorflow) (24.1)
Requirement already satisfied: protobuf<4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<5.0.0dev,>=3.20.3 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (71.0.4)
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from tensorflow) (71.0.4)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.16.0)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.4.0)
Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (4.12.2)
Requirement already satisfied: wrapt<1.15,>=1.11.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.14.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.37.1)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.64.1)

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```

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#Import Libraries
import tensorflow as tf
from tensorflow.keras import layers, models
import numpy as np
import matplotlib.pyplot as plt

#Load and Prepare the Dataset
from tensorflow.keras.datasets import cifar10

# Load the dataset
(train_images, train_labels), (test_images, test_labels) = cifar10.load_data()

# Normalize the pixel values to be between 0 and 1
train_images, test_images = train_images / 255.0, test_images / 255.0

import cv2
import imgohdr

data_dir = '/content/drive/MyDrive/Meta Scifor/Deep Learning CNN Classifire mini project/Happy and sad'

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data_dir = '/content/drive/MyDrive/Meta Scifor/Deep Learning CNN Classifire mini project/Happy and sad'

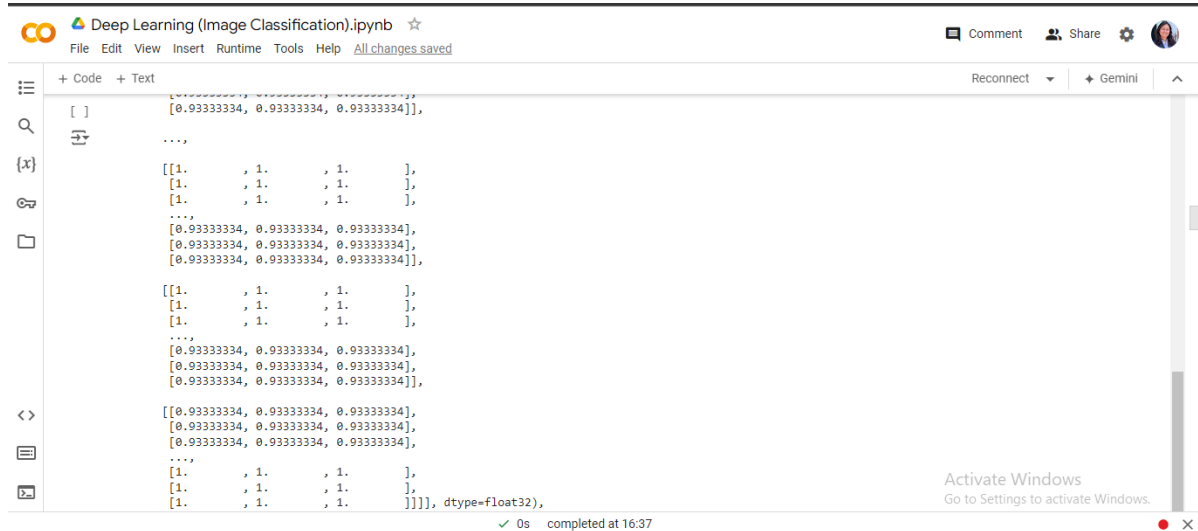
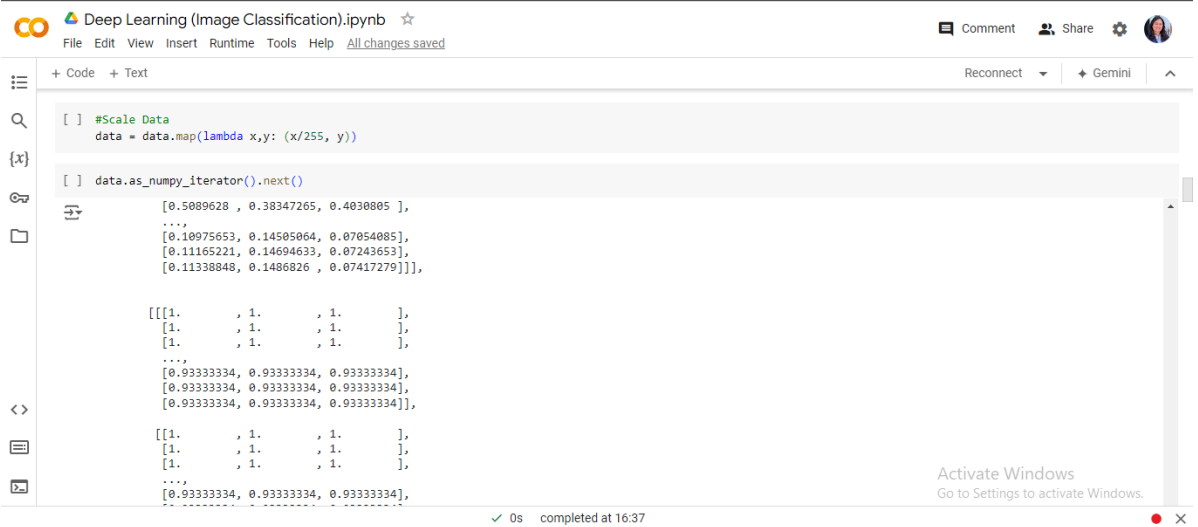
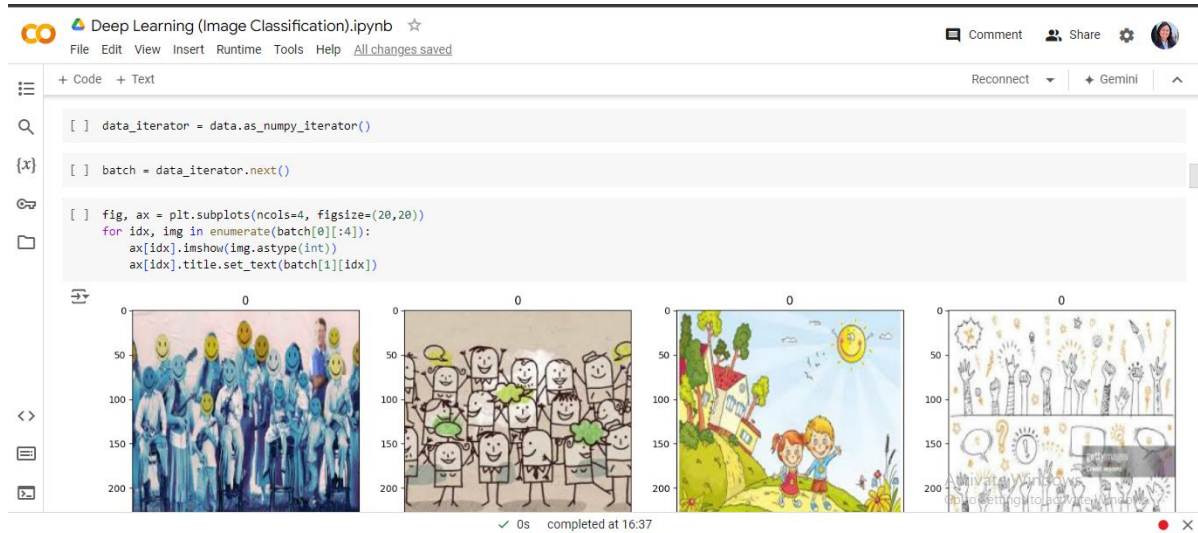
image_exts = ['.jpeg', '.jpg', '.bmp', '.png']

