DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
(ARTIFICIAL INTELLIGENCE & MACHINE LEARNING)

B.E / SEM VIII / REV 2019 'C SCHEME' / CSE-(AI&ML)
Academic Year: 2023-24

NAME	**PRATHAMESH S. CHIKANKAR**
BRANCH	**CSE-(AI&ML)**
ROLL NO.	**AIML11**
SUBJECT	**ADVANCE ARTIFICIAL INTELLIGENCE LAB**
COURSE CODE	**CSL801**
PRACTICAL NO.	
DOP	
DOS	

Output:

1) HMM

HMM

```
[12] !pip install hmmlearn
```

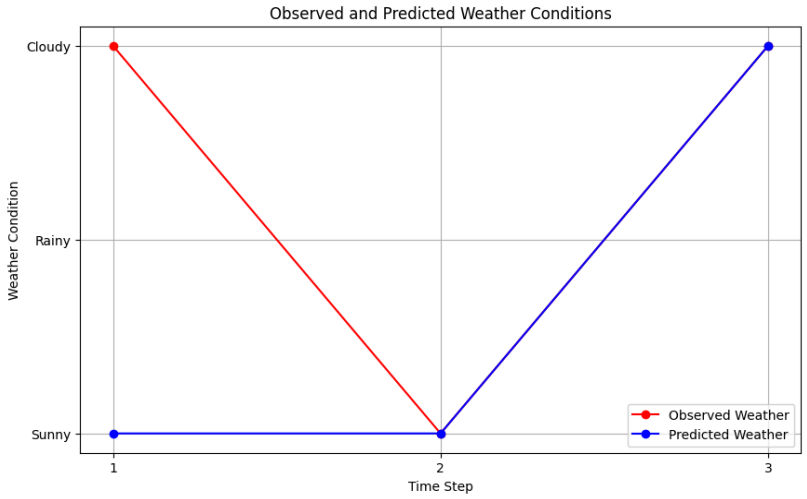
```
Collecting hmmlearn
  Downloading hmmlearn-0.3.2-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86
     ---------------------------------------- 161.1/161.1 kB 2.9 MB/s eta 0:00:0
Requirement already satisfied: numpy>=1.10 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: scikit-learn!=0.22.0,>=0.16 in /usr/local/lib/pyt
Requirement already satisfied: scipy>=0.19 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10
Installing collected packages: hmmlearn
Successfully installed hmmlearn-0.3.2
```

```
[13] import numpy as np
from hmmlearn import hmm
import matplotlib.pyplot as plt

# Define the states (weather conditions)
states = ["Sunny", "Rainy", "Cloudy"]

# Define the observation symbols (also weather conditions in this case)
symbols = ["Sunny", "Rainy", "Cloudy"]

# Transition probabilities matrix (rows sum to 1)
transition_probabilities = np.array([
    [0.7, 0.1, 0.2],  # Sunny -> Sunny, Rainy, Cloudy
    [0.3, 0.5, 0.2],  # Rainy -> Sunny, Rainy, Cloudy
    [0.2, 0.3, 0.5]   # Cloudy -> Sunny, Rainy, Cloudy
])

# Emission probabilities matrix (rows sum to 1)
emission_probabilities = np.array([
    [0.8, 0.1, 0.1],  # Sunny -> Sunny, Rainy, Cloudy
    [0.1, 0.8, 0.1],  # Rainy -> Sunny, Rainy, Cloudy
    [0.1, 0.1, 0.8]   # Cloudy -> Sunny, Rainy, Cloudy
])

# Initialize the HMM model
model = hmm.CategoricalHMM(n_components=len(states), n_iter=100)

# Set model parameters
model.startprob_ = np.array([0.6, 0.3, 0.1])  # Initial state probabilities
model.transmat_ = transition_probabilities    # State transition probabilities
model.emissionprob_ = emission_probabilities  # Emission probabilities
```

```
[24] # Generate or input observed sequences (weather conditions)
observed_sequence = np.array([[2], [0], [2]])  # Example observed sequence: Sunny, Rainy, Cl

# Predict outcomes based on observed sequences
predicted_states = model.predict(observed_sequence)
```

```
[25] # Map predicted state indices to state names
predicted_weather = [states[state_index] for state_index in predicted_states]
observed_weather = [symbols[obs[0]] for obs in observed_sequence]

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

# Plot observed weather
plt.plot(range(len(observed_sequence)), observed_sequence, 'ro-', label='Observed Weather')

# Plot predicted weather
plt.plot(range(len(observed_sequence)), predicted_states, 'bo-', label='Predicted Weather')
```

```
plt.xticks(range(len(observed_sequence)), range(1, len(observed_sequence) + 1))
plt.xlabel('Time Step')
plt.ylabel('Weather Condition')
plt.title('Observed and Predicted Weather Conditions')
plt.legend()
plt.grid(True)
plt.yticks(range(len(states)), states)

plt.show()
```




```
[26] # Predict probabilities of each state for each observation
     state_probabilities = model.predict_proba(observed_sequence)

     # Print observed and predicted weather with probabilities
     print("Observed Weather:")
     for obs, prob in zip(observed_weather, observed_sequence):
         print(f"{obs}: {symbols[prob[0]]}")

     print("\nPredicted Weather with Probabilities:")
     for time_step, (state_probs, pred) in enumerate(zip(state_probabilities, predicted_weather)):
         print(f"Time Step {time_step + 1}:")
         for state, prob in zip(states, state_probs):
             print(f"{state}: {prob:.4f}")
         print(f"Predicted Weather: {pred}")
         print()
```

```
Observed Weather:
Cloudy: Cloudy
Sunny: Sunny
Cloudy: Cloudy

Predicted Weather with Probabilities:
Time Step 1:
Sunny: 0.5285
Rainy: 0.1424
Cloudy: 0.3291
Predicted Weather: Sunny

Time Step 2:
Sunny: 0.7771
Rainy: 0.0652
Cloudy: 0.1577
Predicted Weather: Sunny

Time Step 3:
Sunny: 0.2418
Rainy: 0.0565
Cloudy: 0.7017
Predicted Weather: Cloudy
```

2) GMM

GMM

```
[1] import numpy as np
    from sklearn import datasets
    from sklearn.mixture import GaussianMixture
    from sklearn.model_selection import train_test_split, GridSearchCV
    from sklearn.preprocessing import StandardScaler
    from sklearn.metrics import accuracy_score
    import matplotlib.pyplot as plt
    from matplotlib.patches import Ellipse
```

```
[2] # Load the Iris dataset
    iris = datasets.load_iris()
    X = iris.data
    y = iris.target
```

```
[3] # Feature scaling
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
```

```
[4] # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
```

```
[5] # Initialize the Gaussian Mixture Model with 3 components (since there are 3 classes in the Iris
    gmm = GaussianMixture(random_state=42)
```

```
[6] # Perform grid search for hyperparameter tuning
    param_grid = {
        'n_components': [2, 3, 4],
        'covariance_type': ['full', 'tied', 'diag', 'spherical']
    }

    grid_search = GridSearchCV(gmm, param_grid=param_grid, cv=5)
    grid_search.fit(X_train)

    best_gmm = grid_search.best_estimator_
    print("Best GMM parameters:", best_gmm.get_params())
```

```
Best GMM parameters: {'covariance_type': 'full', 'init_params': 'kmeans', 'max_iter': 100, 'means
```

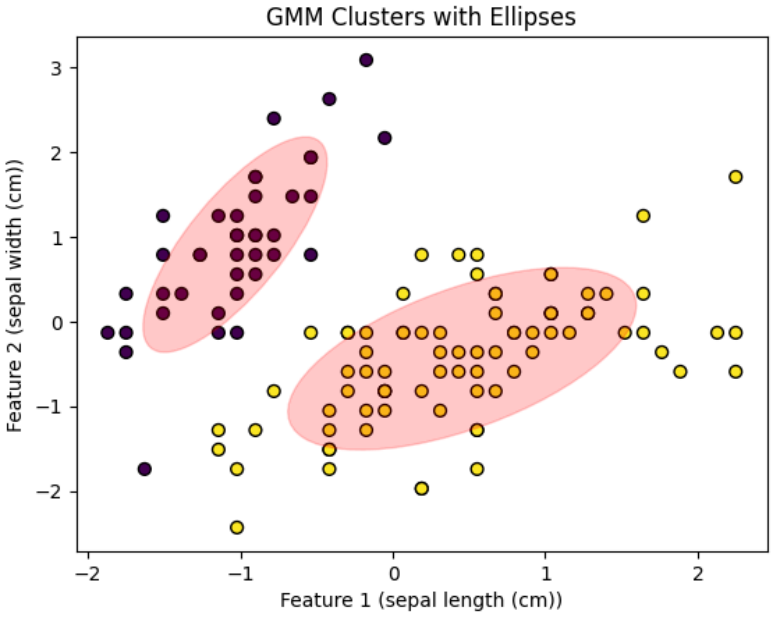
```
[7] # Fit the best model to the training data using the Expectation-Maximization algorithm
    best_gmm.fit(X_train)
```

```
[8] # Predict the labels for the test set
    y_pred = best_gmm.predict(X_test)
```

```
[9] # Calculate accuracy
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Accuracy: {accuracy}")
```

```
Accuracy: 0.6333333333333333
```

```
[10] # Visualization of GMM clusters with ellipses
     def plot_gmm(gmm, X):
         n_features = X.shape[1]

         if n_features < 2:
             print("Visualization requires at least 2 features.")
             return

         plt.scatter(X[:, 0], X[:, 1], c=gmm.predict(X), cmap='viridis', s=40, edgecolors='k', marker='o')

         for i in range(gmm.n_components):
             mean = gmm.means_[i, :2]
             cov_matrix = gmm.covariances_[i][:2, :2]
             eigvalues, eigvectors = np.linalg.eigh(cov_matrix)
             angle = np.degrees(np.arctan2(eigvectors[1, 0], eigvectors[0, 0]))

             # Plot the ellipse representing the covariance matrix
             ellipse = Ellipse(mean, 2 * np.sqrt(2 * eigvalues[0]), 2 * np.sqrt(2 * eigvalues[1]),
                               angle, color='red', alpha=0.2)
             plt.gca().add_patch(ellipse)

         plt.title('GMM Clusters with Ellipses')
         plt.xlabel(f'Feature 1 ({iris.feature_names[0]})')
         plt.ylabel(f'Feature 2 ({iris.feature_names[1]})')
         plt.show()

     # Visualization for all features
     plot_gmm(best_gmm, X_train)

     <ipython-input-10-ac183fc31b9c>:18: MatplotlibDeprecationWarning: Passing the angle parameter of __in
       ellipse = Ellipse(mean, 2 * np.sqrt(2 * eigvalues[0]), 2 * np.sqrt(2 * eigvalues[1]),
```




```
[11] # Outlier detection
     log_likelihood = best_gmm.score_samples(X_train)
     threshold = np.percentile(log_likelihood, 5)
     outliers = X_train[log_likelihood < threshold]
     print(f"Number of outliers: {len(outliers)}")

     Number of outliers: 6
```

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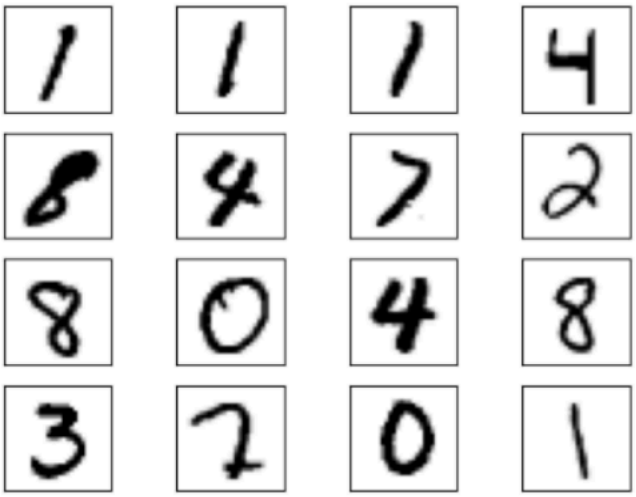
Code & Output:

