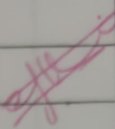
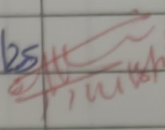
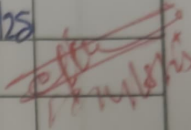
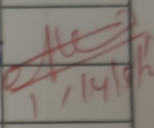
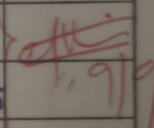
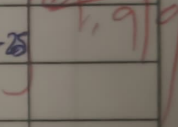
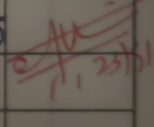


NAME K.D.D. Sai Abhisam

SUBJECT Deep learning lab obs

STD. \_\_\_\_\_ DIV. \_\_\_\_\_ ROLL NO. \_\_\_\_\_ SCHOOL \_\_\_\_\_

Sr. No.	Page No.	Title	Date	Teacher's Sign / Remarks
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2		Implement a classifier using open-source data set	7/8/25	
3		Study of the classifiers with respect to statistical parameters	7/8/25	
4		Build a simple feed forward neural network to recognize hand written characters	14/8/25	
5		Study of activation function and its role	28-8-25	
6		Implement gradient descent & back propagation in deep neural network	09-9-25	
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16/9/25

## Week-7 - Build a CNN model to classify cats and dogs images

Aim:- to classify the cats & dogs images using CNN model.

### Objective:-

- \* A Convolutional neural network (CNN) is a type of neural network specifically designed to process data with grid like images
- \* the primary goal of a CNN model using tensorflow to classify images of cats and dogs. by end of this lab.
  - ① load and preprocess an image dataset.
  - ② Construct a CNN architecture.
  - ③ train the model on the dataset.
  - ④ Evaluate the model's performance.

### Pseudo Code:

#### # Step: 1 - Setup

import ~~tensorflow~~ <sup>matplotlib</sup>, matplotlib

define image Cimage-width = ? , image height = ?  
n8

define batch size =

define epoch = 20

#### # Step: 2 - data Preparation

Initialize training data generator with

- shuffle = 1/555

- data augmentation (rotate, shift, zoom, flip)

Initialize validation generator file

load training data & validation data

#### # Step: 3 - Build CNN model

Create sequential model

flatten output

Add dense layer (512 units, ReLU)

# Step: 4 - Compile model

optimizer = Adam

loss = Binary cross entropy

metrics = accuracy

# Step: 5 - train model

FIT Model Using:

- training generator
- validation generator
- steps per epoch =  $\frac{\text{training-samples}}{\text{batch size}}$
- validation steps =  $\frac{\text{validation-s}}{\text{batch-size}}$  - epochs

# Step: 6 :- Evaluate and Visualize

Plot training vs validation accuracy per plot.

Plot training vs validation loss per epoch.