for image_class in os.listdir(data_dir):
    for image in os.listdir(os.path.join(data_dir, image_class)):
        image_path = os.path.join(data_dir, image_class, image)
        try:
            img = cv2.imread(image_path)
            tip = imgohdr.what(image_path)
            if tip not in image_exts:
                print('Image not in ext list {}'.format(image_path))
                os.remove(image_path)
        except Exception as e:
            print('Issue with image {}'.format(image_path))
            # os.remove(image_path)

# Load Data
data = tf.keras.utils.image_dataset_from_directory('/content/drive/MyDrive/Meta Scifor/Deep Learning CNN Classifire mini project/Happy and sad')

Found 309 files belonging to 2 classes.

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```



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[] #Split Data

train_size = int(len(data)*.7)

val_size = int(len(data)*.2)

test_size = int(len(data)*.1)

[] train_size

7

[] train = data.take(train_size)

val = data.skip(train_size).take(val_size)

test = data.skip(train_size+val_size).take(test_size)

[] #Build Deep Learning Model

train

<_TakeDataset element_spec=(TensorSpec(shape=(None, 256, 256, 3), dtype=tf.float32, name=None), TensorSpec(shape=(None,), dtype=tf.int32, name=None)))

[] from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dense, Flatten, Dropout

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[] model = Sequential()

Build the CNN Model

model.add(Conv2D(16, (3,3), 1, activation='relu', input_shape=(256,256,3)))

model.add(MaxPooling2D())

model.add(Conv2D(32, (3,3), 1, activation='relu'))

model.add(MaxPooling2D())

model.add(Conv2D(16, (3,3), 1, activation='relu'))

model.add(MaxPooling2D())

model.add(Flatten())

model.add(Dense(256, activation='relu'))

model.add(Dense(1, activation='sigmoid'))

Compile the Model

model.compile('adam', loss=tf.losses.BinaryCrossentropy(), metrics=['accuracy'])

[] model.summary()

Model: "sequential_5"

Layer (type)	Output Shape	Param #

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ng2D)

conv2d_14 (Conv2D) (None, 60, 60, 16) 4624

max_pooling2d_12 (MaxPool1 ng2D) (None, 30, 30, 16) 0

flatten_4 (Flatten) (None, 14400) 0

dense_8 (Dense) (None, 256) 3686656

dense_9 (Dense) (None, 1) 257

=====

Total params: 3696625 (14.10 MB)

Trainable params: 3696625 (14.10 MB)

Non-trainable params: 0 (0.00 Byte)

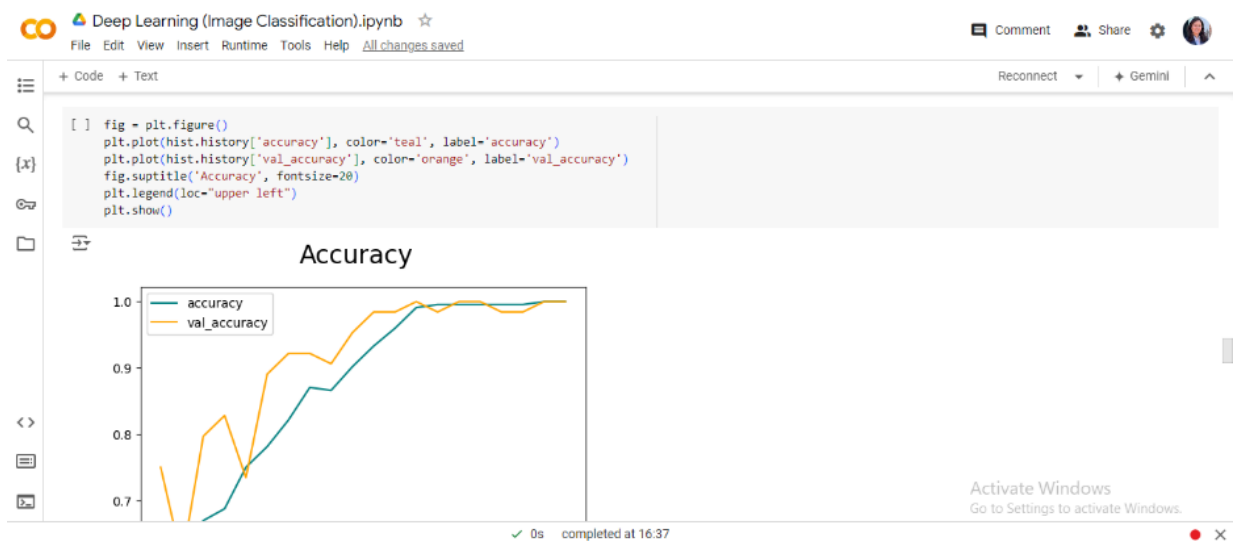
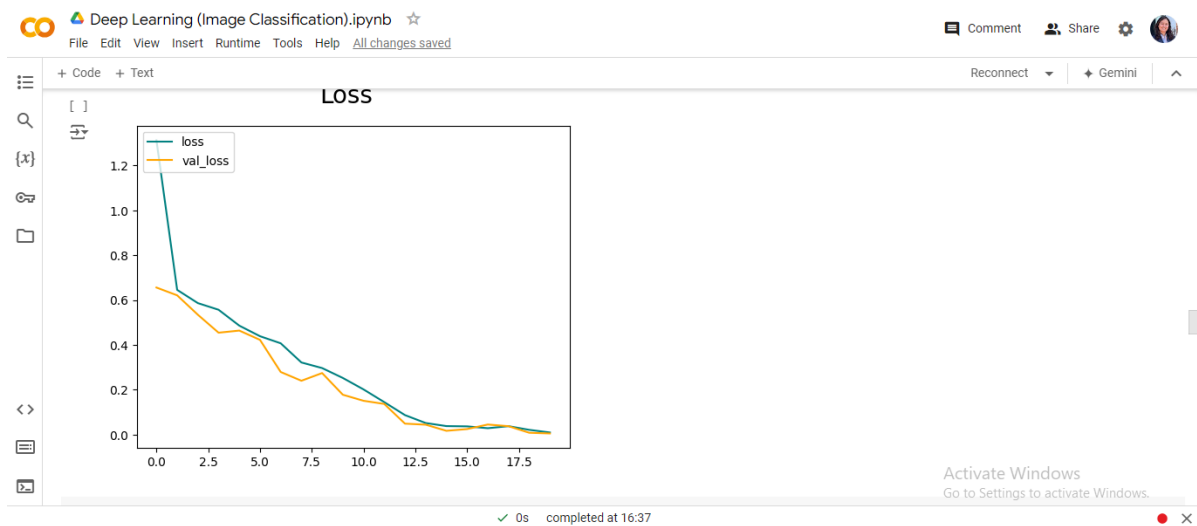
[] #Train