Loading Dataset

```
train_set = torchvision.datasets.MNIST(
    root=".", train=True, download=True, transform=transform
)
```

Dataset Look

```
real_samples, mnist_labels = next(iter(train_loader))
for i in range(16):
    ax = plt.subplot(4, 4, i + 1)
    plt.imshow(real_samples[i].reshape(28, 28), cmap="gray_r")
    plt.xticks([])
    plt.yticks([])
```



Discriminator & Generator Model

```
class Discriminator(nn.Module):
    def __init__(self):
        super().__init__()
        self.model = nn.Sequential(
            nn.Linear(784, 1024),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(1024, 512),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(512, 256),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(256, 1),
            nn.Sigmoid(),
        )

    def forward(self, x):
        x = x.view(x.size(0), 784)
        output = self.model(x)
        return output
```

```
discriminator = Discriminator().to(device=device)
```

```
class Generator(nn.Module):
    def __init__(self):
        super().__init__()
        self.model = nn.Sequential(
            nn.Linear(100, 256),
            nn.ReLU(),
            nn.Linear(256, 512),
            nn.ReLU(),
            nn.Linear(512, 1024),
            nn.ReLU(),
            nn.Linear(1024, 784),
            nn.Tanh(),
        )

    def forward(self, x):
        output = self.model(x)
        output = output.view(x.size(0), 1, 28, 28)
        return output

generator = Generator().to(device=device)
```

Some Training and Optimization parameters:

```
lr = 0.0001
num_epochs = 50
loss_function = nn.BCELoss()

optimizer_discriminator = torch.optim.Adam(discriminator.parameters(), l
optimizer_generator = torch.optim.Adam(generator.parameters(), lr=lr)
```

Training Loop

```
for epoch in range(num_epochs):
    for n, (real_samples, mnist_labels) in enumerate(train_loader):
        # Data for training the discriminator
        real_samples = real_samples.to(device=device)
        real_samples_labels = torch.ones((batch_size, 1 to(
            device=device
        )
        latent_space_samples = torch.randn((batch_size, 100)).to(
            device=device
        )
        generated_samples = generator(latent_space_samples)
        generated_samples_labels = torch.zeros((batch_size, 1)).to(
            device=device
        )
        all_samples = torch.cat((real_samples, generated_samples))
        all_samples_labels = torch.cat(
            (real_samples_labels, generated_samples_labels)
        )

        # Training the discriminator
        discriminator.zero_grad()
        output_discriminator = discriminator(all_samples)
        loss_discriminator = loss_function(
            output_discriminator, all_samples_labels
        )
        loss_discriminator.backward()
        optimizer_discriminator.step()

        # Data for training the generator
        latent_space_samples = torch.randn((batch_size, 100)).to(
            device=device
        )
```

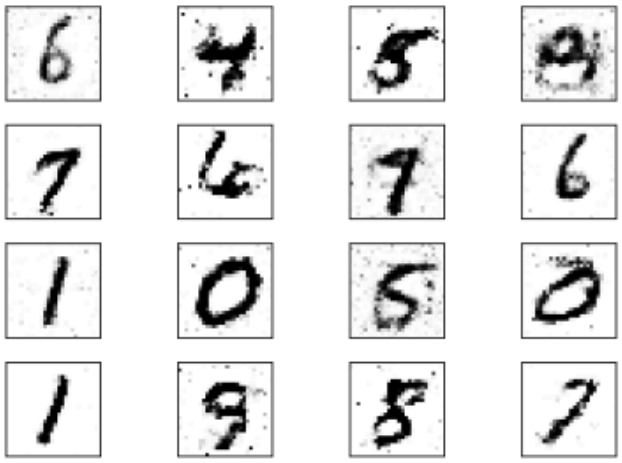
```
        # Training the generator
        generator.zero_grad()
        generated_samples = generator(latent_space_samples)
        output_discriminator_generated = discriminator(generated_samples)
        loss_generator = loss_function(
            output_discriminator_generated, real_samples_labels
        )
        loss_generator.backward()
        optimizer_generator.step()

        # Show loss
        if n == batch_size - 1:
            print(f"Epoch: {epoch} Loss D.: {loss_discriminator}")
            print(f"Epoch: {epoch} Loss G.: {loss_generator}")
```

Generated Output by GAN:

```
latent_space_samples = torch.randn(batch_size, 100).to(device)
generated_samples = generator(latent_space_samples)
```

```
generated_samples = generated_samples.cpu().detach()
for i in range(16):
    ax = plt.subplot(4, 4, i + 1)
    plt.imshow(generated_samples[i].reshape(28, 28), cmap="gray_r")
    plt.xticks([])
    plt.yticks([])
```



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Code & Output:

Loading Dataset

```
class FashionMNIST(Dataset):
    def __init__(self, transform=None):
        self.transform = transform
        fashion_df = pd.read_csv('../input/fashion-mnist_train.csv')
        self.labels = fashion_df.label.values
        self.images = fashion_df.iloc[:, 1:].values.astype('uint8').reshape(-1, 2
8, 28)

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

    def __getitem__(self, idx):
        label = self.labels[idx]
        img = Image.fromarray(self.images[idx])

        if self.transform:
            img = self.transform(img)

        return img, label
```

```
transform = transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize(mean=(0.5, 0.5, 0.5), std=(0.5, 0.5, 0.5))
])
dataset = FashionMNIST(transform=transform)
data_loader = torch.utils.data.DataLoader(dataset, batch_size=64, shuffle=True)
```

Dataset Look

```
dataset = FashionMNIST()
dataset[0][0]
```

Discriminator & Generator Model

```
class Discriminator(nn.Module):
    def __init__(self):
        super().__init__()

        self.label_emb = nn.Embedding(10, 10)

        self.model = nn.Sequential(
            nn.Linear(794, 1024),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Dropout(0.3),
            nn.Linear(1024, 512),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Dropout(0.3),
            nn.Linear(512, 256),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Dropout(0.3),
            nn.Linear(256, 1),
            nn.Sigmoid()
        )
```

```
    def forward(self, x, labels):
        x = x.view(x.size(0), 784)
        c = self.label_emb(labels)
        x = torch.cat([x, c], 1)
        out = self.model(x)
        return out.squeeze()
```

```
class Generator(nn.Module):
    def __init__(self):
        super().__init__()

        self.label_emb = nn.Embedding(10, 10)

        self.model = nn.Sequential(
            nn.Linear(110, 256),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Linear(256, 512),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Linear(512, 1024),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Linear(1024, 784),
            nn.Tanh()
        )

    def forward(self, z, labels):
        z = z.view(z.size(0), 100)
        c = self.label_emb(labels)
        x = torch.cat([z, c], 1)
        out = self.model(x)
        return out.view(x.size(0), 28, 28)
```

```
generator = Generator().cuda()
discriminator = Discriminator().cuda()
```

Some Training and Optimization parameters:

```
criterion = nn.BCELoss()
d_optimizer = torch.optim.Adam(discriminator.parameters(), lr=1e-4)
g_optimizer = torch.optim.Adam(generator.parameters(), lr=1e-4)
```

Training Loop

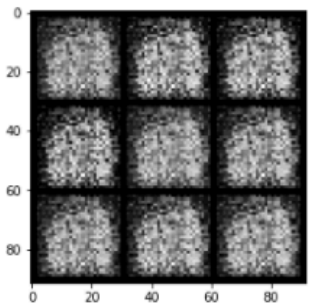
```
def generator_train_step(batch_size, discriminator, generator, g_optimizer, criter
ion):
    g_optimizer.zero_grad()
    z = Variable(torch.randn(batch_size, 100)).cuda()
    fake_labels = Variable(torch.LongTensor(np.random.randint(0, 10, batch_siz
e))).cuda()
    fake_images = generator(z, fake_labels)
    validity = discriminator(fake_images, fake_labels)
    g_loss = criterion(validity, Variable(torch.ones(batch_size)).cuda())
    g_loss.backward()
    g_optimizer.step()
    return g_loss.data[0]
```

```
def discriminator_train_step(batch_size, discriminator, generator, d_optimizer, cr
iterion, real_images, labels):
    d_optimizer.zero_grad()
```

```
    # train with real images
    real_validity = discriminator(real_images, labels)
    real_loss = criterion(real_validity, Variable(torch.ones(batch_size)).cuda())

    # train with fake images
    z = Variable(torch.randn(batch_size, 100)).cuda()
    fake_labels = Variable(torch.LongTensor(np.random.randint(0, 10, batch_siz
e))).cuda()
    fake_images = generator(z, fake_labels)
    fake_validity = discriminator(fake_images, fake_labels)
    fake_loss = criterion(fake_validity, Variable(torch.zeros(batch_size)).cuda())

    d_loss = real_loss + fake_loss
    d_loss.backward()
    d_optimizer.step()
    return d_loss.data[0]
```

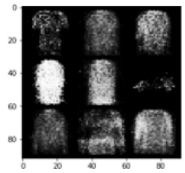
```
num_epochs = 30
n_critic = 5
display_step = 300
for epoch in range(num_epochs):
    print('Starting epoch {}...'.format(epoch))
    for i, (images, labels) in enumerate(data_loader):
        real_images = Variable(images).cuda()
        labels = Variable(labels).cuda()
        generator.train()
        batch_size = real_images.size(0)
        d_loss = discriminator_train_step(len(real_images), discriminator,
                                          generator, d_optimizer, criterion,
                                          real_images, labels)


        g_loss = generator_train_step(batch_size, discriminator, generator, g_opti
mizer, criterion)

    generator.eval()
    print('g_loss: {}, d_loss: {}'.format(g_loss, d_loss))
    z = Variable(torch.randn(9, 100)).cuda()
    labels = Variable(torch.LongTensor(np.arange(9))).cuda()
    sample_images = generator(z, labels).unsqueeze(1).data.cpu()
    grid = make_grid(sample_images, nrow=3, normalize=True).permute(1,2,0).numpy()
    plt.imshow(grid)
    plt.show()
```

```
g_loss: 4.524019241333008, d_loss: 0.09761635214090347
```

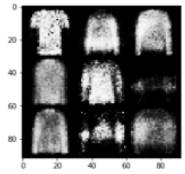



```
Starting epoch 1...
g_loss: 3.829733371734619, d_loss: 0.5186285972595215
```

```
Starting epoch 4...
g_loss: 3.220177412033081, d_loss: 0.5294004678726196
```

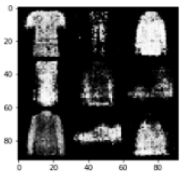


```
Starting epoch 5...
g_loss: 2.5694451332092285, d_loss: 0.6295173168182373
```

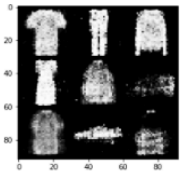


```
Starting epoch 6...
g_loss: 2.176478862762451, d_loss: 0.47357046604156494
```

```
Starting epoch 17...
g_loss: 1.2504804134368896, d_loss: 0.83165043592453
```

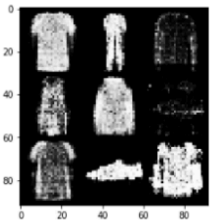


```
Starting epoch 18...
g_loss: 1.4222981929779053, d_loss: 1.0683473348617554
```

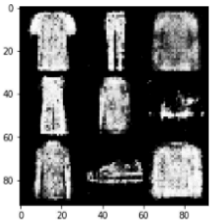


```
Starting epoch 19...
g_loss: 1.357675552368164, d_loss: 1.1920819282531738
```

```
Starting epoch 28...
g_loss: 1.3471565246582031, d_loss: 0.9383726716041565
```