Print final validation loss and accuracy

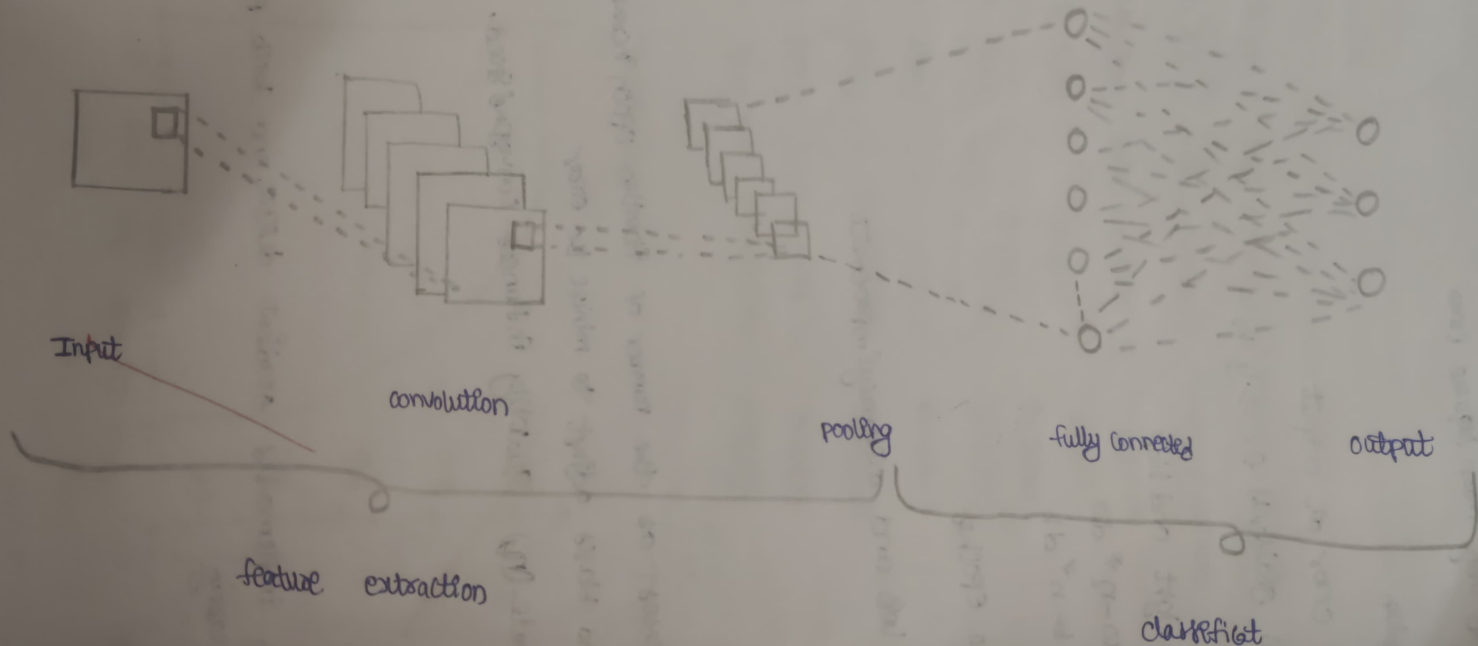
end

Observations :-

- ① loss decreased as the number of epochs increased
- ② weights and biases adjusted continuously to minimize the error
- ③ learning rate influenced the speed of convergence
- ④ Accuracy gradually improved and reached stable values

Result :- the implementation of CNN model was successfully implemented using ~~tensorflow~~ <sup>keras</sup> to verify the images of cats & dogs.

# CNN Architecture



## output

Epoch [1/10] train : loss : 0.6597 , val loss : 0.6277  
train : acc : 0.6013 , val acc : 0.6495

Epoch [2/10] t-loss : 0.5968 , val-loss : 0.5953  
t-acc : 0.6477 , val-acc : 0.6730

Epoch [3/10] t-loss : 0.5650 , val-loss : 0.5498  
t-acc : 0.7017 , val-acc : 0.7185

Epoch [4/10] t-loss : 0.5402 , val-loss : 0.5548  
t-acc : 0.7234 , val-acc : 0.7100

Epoch [5/10] t-loss : 0.5133 , val-loss : 0.5238  
t-acc : 0.7420 , val-acc : 0.7310

Epoch [6/10] t-loss : 0.4891 , val-loss : 0.5285  
t-acc : 0.7619 , val-acc : 0.7335

Epoch [7/10] t-loss : 0.4742 , val-loss : 0.5031  
t-acc : 0.7696 , val-acc : 0.7460

Epoch [8/10] t-loss : 0.4521 , val-loss : 0.4998  
t-acc : 0.7841 , val-acc : 0.7445