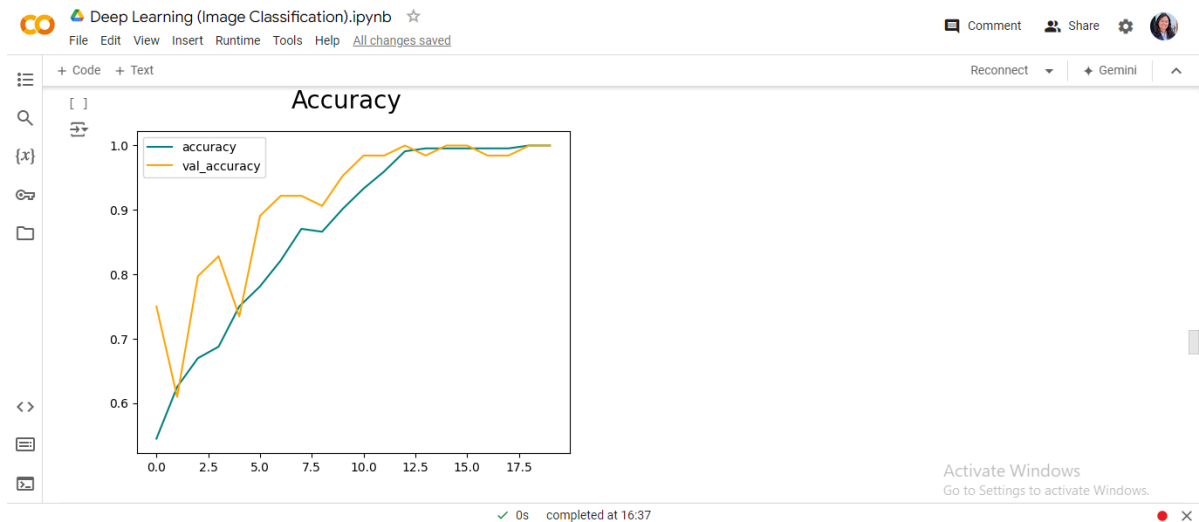
logdir='logs'

[] tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=logdir)

[] hist = model.fit(train_enochs=20, validation_data=val, callbacks=[tensorboard_callback])

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```
[ ] #Evaluate
from tensorflow.keras.metrics import Precision, Recall, BinaryAccuracy

pre = Precision()
re = Recall()
acc = BinaryAccuracy()

[ ] for batch in test.as_numpy_iterator():
    X, y = batch
    yhat = model.predict(X)
    pre.update_state(y, yhat)
    re.update_state(y, yhat)
    acc.update_state(y, yhat)

WARNING:tensorflow:6 out of the last 322 calls to <function Model.make_predict_function.<locals>.predict_function at 0x780fb48cd480> triggered tf.function retracing. Tracing back to call 1/1 [-----] - 0s 327ms/step