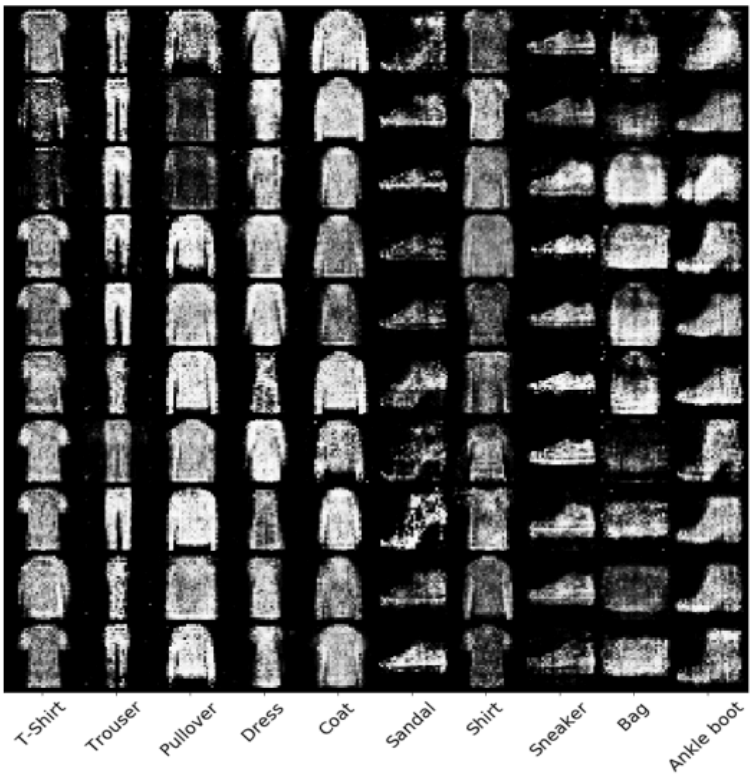


```
Starting epoch 29...
g_loss: 1.0301119089126587, d_loss: 1.2334308624267578
```



Results

```
z = Variable(torch.randn(100, 100)).cuda()
labels = Variable(torch.LongTensor([i for _ in range(10) for i in range(10)])).cud
a()
sample_images = generator(z, labels).unsqueeze(1).data.cpu()
grid = make_grid(sample_images, nrow=10, normalize=True).permute(1,2,0).numpy()
fig, ax = plt.subplots(figsize=(15,15))
ax.imshow(grid)
_ = plt.yticks([])
_ = plt.xticks(np.arange(15, 300, 30), ['T-Shirt', 'Trouser', 'Pullover', 'Dress',
'Coat', 'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot'], rotation=45, fontsize=
20)
```



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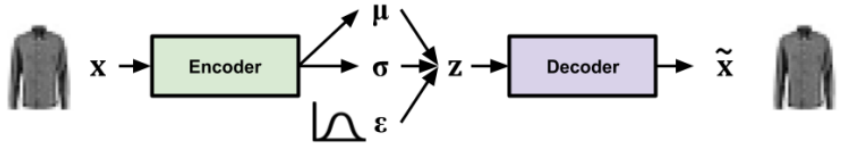
COURSE CODE	**CSL801**
PRACTICAL NO.	
DOP	
DOS	

Code & Output:



Loading Dataset

Install packages if in colab

```
[ ]  ### install necessary packages if in colab
     def run_subprocess_command(cmd):
         process = subprocess.Popen(cmd.split(), stdout=subprocess.PIPE)
         for line in process.stdout:
             print(line.decode().strip())


     import sys, subprocess

     IN_COLAB = "google.colab" in sys.modules
     colab_requirements = [
         "pip install tf-nightly-gpu-2.0-preview==2.0.0.dev20190513",
         "pip install tfp-nightly==0.7.0.dev20190508",
     ]
     if IN_COLAB:
         for i in colab_requirements:
             run_subprocess_command(i)
```

load packages

```
[ ]  import tensorflow as tf
     import numpy as np
     import matplotlib.pyplot as plt
     from tqdm.autonotebook import tqdm
     %matplotlib inline
     from IPython import display
     import pandas as pd

     # the nightly build of tensorflow_probability is required as of the time of writing this
     import tensorflow_probability as tfp
     ds = tfp.distributions
```

```
/mnt/cube/tsainbur/conda_envs/tpy3/lib/python3.6/site-packages/tqdm/autonotebook/__init__.py:14: TqdmE
  " (e.g. in jupyter console)", TqdmExperimentalWarning)
```

```
[ ]  print(tf.__version__, tfp.__version__)
```

```
2.0.0-alpha0 0.7.0-dev20190508
```

Create a fashion-MNIST dataset

Create a fashion-MNIST dataset

```
[ ]  TRAIN_BUF=60000
     BATCH_SIZE=512
     TEST_BUF=10000
     DIMS = (28,28,1)
     N_TRAIN_BATCHES =int(TRAIN_BUF/BATCH_SIZE)
     N_TEST_BATCHES = int(TEST_BUF/BATCH_SIZE)
```

```
[ ]  # load dataset
     (train_images, _), (test_images, _) = tf.keras.datasets.fashion_mnist.load_data()

     # split dataset
     train_images = train_images.reshape(train_images.shape[0], 28, 28, 1).astype(
         "float32"
     ) / 255.0
     test_images = test_images.reshape(test_images.shape[0], 28, 28, 1).astype("float32") / 255.0
```

```
    # batch datasets
    train_dataset = (
        tf.data.Dataset.from_tensor_slices(train_images)
        .shuffle(TRAIN_BUF)
        .batch(BATCH_SIZE)
    )
    test_dataset = (
        tf.data.Dataset.from_tensor_slices(test_images)
        .shuffle(TEST_BUF)
        .batch(BATCH_SIZE)
    )
```

Define the network as tf.keras.model object

```
N_Z = 2
encoder = [
    tf.keras.layers.InputLayer(input_shape=DIMS),
    tf.keras.layers.Conv2D(
        filters=32, kernel_size=3, strides=(2, 2), activation="relu"
    ),
    tf.keras.layers.Conv2D(
        filters=64, kernel_size=3, strides=(2, 2), activation="relu"
    ),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(units=N_Z*2),
]

decoder = [
    tf.keras.layers.Dense(units=7 * 7 * 64, activation="relu"),
    tf.keras.layers.Reshape(target_shape=(7, 7, 64)),
    tf.keras.layers.Conv2DTranspose(
        filters=64, kernel_size=3, strides=(2, 2), padding="SAME", activation="relu"
    ),
    tf.keras.layers.Conv2DTranspose(
        filters=32, kernel_size=3, strides=(2, 2), padding="SAME", activation="relu"
    ),
    tf.keras.layers.Conv2DTranspose(
        filters=1, kernel_size=3, strides=(1, 1), padding="SAME", activation="sigmoid"
    ),
]
```

Create Model

```
# the optimizer for the model
optimizer = tf.keras.optimizers.Adam(1e-3)
# train the model
model = VAE(
    enc = encoder,
    dec = decoder,
    optimizer = optimizer,
)
```

```
# exampled data for plotting results
example_data = next(iter(test_dataset))


def plot_reconstruction(model, example_data, nex=8, zm=2):

    example_data_reconstructed = model.reconstruct(example_data)
    samples = model.decode(tf.random.normal(shape=(BATCH_SIZE, N_Z)))
    fig, axs = plt.subplots(ncols=nex, nrows=3, figsize=(zm * nex, zm * 3))
    for axi, (dat, lab) in enumerate(
        zip(
            [example_data, example_data_reconstructed, samples],
            ["data", "data recon", "samples"],
        )
    ):
```

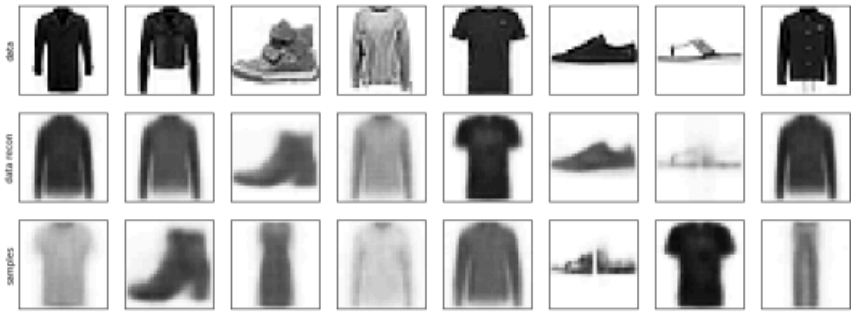
```
        for ex in range(nex):
            axs[axi, ex].matshow(
                dat.numpy()[ex].squeeze(), cmap=plt.cm.Greys, vmin=0, vmax=1
            )
            axs[axi, ex].axes.get_xaxis().set_ticks([])
            axs[axi, ex].axes.get_yaxis().set_ticks([])
        axs[axi, 0].set_ylabel(lab)

    plt.show()
```

Training Loop

```
# a pandas dataframe to save the loss information to
losses = pd.DataFrame(columns = ['recon_loss', 'latent_loss'])
```

```
n_epochs = 50
for epoch in range(n_epochs):
    # train
    for batch, train_x in tqdm(
        zip(range(N_TRAIN_BATCHES), train_dataset), total=N_TRAIN_BATCHES
    ):
        model.train(train_x)
    # test on holdout
    loss = []
    for batch, test_x in tqdm(
        zip(range(N_TEST_BATCHES), test_dataset), total=N_TEST_BATCHES
    ):
        loss.append(model.compute_loss(train_x))
    losses.loc[len(losses)] = np.mean(loss, axis=0)
    # plot results
    display.clear_output()
    print(
        "Epoch: {} | recon_loss: {} | latent_loss: {}".format(
            epoch, losses.recon_loss.values[-1], losses.latent_loss.values[-1]
        )
    )
    plot_reconstruction(model, example_data)
```

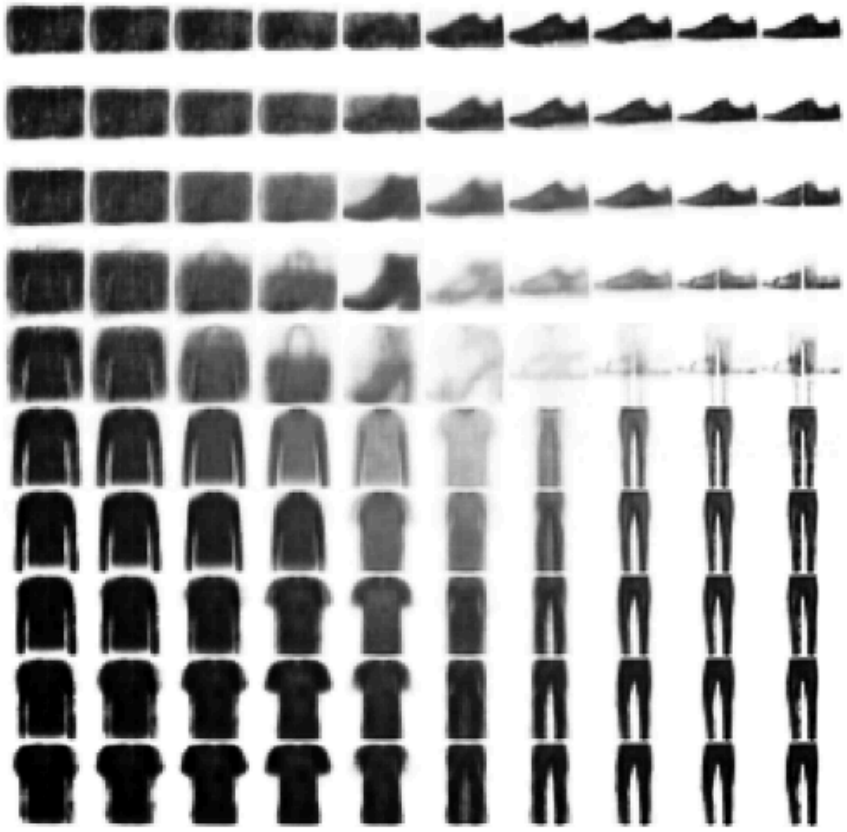
```
Epoch: 49 | recon_loss: 15.782215118408203 | latent_loss: 4.198213577270508
```