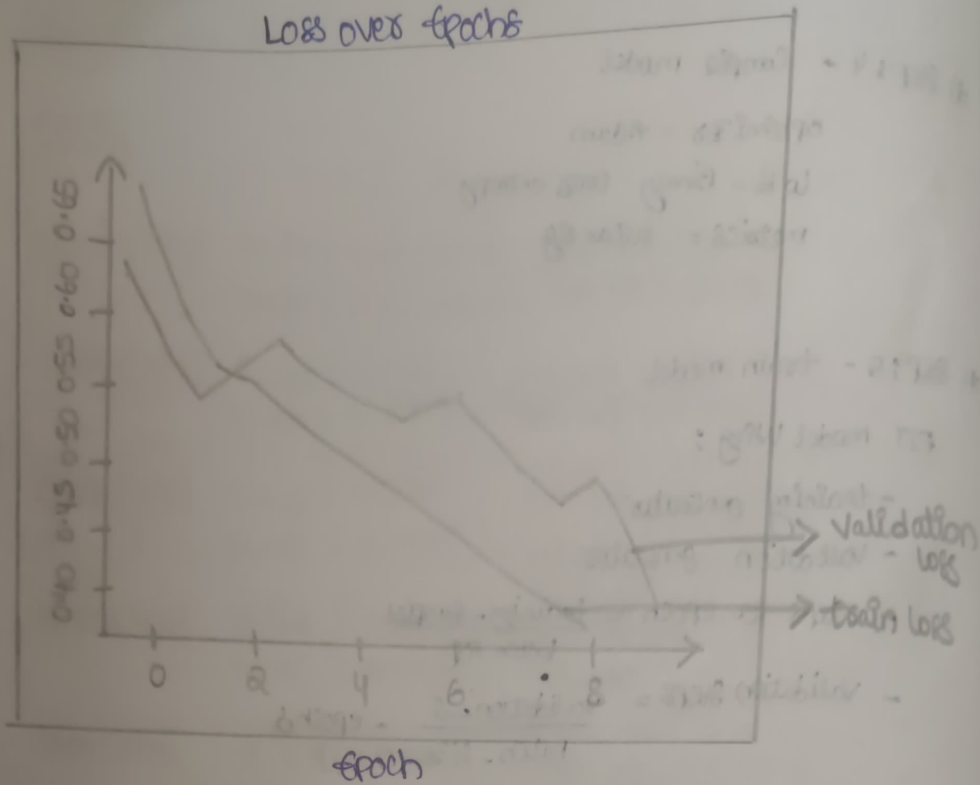
Epoch [9/10] t-loss : 0.4195 , val-loss : 0.5244  
t-acc : 0.8031 , val-acc : 0.7420

Epoch [10/10] t-loss : 0.4002 , val-loss : 0.5013  
t-acc : 0.8130 , val-acc : 0.7505



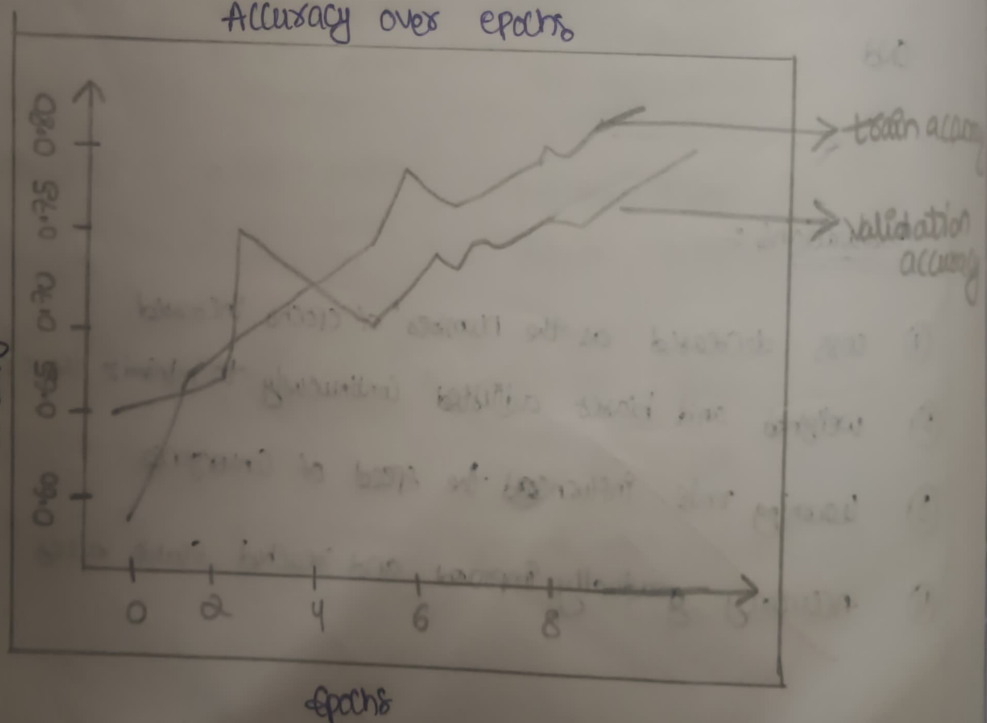
# Loss over epochs

Loss



# Accuracy over epochs

Accuracy



## Result :-

The implementation of CNN model was successfully implemented using PyTorch to verify the images of cats & dogs