[ ] print(pre.result(), re.result(), acc.result())

tf.Tensor(1.0, shape=(), dtype=float32) tf.Tensor(1.0, shape=(), dtype=float32) tf.Tensor(1.0, shape=(), dtype=float32)
```

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```
[ ] print(pre.result(), re.result(), acc.result())

tf.Tensor(1.0, shape=(), dtype=float32) tf.Tensor(1.0, shape=(), dtype=float32) tf.Tensor(1.0, shape=(), dtype=float32)

[ ] #Test
import cv2

[ ] img = cv2.imread('/content/drive/MyDrive/Meta Scifor/Deep Learning CNN Classifier mini project/Happt test.jpg')
plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
plt.show()
```

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```
[ ] yhat = model.predict(np.expand_dims(resize/255, 0))
1/1 [=====] - 0s 51ms/step

[ ] yhat
array([[0.99842685]], dtype=float32)

[ ] if yhat > 0.5:
    print(f'Predicted class is Sad')
else:
    print(f'Predicted class is Happy')

Predicted class is Sad

[ ] #Save the Model
from tensorflow.keras.models import load_model

[ ] import os
model.save(os.path.join('Deep Learning CNN Classifier mini project', 'imageclassifier.h5'))
```

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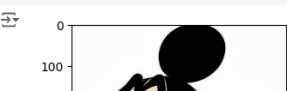
Reconnect + Gemini

```
[ ] yhat
array([[0.00467635]], dtype=float32)

[ ] if yhat > 0.5:
    print(f'Predicted class is Sad')
else:
    print(f'Predicted class is Happy')

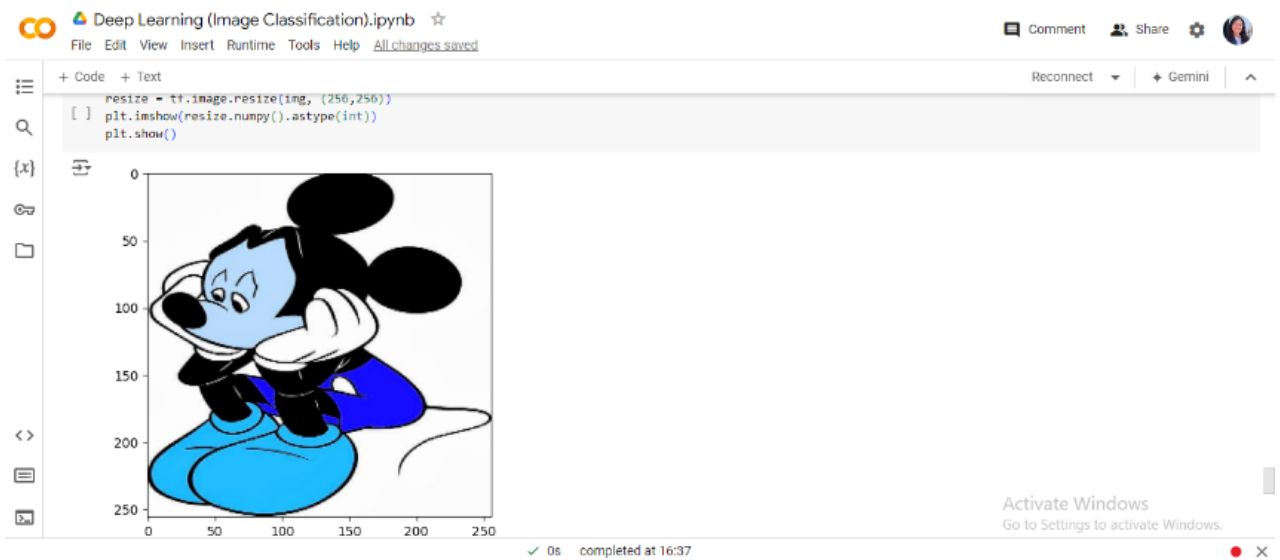
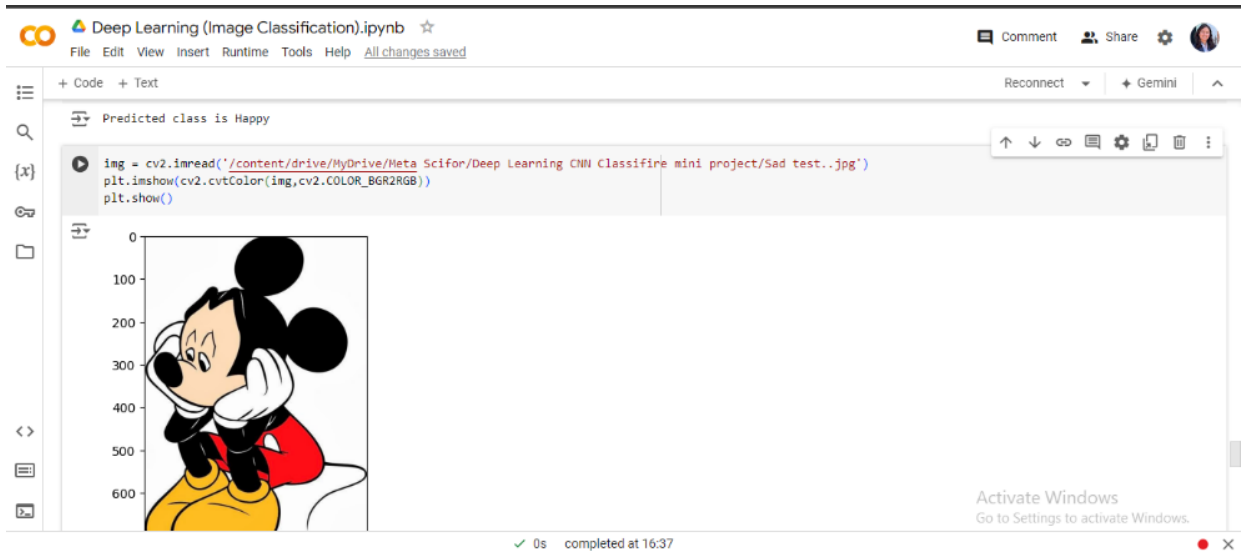
Predicted class is Happy