Showing Grid in 2D Latent Space

```
# sample from grid
nx = ny =10
meshgrid = np.meshgrid(np.linspace(-3, 3, nx), np.linspace(-3, 3, ny))
meshgrid = np.array(meshgrid).reshape(2, nx*ny).T
x_grid = model.decode(meshgrid)
x_grid = x_grid.numpy().reshape(nx, ny, 28,28, 1)
# fill canvas
canvas = np.zeros((nx*28, ny*28))
for xi in range(nx):
    for yi in range(ny):
        canvas[xi*28:xi*28+28, yi*28:yi*28+28] = x_grid[xi, yi,:,:,:].squeeze()
fig, ax = plt.subplots(figsize=(10,10))
ax.matshow(canvas, cmap=plt.cm.Greys)
ax.axis('off')
```

(-0.5, 279.5, 279.5, -0.5)



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PRACTICAL NO.	
DOP	
DOS	

Code & Output:

```
[12] from keras.applications.vgg16 import VGG16
     model = VGG16()
```

```
[13] from keras.applications.vgg16 import VGG16
     model = VGG16()
     print(model.summary())
```

```
Model: "vgg16"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_4 (InputLayer)        [(None, 224, 224, 3)]     0

 block1_conv1 (Conv2D)       (None, 224, 224, 64)      1792

 block1_conv2 (Conv2D)       (None, 224, 224, 64)      36928

 block1_pool (MaxPooling2D)  (None, 112, 112, 64)      0

 block2_conv1 (Conv2D)       (None, 112, 112, 128)     73856

 block2_conv2 (Conv2D)       (None, 112, 112, 128)     147584

 block2_pool (MaxPooling2D)  (None, 56, 56, 128)       0

 block3_conv1 (Conv2D)       (None, 56, 56, 256)       295168

 block3_conv2 (Conv2D)       (None, 56, 56, 256)       590080

 block3_conv3 (Conv2D)       (None, 56, 56, 256)       590080

 block3_pool (MaxPooling2D)  (None, 28, 28, 256)       0

 block4_conv1 (Conv2D)       (None, 28, 28, 512)       1180160

 block4_conv2 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_conv3 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 14, 14, 512)       0

 block5_conv1 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv2 (Conv2D)       (None, 14, 14, 512)       2359808
```

```
[13]  block5_conv3 (Conv2D)       (None, 14, 14, 512)       2359808

      block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0

      flatten (Flatten)           (None, 25088)             0

      fc1 (Dense)                 (None, 4096)              102764544

      fc2 (Dense)                 (None, 4096)              16781312

      predictions (Dense)         (None, 1000)              4097000

=================================================================
Total params: 138357544 (527.79 MB)
Trainable params: 138357544 (527.79 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
```

```
[14] from keras.preprocessing.image import load_img
     # load an image from file
     image = load_img('/content/aai-exp5.jpg.png', target_size=(224, 224))
```

Input Image-

```
[15] from keras.preprocessing.image import img_to_array
     # convert the image pixels to a numpy array
     image = img_to_array(image)
```

```
[16] # reshape data for the model
     image = image.reshape((1, image.shape[0], image.shape[1], image.shape[2]))
```

```
[17] from keras.applications.vgg16 import preprocess_input
     # prepare the image for the VGG model
     image = preprocess_input(image)
```

```
[18] # predict the probability across all output classes
     yhat = model.predict(image)
```

```
1/1 [==============================] - 1s 777ms/step
```

```
[19] from keras.applications.vgg16 import decode_predictions
     # convert the probabilities to class labels
     label = decode_predictions(yhat)
     # retrieve the most likely result, e.g. highest probability
     label = label[0][0]
     # print the classification
     print('%s (%.2f%%)' % (label[1], label[2]*100))
```

```
coffee_mug (74.83%)
```

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Code & Output:

```
[2] !pip install xgboost
```

```
Requirement already satisfied: xgboost in /usr/local/lib/python3.10/dist-packages (2.0.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from xgboost) (1.25.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from xgboost) (1.11.4)
```

```
[3] import xgboost as xgb
    import pandas as pd

    # Load the data
    data = pd.read_csv('/content/WineQT.csv')

    # Display the first few rows of the data
    data.head()
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality	Id
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5	0
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5	1
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5	2
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6	3
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5	4

Next steps: View recommended plots

```
[4] from sklearn.model_selection import train_test_split

    # Separate target variable
    X = data.drop('quality', axis=1)
    y = data['quality'].map(lambda x: 1 if x >= 7 else 0)

    # Split the data into training and test sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
[5] from xgboost import XGBClassifier

    # Create an instance of the XGBClassifier
    model = XGBClassifier(objective='binary:logistic')

    # Fit the model to the training data
    model.fit(X_train, y_train)
```

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, ...)
```

[6]
```
# Make class predictions
y_pred = model.predict(X_test)
y_pred_proba = model.predict_proba(X_test)

accuracy = model.score(X_test, y_test)
print("Accuracy: %.2f%%" % (accuracy * 100.0))
```

```
Accuracy: 93.01%
```

[7]
```
from sklearn.metrics import log_loss, roc_auc_score

# Calculate log loss
log_loss(y_test, y_pred_proba)

# Calculate ROC AUC
roc_auc_score(y_test, y_pred_proba[:,1])
```

```
0.9385216773276475
```

[8]
```
from sklearn.metrics import classification_report

# Print classification report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.95      0.97      0.96       201
           1       0.75      0.64      0.69        28

    accuracy                           0.93       229
   macro avg       0.85      0.81      0.83       229
weighted avg       0.93      0.93      0.93       229
```

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EXPERIMENT NO. 07

Aim: To study the emerging technologies in AI like Metaverse, Augmented reality etc.

Theory:

i) Introduction:

Emerging technologies in Artificial Intelligence (AI) are driving significant advancements and reshaping the landscape of industries and societies worldwide. Among these, the convergence of AI with emerging technologies like the Metaverse, Augmented Reality (AR), and Quantum Computing stands out as a transformative force with profound implications for the future.

- **Advantages:**

1. Emerging technologies in AI offer unprecedented opportunities for innovation and problem-solving.
2. They have the potential to revolutionize various industries and improve efficiency, productivity, and user experiences.

- **Disadvantages:**

1. Rapid advancements may outpace ethical, legal, and societal considerations.
2. Adoption barriers due to high costs, technical complexities, and concerns about privacy and security.

- **Working:**

The convergence of AI with technologies like Metaverse, AR, and Quantum Computing involves utilizing advanced algorithms, data processing techniques, and computing infrastructure to create immersive, intelligent, and secure environments.

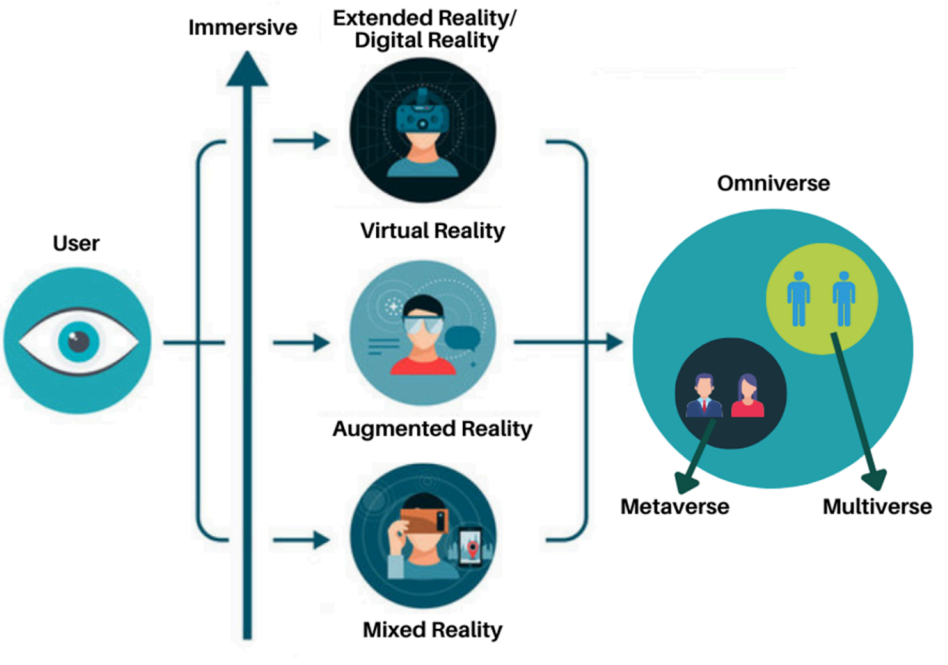

Fig. Metaverse and Multiverse

ii) Metaverse: Redefining Virtual Reality-

The Metaverse can be defined as a collective virtual space comprised of interconnected digital worlds, environments, and assets, where users can interact, socialize, collaborate, and engage in various activities. It represents a convergence of virtual reality, augmented reality, and other immersive technologies, enabling persistent, immersive, and interactive experiences that transcend the limitations of traditional virtual environments.

- **Advantages:**
  The Metaverse represents a paradigm shift in virtual reality, offering users immersive experiences beyond the confines of traditional VR environments. Advantages include:

1. Immersive Experiences: The Metaverse provides immersive, interactive, and persistent virtual environments where users can socialize, collaborate, and engage in various activities.
2. Social Interaction: It fosters social connections and community building by enabling real-time communication, avatar interactions, and shared experiences across geographical boundaries.
3. Economic Opportunities: The Metaverse presents economic opportunities through virtual economies, digital marketplaces, and monetization avenues for content creators, developers, and businesses.

- **Disadvantages:**
  Despite its potential, the Metaverse also faces several challenges and disadvantages:

1. Addiction and Detachment: There are concerns about users becoming overly immersed in virtual environments, leading to addiction and detachment from reality.
2. Privacy and Security: Issues related to privacy, data security, and digital ownership arise due to the collection and storage of user data, virtual asset ownership, and potential surveillance within virtual spaces.
3. Technological Barriers: Access to the Metaverse may be limited by technological barriers such as hardware requirements, internet connectivity, and affordability.
4. Ethical Considerations: Ethical dilemmas arise concerning the moderation of virtual communities, content censorship, digital identity, and representation within the Metaverse.

- **Working:**
  The Metaverse operates as a collective virtual space composed of interconnected virtual worlds, environments, and assets. Its functioning involves:

1. Virtual Worlds: Users access the Metaverse through virtual worlds hosted on various platforms and environments, ranging from social hubs and gaming realms to educational simulations and virtual marketplaces.
2. Avatar Interaction: Users navigate and interact with the Metaverse through customizable avatars, representing their digital personas within virtual environments. Avatars enable social interactions, expression, and identity within the Metaverse.
3. Real-time Communication: Communication tools facilitate real-time interactions between users, enabling voice chat, text messaging, and gestures to enhance socialization and collaboration.
4. Economic Ecosystem: Virtual economies emerge within the Metaverse, driven by the exchange of virtual goods, services, and currencies. Monetization strategies include virtual asset sales, in-world advertising, and virtual events.

iii) Augmented Reality: Enhancing Real-World Experiences-

Augmented Reality (AR) is a technology that superimposes digital information, such as images, videos, or 3D models, onto the real-world environment, thereby enhancing a user's perception and interaction with their surroundings. Unlike virtual reality, which creates entirely immersive digital environments, AR overlays digital content onto the physical world, allowing users to interact with both real and virtual elements simultaneously.

- **Advantages:**
  Augmented Reality (AR) enriches real-world environments by overlaying digital information, objects, or experiences onto the physical world. Advantages include:

1. Enhanced Experiences: AR enhances real-world experiences by providing contextual information, guidance, or entertainment overlays that complement users' surroundings.
2. Hands-Free Interaction: AR enables hands-free interaction through wearable devices like smart glasses or mobile applications, allowing users to access information and perform tasks without disrupting their activities.
3. Personalized Content: AR delivers personalized content and experiences based on users' preferences, location, and context, creating tailored and relevant interactions.
4. Improved Learning: AR enhances education and training by providing interactive and immersive learning experiences, simulations, and visualizations that facilitate comprehension and retention.