Final validation loss :- 0.5013

final validation accuracy :- 0.7505

~~5/11/23~~  
~~23/9/23~~

```
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader, Subset
from torchvision import datasets, transforms
import matplotlib.pyplot as plt
import numpy as np

# Configuration
IMG_WIDTH = 32 # CIFAR-10 images are 32x32
IMG_HEIGHT = 32
BATCH_SIZE = 64
EPOCHS = 10
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

#### # Data Preparation

```
transform = transforms.Compose([
    transforms.ToTensor()
])
```

#### # Download CIFAR10 dataset

```
full_train_dataset = datasets.CIFAR10(root='./data', train=True, download=True, transform=transform)
full_valid_dataset = datasets.CIFAR10(root='./data', train=False, download=True, transform=transform)
```

#### # Filter dataset: Keep only 'cat' (label 3) and 'dog' (label 5) classes

```
def filter_cats_dogs(dataset):
    cat_dog_indices = [i for i, (_, label) in enumerate(dataset) if label in [3, 5]]
    return Subset(dataset, cat_dog_indices)
```

```
train_dataset = filter_cats_dogs(full_train_dataset)
valid_dataset = filter_cats_dogs(full_valid_dataset)
```





```
model.eval()
val_loss, val_correct, val_total = 0.0, 0, 0
with torch.no_grad():
    for inputs, labels in valid_loader:
        inputs, labels = inputs.to(device), labels.to(device).unsqueeze(1)
        outputs = model(inputs)
        loss = criterion(outputs, labels)

        val_loss += loss.item() * inputs.size(0)
        predicted = (outputs > 0.5).float()
        val_correct += (predicted == labels).sum().item()
        val_total += labels.size(0)

val_loss /= val_total
val_acc = val_correct / val_total
val_losses.append(val_loss)
val_accuracies.append(val_acc)

print(f"Epoch [{epoch+1}/{EPOCHS}] "
      f"Train Loss: {train_loss:.4f} | Train Acc: {train_acc:.4f} | "
      f"Val Loss: {val_loss:.4f} | Val Acc: {val_acc:.4f}")

# Visualization
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(train_losses, label='Train Loss')
plt.plot(val_losses, label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.title('Loss Over Epochs')

plt.subplot(1, 2, 2)
plt.plot(train_accuracies, label='Train Accuracy')
plt.plot(val_accuracies, label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Accuracy Over Epochs')

plt.tight_layout()
plt.show()
```



```
# Update labels to binary (cat=0, dog=1)
class BinaryCIFAR10(torch.utils.data.Dataset):
    def __init__(self, subset):
        self.subset = subset

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

    def __getitem__(self, idx):
        img, label = self.subset[idx]
        binary_label = 0 if label == 3 else 1 # 3 → cat → 0, 5 → dog → 1
        return img, torch.tensor(binary_label, dtype=torch.float32)

train_dataset = BinaryCIFAR10(train_dataset)
valid_dataset = BinaryCIFAR10(valid_dataset)

train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE, shuffle=True)
valid_loader = DataLoader(valid_dataset, batch_size=BATCH_SIZE, shuffle=False)

# Model Definition
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        self.conv1 = nn.Conv2d(3, 32, 3)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(32, 64, 3)
        self.fc1 = nn.Linear(64 * 6 * 6, 512)
        self.fc2 = nn.Linear(512, 1)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 64 * 6 * 6)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        return x
```

```
model = SimpleCNN().to(device)
criterion = nn.BCELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
```

#### # Training Loop

```
train_losses, val_losses = [], []
train_accuracies, val_accuracies = [], []
```

```
for epoch in range(EPOCHS):
    model.train()
    running_loss, correct, total = 0.0, 0, 0

    for inputs, labels in train_loader:
        inputs, labels = inputs.to(device), labels.to(device).unsqueeze(1)

        optimizer.zero_grad()
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        running_loss += loss.item() * inputs.size(0)
        predicted = (outputs > 0.5).float()
        correct += (predicted == labels).sum().item()
        total += labels.size(0)

    train_loss = running_loss / total
    train_acc = correct / total
    train_losses.append(train_loss)
    train_accuracies.append(train_acc)
```