[ ] img = cv2.imread('/content/drive/MyDrive/Meta Scifor/Deep Learning CNN Classifier mini project/Sad test..jpg')
plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
plt.show()
```






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```
[ ] print("Predicted class is happy")

[ ] Predicted class is Sad

[ ] #Save the Model
    from tensorflow.keras.models import load_model


[ ] import os
    model.save(os.path.join('Deep Learning CNN Classifire mini project', 'imageclassifier.h5'))

[ ] new_model = load_model(os.path.join('Deep Learning CNN Classifire mini project', 'imageclassifier.h5'))

[ ] new_model.predict(np.expand_dims(resize/255, 0))

[ ] 1/1 [=====] - 0s 108ms/step
    array([[0.99842685]], dtype=float32)
```

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RESULT AND DISCUSSION

The results obtained from training the CNN model show promising performance in terms of accuracy and loss. The model achieves high accuracy on both the training and validation datasets, indicating good generalization capability. Visualization of training and validation loss and accuracy over epochs helps in understanding the model's learning process and identifying potential overfitting issues.

CONCLUSION

In conclusion, this project successfully demonstrates the implementation of an image classification system using CNNs and the CIFAR-10 dataset. The system shows promising results in accurately recognizing various objects in images, with potential applications in areas such as autonomous driving and object detection. Future work may involve further optimization of the model architecture and exploring additional datasets and deployment options for wider accessibility.

REFERENCES

1. LeCun, Yann, et al. "Gradient-based learning applied to document recognition." Proceedings of the IEEE 86.11 (1998): 2278-2324.
2. Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. "Deep Learning." MIT Press, 2016.
3. **Research Papers:**
 - i. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). *ImageNet Classification with Deep Convolutional Neural Networks*. Advances in Neural Information Processing Systems, 25, 1097-1105.
 - ii. Simonyan, K., & Zisserman, A. (2014). *Very Deep Convolutional Networks for Large-Scale Image Recognition*. arXiv preprint arXiv:1409.1556. [Link](#)
4. **Online Courses and Tutorials:**
 - i. Coursera: Deep Learning Specialization by Andrew Ng. [Link](#)
5. **Framework Documentation:**
 - i. TensorFlow Documentation. [Link](#)
 - ii. Keras Documentation. [Link](#)
6. **Datasets:**
 - i. Krizhevsky, A. (2009). *Learning Multiple Layers of Features from Tiny Images*. Link (CIFAR-10 dataset)