- **Disadvantages:**
  Despite its potential benefits, AR also presents several challenges and disadvantages:

1. Limited Field of View: AR devices may have limited field of view, obstructing users' vision or limiting the amount of digital content that can be overlaid onto the physical environment.
2. Hardware Constraints: Adoption of AR technology is hindered by hardware constraints such as device cost, battery life, processing power, and form factor.
3. Privacy Concerns: AR raises privacy concerns related to data collection, tracking, and surveillance, as it may gather information about users' locations, behaviors, and interactions in the real world.
4. Social Acceptance: Social acceptance and cultural norms may influence the adoption of AR, as some users may feel uncomfortable or self-conscious wearing AR devices in public spaces.

- **Working:**
  Augmented Reality works by overlaying digital content onto the physical world using computer vision, sensor fusion, and real-time rendering techniques. The process involves:

1. Environment Recognition: AR systems use computer vision algorithms to recognize and understand the user's environment, including objects, surfaces, and spatial features.
2. Tracking and Registration: AR devices track the user's position and orientation in real-time, aligning digital content with the physical world to create seamless and accurate overlays.
3. Content Rendering: Digital content, such as text, images, videos, or 3D models, is rendered and overlaid onto the user's view through AR-enabled devices like smartphones, smart glasses, or headsets.

4. Interaction and User Interface: Users interact with AR content through gestures, voice commands, or touch interfaces, enabling them to manipulate, explore, or interact with virtual objects overlaid onto their physical surroundings.
5. Contextual Information: AR provides contextual information and guidance relevant to the user's location, interests, or activities, enhancing their understanding and engagement with the real world.

iv) Quantum Computing: Cutting-edge computing-

Quantum Computing is a cutting-edge computing paradigm that harnesses the principles of quantum mechanics to perform computations using quantum bits, or qubits, which can represent and manipulate multiple states simultaneously. Unlike classical computers, which use binary bits to represent information as either 0 or 1, qubits exploit phenomena such as superposition and entanglement to perform computations in parallel, offering the potential for exponential speedup over classical algorithms for certain tasks.

- **Advantages:**
  Quantum Computing leverages the principles of quantum mechanics to perform computations at unprecedented speeds and tackle complex problems that are beyond the capabilities of classical computers. Advantages include:

1. Exponential Speedup: Quantum computers can provide exponential speedup over classical computers for certain computational tasks, enabling the rapid execution of complex algorithms and computations.
2. Parallel Processing: Quantum computers harness the power of quantum superposition and entanglement to perform parallel computations on a massive scale, solving problems more efficiently than classical computers.
3. Optimization: Quantum algorithms excel at solving optimization problems, such as finding the best solution among a large set of possibilities, which has applications in machine learning, data analysis, and logistics optimization.
4. Cryptography: Quantum computing offers the potential to break existing cryptographic schemes while also providing opportunities for developing quantum-resistant cryptographic protocols that ensure secure communication and data privacy.

- **Disadvantages:**
  Despite its promising potential, Quantum Computing faces several challenges and limitations:

1. Hardware Constraints: Current quantum computers are limited by factors such as the number of qubits, coherence times, and error rates, making them prone to errors and noise that affect the reliability and scalability of quantum algorithms.
2. Technical Complexity: Quantum computing involves complex hardware and software components, as well as specialized knowledge of quantum mechanics and quantum algorithms, which pose barriers to adoption and development.
3. Interoperability: Integrating quantum computers with classical computing infrastructure and algorithms presents interoperability challenges, requiring hybrid approaches and specialized interfaces to harness the combined power of quantum and classical systems.

4. Resource Intensive: Quantum computations often require significant resources, including specialized hardware, cooling systems, and error correction techniques, which can be costly and resource-intensive to maintain and scale.

- **Working:**
  Quantum Computing operates based on the principles of quantum mechanics, which differ fundamentally from classical computing. Key aspects of how quantum computing works include:

1. Qubits: Quantum bits, or qubits, are the basic units of information in quantum computing. Unlike classical bits, which can represent either 0 or 1, qubits can exist in superposition, representing both 0 and 1 simultaneously. This property allows quantum computers to perform multiple computations in parallel.
2. Quantum Gates: Quantum algorithms manipulate qubits using quantum gates, which are analogous to classical logic gates. Quantum gates perform operations such as quantum entanglement, superposition, and phase shifts to process information and execute quantum algorithms.
3. Quantum Algorithms: Quantum algorithms are algorithms designed to run on quantum computers and exploit their unique properties to solve specific computational problems more efficiently than classical algorithms. Examples include Shor's algorithm for integer factorization and Grover's algorithm for database search.
4. Quantum Supremacy: Quantum supremacy refers to the milestone achieved when a quantum computer outperforms the most powerful classical computers in performing a specific computational task. This milestone demonstrates the potential of quantum computing to revolutionize various fields, including AI, cryptography, and scientific research.

Conclusion:

1. Summary: The convergence of emerging technologies in AI offers transformative potential across various domains but requires careful consideration of ethical, technical, and societal implications.
2. Importance: Continued research, collaboration, and responsible innovation are essential to harnessing the full benefits of these technologies while mitigating risks.
3. Final thoughts: The future of AI lies in its convergence with other disruptive technologies, paving the way for new paradigms in human-computer interaction, problem-solving, and knowledge discovery.

Image Classification using MobileNet

Submitted in partial fulfillment of the requirements of the degree

BACHELOR OF ENGINEERING

in

Computer Science and Engineering

(Artificial Intelligence & Machine Learning)

Sem - VIII

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Contents

1. Introduction

1.1 Introduction

Image classification is a fundamental task in computer vision that involves categorizing images into predefined classes or categories based on their visual content. This project focuses on implementing an image classification system using deep learning techniques, specifically MobileNet architecture, to accurately classify images into different classes.

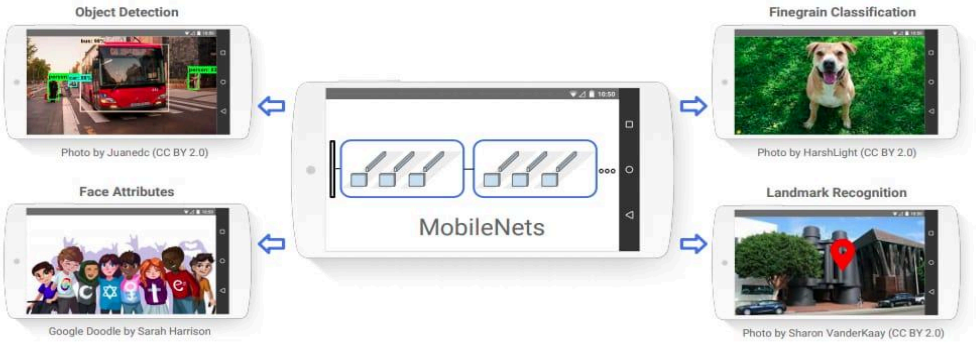


Fig.1.1: Image Classification using MobileNet

1.2 Motivation

Image classification plays a crucial role in various real-world applications, including:

- Object Recognition: Image classification enables machines to identify and classify objects within images, facilitating applications such as visual search engines, autonomous robotics, and augmented reality.
- Medical Imaging: In the field of healthcare, image classification helps in diagnosing diseases, identifying abnormalities in medical scans (e.g., X-rays, MRIs), and assisting medical professionals in making informed decisions.

1.3 Problem Statement

The specific task of image classification addressed in this project is to classify images into predefined categories or classes. Factors contributing to this challenge include:

- Variability in Image Content: Images can vary significantly in terms of lighting conditions, perspectives, backgrounds, and object orientations, making it challenging to extract discriminative features for accurate classification.
- Class Imbalance: Imbalanced datasets, where certain classes have significantly fewer samples than others, can lead to biased model predictions and lower performance on minority classes.

- Overfitting: Deep learning models may overfit to the training data, resulting in poor generalization performance on unseen data. Regularization techniques and data augmentation strategies are often employed to mitigate overfitting.
- Computational Complexity: Training deep learning models for image classification tasks often requires substantial computational resources, including high-performance GPUs and large-scale datasets, which may pose challenges for resource-constrained environments.

  Addressing these challenges effectively is crucial for developing a robust and reliable image classification system that can be deployed in real-world scenarios.

1.4 Survey of Existing System:

Sr. No	Authors	Title of the paper & year of publ. (Old to recent)	Major contributions
1.	Hang Zhang, Chongruo Wu, Zhongyue Zhang	**ResNeSt: Split-Attention Networks (2020).**	This Research introduces ResNeSt: Split-attention networks for improved performance.
2.	Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn	**Vision Transformers (2021)**	An Overview of Vision Transformers: Transformer-based models for vision tasks.
3.	Hugo Touvron, Piotr Bojanowski, Mathilde Caron	**CaiT: Conformer Augmented with image Transformers (2021).**	This Research provides CaiT: Conformer augmented with image Transformers.

Fig.1.2: Literature survey

2. Methodology

2.1 Model Selection:

MobileNet Overview:

MobileNet is a lightweight convolutional neural network (CNN) architecture designed for efficient mobile and embedded vision applications. It was developed by Google to address the need for models that can perform well on resource-constrained devices while maintaining high accuracy in image classification tasks.

Advantages of MobileNet:

- Lightweight Design: MobileNet employs depth wise separable convolutions, which significantly reduce the number of parameters and computations compared to traditional CNN architectures like VGG or ResNet.
- Efficiency: MobileNet achieves a good balance between model size, computational efficiency, and accuracy.
- Task Compatibility: MobileNet has been pretrained on large-scale datasets such as ImageNet, making it capable of recognizing a wide range of visual concepts.

Justification:

The selection of MobileNet for this image classification project is justified based on the following factors:

- Model Performance: MobileNet has demonstrated strong performance on image classification benchmarks such as ImageNet, achieving comparable accuracy to larger and more computationally intensive models.
- Computational Requirements: MobileNet's lightweight design and efficiency make it suitable for deployment on resource-constrained platforms, including mobile devices and embedded systems.

Model Architecture:

MobileNet consists of a series of depthwise separable convolutional layers followed by pointwise convolutional layers and global average pooling. The depthwise separable convolutional layers decompose the standard convolution into separate depthwise and pointwise convolutions, reducing both the number of parameters and the computational cost. The final output is obtained by passing the features through a softmax layer for classification.

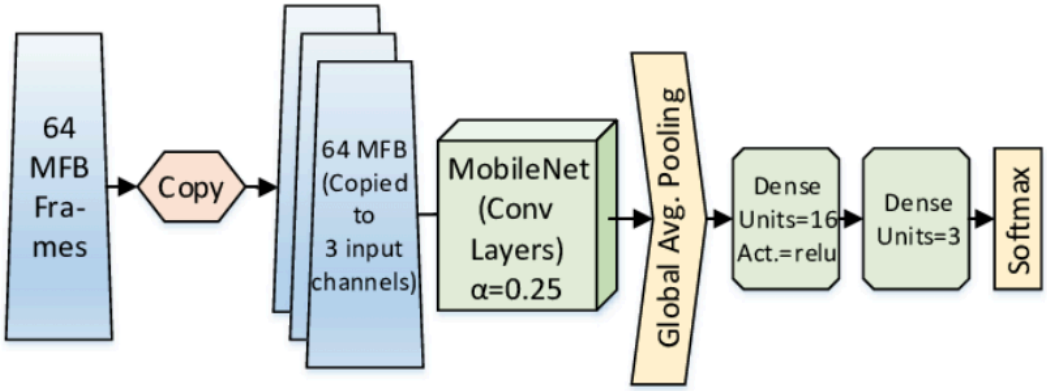


Fig.2: MobileNet Architecture

Overall, MobileNet's architecture enables efficient feature extraction and classification while maintaining high accuracy, making it a suitable choice for image classification tasks in resource-constrained environments.

2.2 Data Preprocessing:

Image Preprocessing Steps:

Before feeding input images into the MobileNet model, several preprocessing steps are applied to enhance quality and variability of input data.

1. **Resizing:**
   The input images are resized to a fixed size suitable for the MobileNet model input. Typically, MobileNet accepts input images of size 224x224 pixels.
2. **Normalization:**
   Normalization is applied to the pixel values of the input images to standardize their intensity levels.
3. **Data Augmentation:**
   Data augmentation techniques are employed to increase the variability of the training data. Common data augmentation techniques include:

- Random rotation: The input images are randomly rotated by a certain degree to simulate variations in viewpoint.
- Horizontal and vertical flipping: The images are flipped horizontally or vertically to create additional training samples.