```

# Final Evaluation
model.eval()
final_loss, final_correct, final_total = 0.0, 0, 0
with torch.no_grad():
    for inputs, labels in valid_loader:
        inputs, labels = inputs.to(device), labels.to(device).unsqueeze(1)
        outputs = model(inputs)
        loss = criterion(outputs, labels)

        final_loss += loss.item() * inputs.size(0)
        predicted = (outputs > 0.5).float()
        final_correct += (predicted == labels).sum().item()
        final_total += labels.size(0)

final_loss /= final_total
final_accuracy = final_correct / final_total
print(f"\nFinal Validation Loss: {final_loss:.4f}")
print(f"Final Validation Accuracy: {final_accuracy:.4f}")

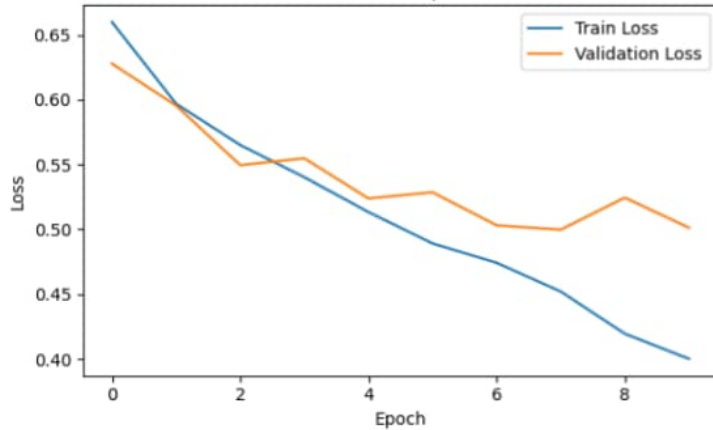
```

```

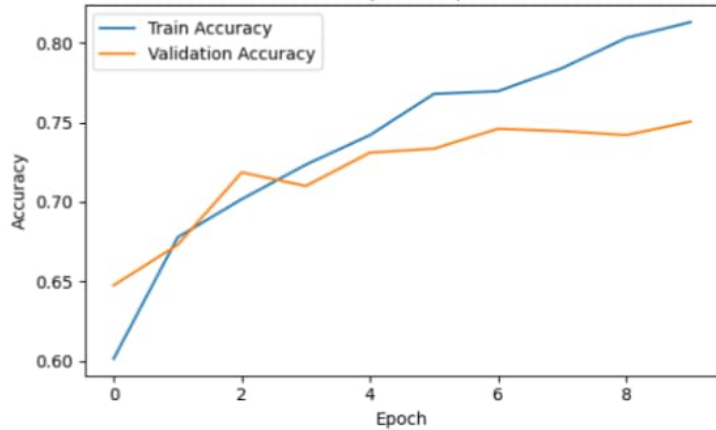
100%|██████████| 170M/170M [00:06<00:00, 26.6MB/s]
Epoch [1/10] Train Loss: 0.6597 | Train Acc: 0.6013 | Val Loss: 0.6277 | Val Acc: 0.6475
Epoch [2/10] Train Loss: 0.5968 | Train Acc: 0.6777 | Val Loss: 0.5953 | Val Acc: 0.6730
Epoch [3/10] Train Loss: 0.5650 | Train Acc: 0.7017 | Val Loss: 0.5495 | Val Acc: 0.7185
Epoch [4/10] Train Loss: 0.5402 | Train Acc: 0.7234 | Val Loss: 0.5548 | Val Acc: 0.7100
Epoch [5/10] Train Loss: 0.5133 | Train Acc: 0.7420 | Val Loss: 0.5238 | Val Acc: 0.7310
Epoch [6/10] Train Loss: 0.4891 | Train Acc: 0.7679 | Val Loss: 0.5285 | Val Acc: 0.7335
Epoch [7/10] Train Loss: 0.4742 | Train Acc: 0.7696 | Val Loss: 0.5031 | Val Acc: 0.7460
Epoch [8/10] Train Loss: 0.4521 | Train Acc: 0.7841 | Val Loss: 0.4998 | Val Acc: 0.7445
Epoch [9/10] Train Loss: 0.4195 | Train Acc: 0.8031 | Val Loss: 0.5244 | Val Acc: 0.7420
Epoch [10/10] Train Loss: 0.4002 | Train Acc: 0.8130 | Val Loss: 0.5013 | Val Acc: 0.7505

```

### Loss Over Epochs



### Accuracy Over Epochs



Final Validation Loss: 0.5013  
 Final Validation Accuracy: 0.7505