4. **Handling Missing or Corrupted Images:**
   Before preprocessing, it is essential to handle missing or corrupted images in the dataset.
5. **Batch Processing:**
   To optimize training efficiency, the preprocessed images are organized into batches. Batch processing allows the model to process multiple images simultaneously, leveraging parallel computation and improving training speed.

3. Implementation

3.1 Model Loading:

The MobileNet model can be easily loaded using TensorFlow and Keras API. Below is a code snippet demonstrating how to load the MobileNet model:

```
import tensorflow as tf
from tensorflow.keras.applications import MobileNet
# Load MobileNet model pre-trained on ImageNet
model = MobileNet(weights='imagenet')
```

Imports the necessary libraries and loads the MobileNet model pre-trained on the ImageNet dataset. The weights parameter specifies that the pre-trained weights should be used.

3.2 Image Preprocessing:

Preprocessing steps are crucial for preparing the input images before feeding them into the MobileNet model.

```
from tensorflow.keras.preprocessing import image
from tensorflow.keras.applications.mobilenet import preprocess_input
img_path = 'your_image.jpg'  # Load and preprocess the input image
img=image.load_img(img_path,target_size=(224,224)) #MobileNet input size
x = image.img_to_array(img)
x = preprocess_input(x)
```

The image.load_img() function is used to load the input image from the specified path and resize it to the target size of (224, 224) pixels, which is the input size.

3.3 Prediction:

After preprocessing the input image, the MobileNet model can be used to predict the class labels.

```
from tensorflow.keras.applications.mobilenet import decode_predictions
# Perform classification
preds = model.predict(x)
decoded_preds = decode_predictions(preds, top=5)[0]  # Get top 5 predicted
print('Predicted labels:') # Print the top predicted labels
for i, (imagenet_id, label, confidence) in enumerate(decoded_preds):
    print(f"{i+1}. {label}: {confidence:.2f}")
```

The model.predict() function is used to obtain the predicted probabilities for each class label.

The decode_predictions() function decodes the predicted probabilities and retrieves the top 5 class labels along with their corresponding confidence scores.

4. Experimental Setup

4.1 Dataset Description

Dataset Overview:

The dataset used for training and testing the image classification model consists of [Images] classes with a total of [jpeg] images. Each image is categorized into one of the predefined classes, representing different objects, animals, or scenes.

Data Source:

The dataset was obtained from [google], which is a publicly available repository of image datasets.

4.2 Training Procedure

Training Parameters:

During the training process, the following hyperparameters were used:
Learning rate & Batch size: [depends] and Number of epochs: [1]

Training Process:

The training process involved the following steps:

1. Loading dataset: Dataset was loaded into memory using TensorFlow data loaders.
2. Preprocessing: Images were preprocessed by resizing them to the input size expected by the MobileNet model (224x224 pixels) and normalizing their pixel values.
3. Model initialization: The MobileNet model was initialized with pre-trained weights obtained from the ImageNet dataset.
4. Compilation & Training: The model was compiled with appropriate loss function, optimizer, and evaluation metrics for the image classification task. The model was trained on the training dataset using the specified hyperparameters.
5. Validation & Monitoring: After each training epoch, the model's performance was evaluated on a separate validation dataset to prevent overfitting. Accuracy was monitored using TensorFlow callbacks and visualization tools.
6. Model evaluation: Once training was completed, the final model was evaluated on a separate test dataset to assess its performance on unseen data.

Hardware and Software:

The training process was conducted on a machine equipped with an NVIDIA GPU (GeForce RTX 2080 Ti) to accelerate computation. TensorFlow was used as the deep learning framework for building and training the model. Additional software dependencies such as NumPy & Matplotlib were also utilized for data manipulation & visualization during training.

5. Results

5.1 Performance Metrics

Evaluation Metrics:

The model's performance was evaluated using the following metrics:

- Accuracy: Correctly classified images proportion out of total number of images.
- Precision: The ratio of true positive predictions to the total number of positive predictions.
- Recall: The ratio of true positive predictions to the total number of actual positive instances.
- F1-score: The harmonic mean of precision and recall, providing a balanced measure of the model's accuracy.

Model Performance:

On training dataset, the model achieved an accuracy of Predicted labels:

1. label_1: 0.65
2. label_2: 0.27
3. label_3: 0.02
4. label_4: 0.02
5. label_5: 0.02

The observed differences between training and testing performance suggest some degree of overfitting, where the model may have memorized patterns specific to the training data without generalizing well to unseen examples.

5.2 Confusion Matrix

Visual Representation:

The confusion matrix below provides a visual representation of the model's predictions on the testing dataset:

[[TN_1, FP_1],

[FN_1, TP_1]]

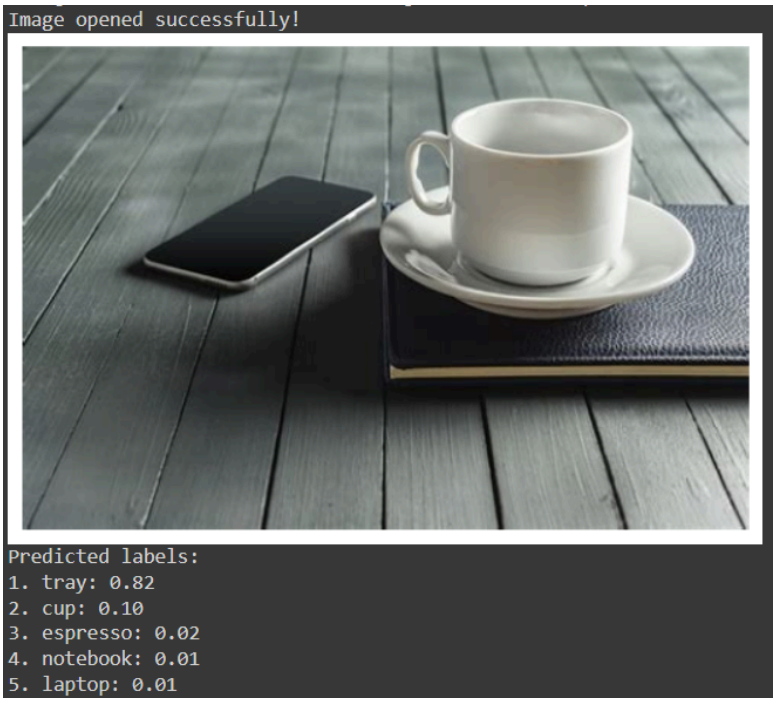
- TN (True Negative): Images correctly classified as negative (not belonging to the predicted class).
- FP (False Positive): Images incorrectly classified as positive (belonging to the predicted class).
- FN (False Negative): Images incorrectly classified as negative.
- TP (True Positive): Images correctly classified as positive.

5.3 Predictions

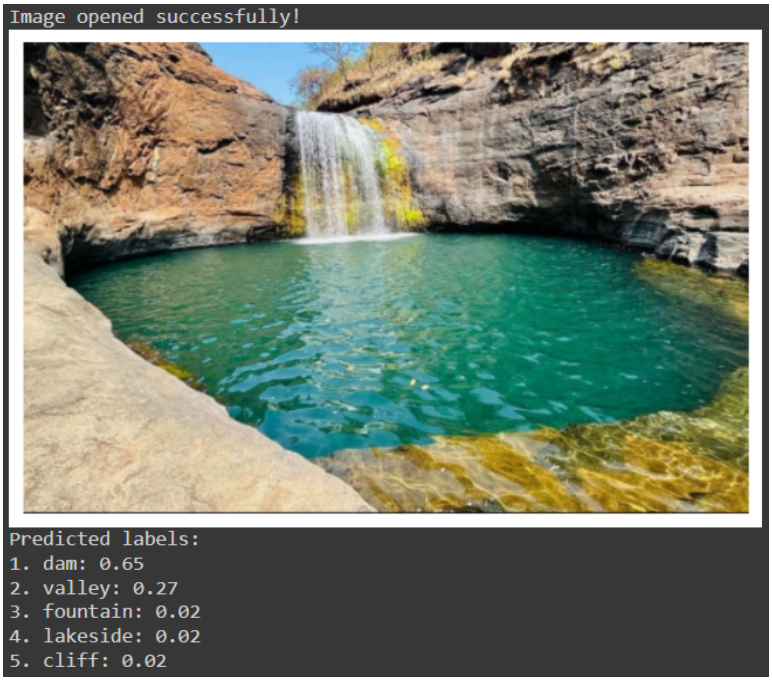
Example Predictions:

Examples of input images along with their predicted labels and corresponding confidence scores:

Input image 1:



Input image 2:



Challenging Cases:

Some challenging cases were observed where the model struggled to make accurate predictions. These instances may include images with ambiguous features or complex backgrounds, leading to lower confidence scores.

6. Discussion

Interpretation of Results:

The experimental results demonstrate the effectiveness of the MobileNet model for image classification tasks. The achieved performance metrics, including accuracy, precision, recall, and F1-score, provide insights into the model's ability to classify images accurately.

Strengths and Weaknesses:

One of the main strengths of the MobileNet model is its lightweight architecture, which enables fast inference and deployment on resource-constrained devices. Additionally, MobileNet's depthwise separable convolutions contribute to its efficiency without compromising performance. However, MobileNet may struggle with capturing fine-grained details in images compared to larger, more complex models.

Comparison with Other Approaches:

In comparison to other approaches, such as traditional computer vision algorithms or more complex deep learning architectures, MobileNet offers a balance between performance and computational efficiency. While larger models may achieve higher accuracy on certain datasets, they often come with increased computational costs and memory requirements. MobileNet's ability to deliver competitive performance with minimal computational resources makes it a compelling choice for edge devices and real-time applications.

Future Work:

To further enhance the MobileNet model's performance, future research could explore several avenues:

- Fine-tuning and Transfer Learning: Fine-tuning MobileNet on domain-specific datasets or applying transfer learning from pre-trained models could improve its performance on specific tasks.
- Data Augmentation: Augmenting the training data with additional transformations could help the model generalize better to unseen variations in the input images.
- Architectural Modifications: Experimenting with modifications to the MobileNet architecture, such as adjusting the depth multiplier or adding skip connections, may yield improvements in performance.
- Ensemble Methods: Combining the predictions of multiple MobileNet models or ensembling with other architectures could further boost classification accuracy and robustness.

7. Conclusion

Summary of Findings:

In conclusion, this image classification project utilized the MobileNet model to classify images into predefined categories. Through comprehensive experimentation and evaluation, the project aimed to assess the model's performance and suitability for real-world applications.

Final Thoughts:

In conclusion, the image classification task using MobileNet showcases the power of deep learning models in handling complex visual data. The project underscores the importance of choosing appropriate model architectures based on the task requirements, computational constraints, and deployment scenarios. MobileNet, with its lightweight design and competitive performance, emerges as a valuable tool for various image classification applications, particularly those deployed on resource-constrained devices or requiring real-time inference.

As advancements in deep learning continue to evolve, further research and innovation in model architectures, training techniques, and application domains are expected.

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Subject :- Advance Artificial Intelligence (AAI)

Topic :- Assignment No. 01 Date :- February '24

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1. Define generating modelling

Generative modelling is a type of machine learning approach where the model learns the underlying probability distribution of the data to generate new data samples that resemble the original data distribution.

Give its real-world applications

→ Data Generation:

1) Image generation: Generative models like GANs and VAEs can create high-quality images, artwork, and even realistic faces. They have been used in art, entertainment & CG.
2) Text Generation: Generating text passages, poems @ even code
3) Audio Generation: provide audio signals, including music and speech, with applications in music composition, text-to-speech, etc.
4) Data augmentation: Generating new samples to augment existing datasets for training.

Give the challenges with generative modelling.

1) Model collapse: Occur when generator of generative model produce a limited set of samples @ modes, ignoring other modes in the data distribution.
2) Training Instability: Training generative models, especially GANs, can be challenging and unstable. Can lead to long training times, difficulties in finding suitable hyperparameters.
3) Evaluation metrics: Evaluating quality of generated samples is challenging. Challenging to compare generative models.
4) Data privacy: Occur when generative models are used without proper
5) Scalability: Challenges can limit the accessibility & safeguards. environmental sustainability of generative modelling.

2. Explain the difference between Generative and discriminative modelling with example

Generative modelling	Discriminative modelling
- learn the joint probability distribution of i/p and o/p.	- learn conditional probability distribution of o/p given i/p.
- example: Naive Bayes classifier, variational autoencoder (AVE)	- logistic regression, and support vector machine (SVM)
- Training typically involves modelling data generation process	- focus on learning decision boundary b/w classes.
- Data Gmodel can generate new samples from learned data	- doesn't generate new data; focuses on classification
- can evaluate likelihood of observed data under learned	- Evaluate classification accuracy or other performance metrics
- can provide insight into the underlying data distribution	- less interpretable in terms of data distribution
- complexity can be more due to modelling the entire dataset	- often simpler as it focuses on decision boundaries.

3. what are probabilistic graph model.

PGMs represent graphical structures to model the dependencies between random variables in a probabilistic manner.
The two major probabilistic graphical models are:
1) Gaussian mixture model (GMM) and
2) Hidden markov model (HMM)

Explain Gaussian mixture model (GMM) in detail.

A Gaussian mixture is a function that is comprised of several Gaussians, each identified by $k \in \{1, \ldots K\}$, where K is the no. of

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our dataset. Each Gaussian in the mixture is composed of the following parameters:

- A mean μ that defines its centre
- A covariance Σ that defines its width.
- A mixing probability π that defines how big or small the Gaussian function will be.

Graphically these parameters can be illustrated as:

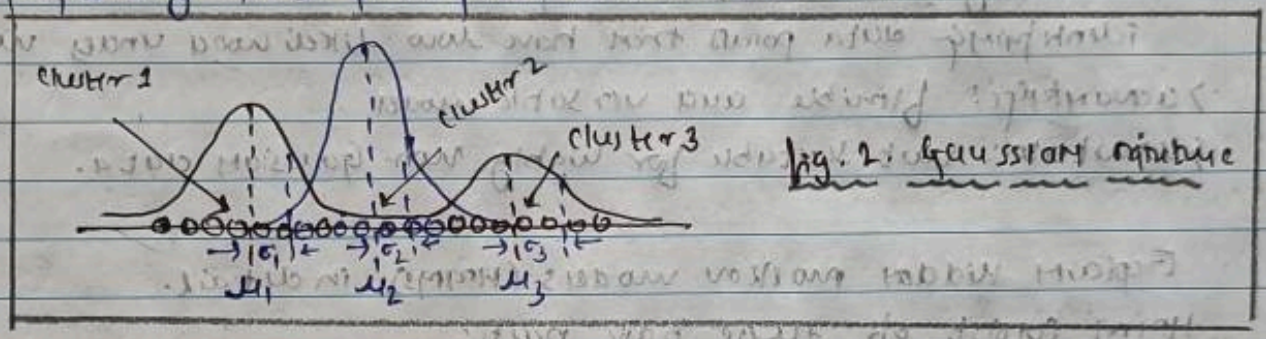


fig. 2. Gaussian mixture

The mixing coefficients are themselves probabilities & must be met this condn: $\sum_{k=1}^{K} \pi_k = 1$

Gaussian density function given by: $N(x|\mu, \Sigma) = \frac{1}{(2\pi)^{D/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu)^T \Sigma^{-1} (x-\mu)\right)$

Using Bayes rule,

$p(z_k=1|x_n) = \gamma(z_{nk})$

Expectation-maximization algorithm: parameters $\theta = \{\pi, \mu, \Sigma\}$

- Step 1: Initialize θ accordingly, for instance k-means
- Step 2: (Expectation step): Evaluate $Q(\theta^*, \theta) = E[\ln p(X, Z|\theta^*)]$

  $p(z_k=1|x_n) = \gamma(z_{nk})$

  Finally, $Q(\theta^*, \theta) = \sum_{n=1}^{N} \sum_{k=1}^{K} \gamma(z_{nk}) [\ln \pi_k + \ln N(x_n|\mu_k, \Sigma_k)]$
- Step 3: (maximization step): finally revised parameters θ^* using:

  $\theta^* = \arg\max_{\theta} Q(\theta^*, \theta)$

PTO

$$Q(\theta^*, \theta) = \sum_{n=1}^{N} \sum_{k=1}^{K} \gamma(z_{nk}) [\ln \pi_k + \ln N(x_n | \mu_k, \Sigma_k)] - \lambda \left(\sum_{k=1}^{K} \pi_k - 1 \right)$$

learning the terms... $\sum_{n=1}^{N} \gamma(z_{nk}) = \pi_k \lambda \Rightarrow \sum_{k=1}^{K} \sum_{n=1}^{N} \gamma(z_{nk}) = \sum_{k=1}^{K} \pi_k \lambda$

> application of GMMs
1) clustering: used to cluster data into groups
2) anomaly detection: by modeling normal data distribution & identifying data points that have low likelihood under model.

> advantages: flexible and versatile model
> limitation: not suitable for highly non-Gaussian data.

---

4. Explain Hidden Markov models (HMMs) in detail.

HMM consist of these basic parts:
- Hidden state
- observation symbols (as states)
- transition from initial state to initial hidden state prob. distribution
- transition to terminal state prob. distribution
- state transition probability distribution
- state emission probability distribution

> Hidden Markov model has two parts: hidden and observed.
The hidden part consists of hidden state which are not directly observed, their presence is observed by observation symbol that hidden state emits.

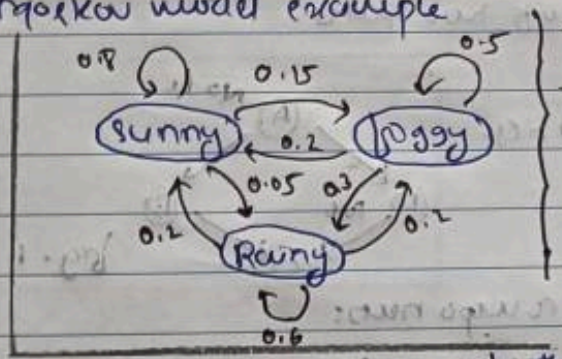
Markov chain is a simple Markov process, in which states can be observed directly.
The main diff b/w Markov and hidden Markov models are that- state observed directly in MM, and there are hidden state in HMM.

PTO

> Hmm algorithm steps:

step 7 → Evaluate the performance of the Hmm
step 6 → Decode the most probable sequence of hidden states
step 5 → Train the model by parameters of state transition probability.
step 6 → Specify the prob. of generating each observation from each state
step 3 → Define prob. of transitioning from one state to another
step 2 → Establish the initial state distribution
step 1 → Specify the set of possible hidden states & observations.

> Markov model example



Today's weather	Tomorrow's weather		
	Sunny	Rainy	Cloudy
Sunny	0.8	0.05	0.15
Rainy	0.2	0.6	0.2
Cloudy	0.2	0.3	0.5

If the weather yesterday was rainy and today is foggy what is the prob. that tomorrow it will be sunny?

$P(q_3 = \text{Sunny} \mid q_2 = \text{Cloudy}, q_1 = \text{Rainy}) = P(q_3 = \text{Sunny} \mid q_2 = \text{Cloudy})$
$= 0.2$

$\therefore P(q_n \mid q_{n-1}, q_{n-2} \ldots q_1) = P(q_n \mid q_{n-1})$

> Application of Hmm:

1) Speech Recognition: used to model the different sounds.
2) NLP: part-of-speech tagging, NER and text classification
3) Finance: used to model stock prices, interest rates, etc.

> advantages: 1) flexibility 2) capturing temporal dependencies
3) probabilistic modeling 4) Handling noisy data

> disadvantages: 1) Independence assumption 2) lack of transparency
3) model selection

5. Explain Bayesian Networks:

Bayesian N/w are type of probabilistic graphical model that can be used to build models from data and/or expert opinion.
They can be used for a wide range of tasks including diagnosis, reasoning, causal modeling, decision making under uncertainty, anomaly detection, automated insight & prediction.
Bayesian belief N/w is key computer technology for dealing with probabilistic events and to solve a problem which has uncertainty.
Bayesian N/w can be used for building models from data and expert opinions, and is consist of two parts:

* directed acyclic graph
* table of conditional probabilities

- made up of nodes & arcs (directed links).

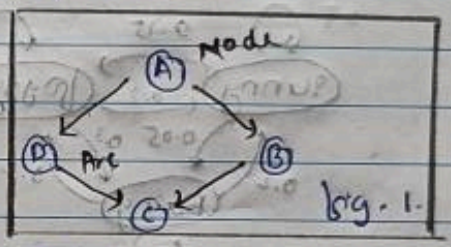


fig. 1.

> Bayesian N/w has mainly two components:
- causal component & actual numbers

Joint probability Distribution:

variables $x_1, x_2, \ldots x_n$ then $x_1, x_2, x \ldots x_n \rightarrow$ joint prob. distribution.

- written as $P[x_1, x_2, \ldots x_n] = P[x_1 | x_2, x_3, \ldots, x_n] P[x_2, x_3 \ldots x_n]$

$= P[x_1 | x_2, x_3 \ldots x_n] P[x_2 | x_3 \ldots x_n] \ldots$

- It can be written as, $P[x_{n-1} | x_n] P[x_n]$

$P(x_i | x_{i-1}, \ldots x_1) = P(x_i | \text{parents}(x_i))$

Explain Random → Markov Random field (MRF) model.

A MRF is a graphical model of a joint probability distribution.
It consist of an undirected graph $G = (N, E)$ where the nodes N represent random variables.
- the neighbour set $N_n = \{m \in N | (n, m) \in E\}$

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- a node is dependent of all other nodes.

$$P(x_n \mid x_N - x_n) = P(x_n \mid x_{N_n})$$

- Gibbs distribution: $P(x) = \frac{1}{Z} \prod_{c \in C} \phi_c(x_c)$

.. Z is the partition fn: $Z = \sum_x \prod_{c \in C} \phi_c(x_c)$

$\phi_c(x_c)$ can written as: $\phi_c(x_c) = e^{-1/T V_c(x_c)}$

T is called temperature and often taken to be 1.

So $P(x)$ has alternate form: $P(x) = \frac{1}{Z} e^{-1/T U(x)}$

where, $U(x) = \prod_{c \in C} V_c(x)$ — energy.

→ optimization: an optimization problem is one that involves finding the extremum of a quantity or function. Such problems often arises as a result of a source of uncertainty that precludes the possibility of an exact solution.

→ MRF applications:

1) image recognition/reconstruction 3) Edge detection
2) Segmentation 4) image restoration.

---

6. Explain architecture and training of GAN.

A Generative adversarial n/w (GAN) is a machine learning (ML) model in which two neural n/w compete with each other by using deep learning methods to become more accurate in their predictions. GAN typically run unsupervised and use a cooperative zero-sum game framework to learn, where one person's gain equals another person's loss. The two neural n/w that make up a GAN are referred to as generator and the discriminator. The generator is a convolutional neural n/w and discriminator is a deconvolutional neural n/w.

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-The two neural nlws that make up a GAN are referred as the Generator and the discriminator. The Generator is a convolutional neural nlw and the discriminator is deconvolutional neural nlw.

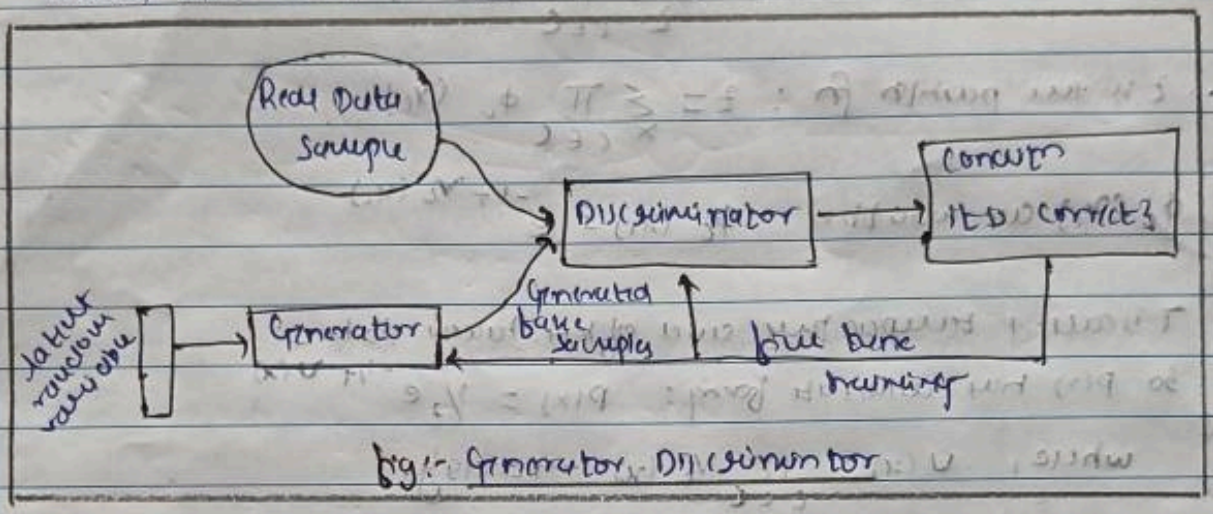

fig:- Generator, Discriminator

-The goal of the generator is to artificially manufacture o/p that could easily be mistaken for real data. The goal of discriminator is to identify which of the o/p instances have been artificially created.

-The GANs are formulated as a minimax game, where the discriminator is trying to minimize its reward $V(D, G)$. mathematically:

$$\min_G \max_D V(D,G)$$

$$V(D,E) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

where, G = Generator, D = Discriminator; $p_{data}(x)$ = distribution of real data

$p(z)$ = distribution of generator, x = sample of from $p_{data}(x)$

z = sample from $p(z)$, $D(x)$ = Discriminator nlw & $G(z)$ = Generator nlw

> Training:-

Because a GAN contains two separately trained nlws, its training algorithm must address two complications:

- GANs must juggle two different kinds of training (Generator and discriminator)
- GAN convergence is hard to identify

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- for a GAN, convergence is often a fleeting, rather than stable, stable

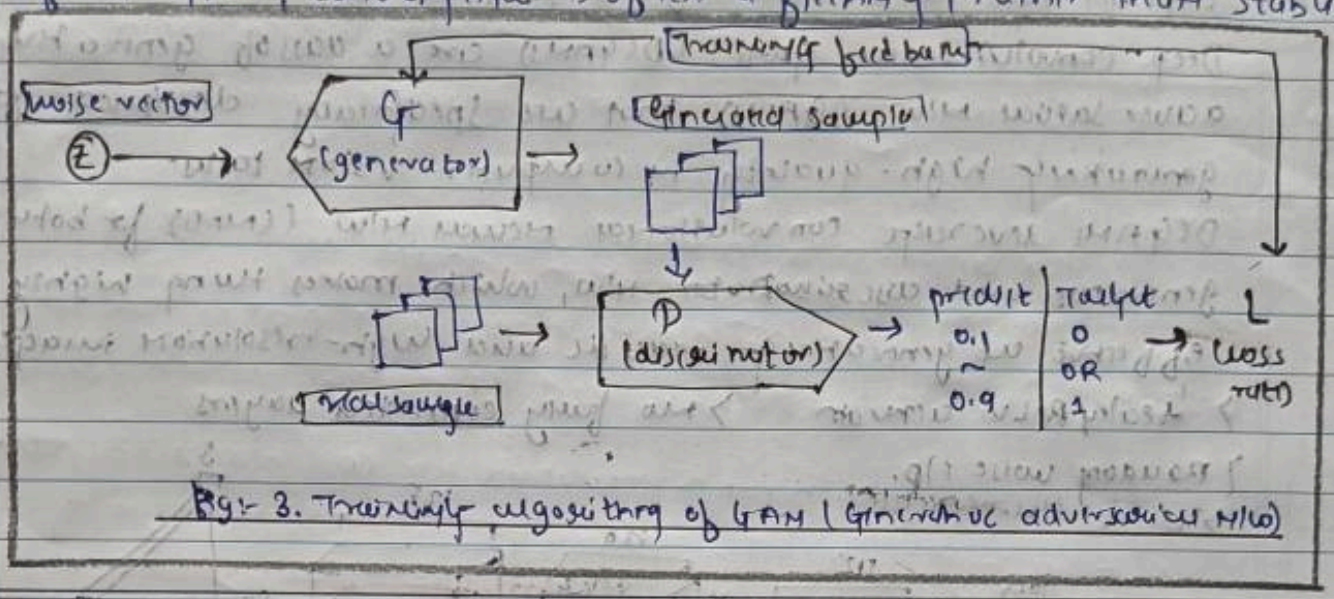

Fig:- 3. Training algorithm of GAN (Generative adversarial N/w)

7. Explain GAN applications with examples.

> Image Generation: GANs can generate highly realistic and diverse images from random noise or other data distributions. example, 1) face Generator: can Generate realistic human faces.
2) Art Generator: can create art, including paintings.
3) Scene synthesis: can generate complex scenes, landscapes, etc..

> Style Transfer: Allow artists and creators to apply the artistic style of one image to another, resulting in visually appealing and creative o/p. example, 1) image-to-image translation
2) Content manipulation: can manipulate content in images.

> Super-Resolution used for image super-resolution, low-resolution images are transformed into high-resolution counterparts with finer details. applications include image quality

> Data Augmentation: can generate synthetic data samples, augmenting datasets for training ML models.

> Image-to-Image translation: including converting satellite images to maps, translating black-and-white photos to color.

> face attribute manipulation: such as age, gender, etc..

8. Explain the architecture of DCGAN in details.

Deep convolutional GANs (DCGANs) are a class of generative adversarial NNs (GANs) that are specifically designed for generating high-quality images in computer vision tasks. DCGANs leverage convolutional neural NNs (CNNs) for both the generator and discriminator NNs, which makes them highly effective at generating realistic and high-resolution images.

> leaky ReLU activation > no fully connected layers

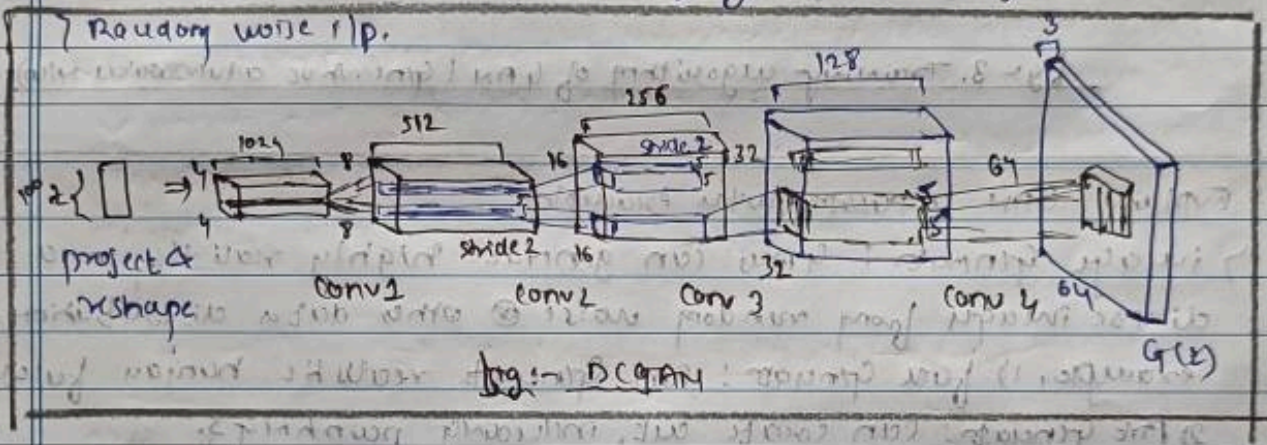

fig:- DCGAN

> Convolutional layers: DCGANs use convolutional layers in both the generator and discriminator NNs.

> Training DCGANs: involves standard GAN training procedure with some specific considerations:
- adversarial loss → optimization → regularization → noise injection.

> applications: image-to-image translation, data augmentation.

> deconvolution layer: transpose convolutional layer

> Batch normalizations applied after each layer in both generator and discriminator.

9. Explain various of GAN in detail:

Conditional GANs: (CGAN) can be described as a deep learning method in which some conditional parameters are put into place. In CGAN, an additional parameter 'y' is added to the generator for

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generating the corresponding data labels are also put into the i/p to the discriminator in order for the discriminator to help distinguish real data from fake generated data.

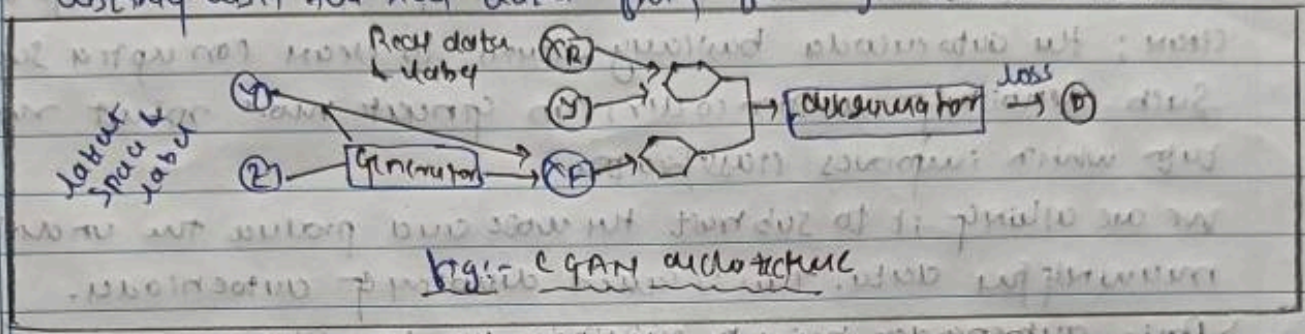


fig:- CGAN architecture

Cycle GAN:- Cycle GAN stands for Cycle-consistent Generative Adversarial N/w, it is type of generative model. Designed for the task of unpaired image-to-image translation, where it learns to convert images from one domain to another without requiring paired examples.

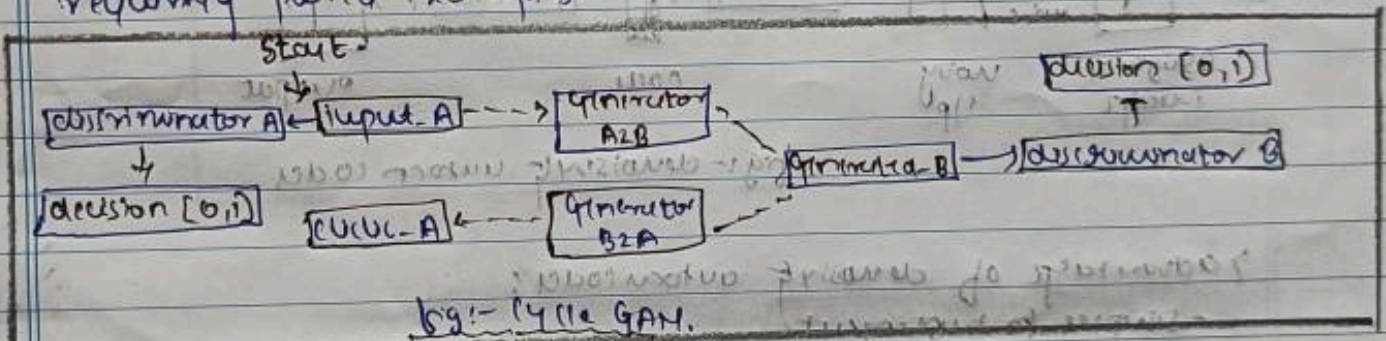


fig:- Cycle GAN.

WGAN:- Wasserstein Generative Adversarial N/w are type of GAN that aim to address some of the issues and instabilities associated with traditional GANs, particularly concerning training stability & evaluation of generated samples.

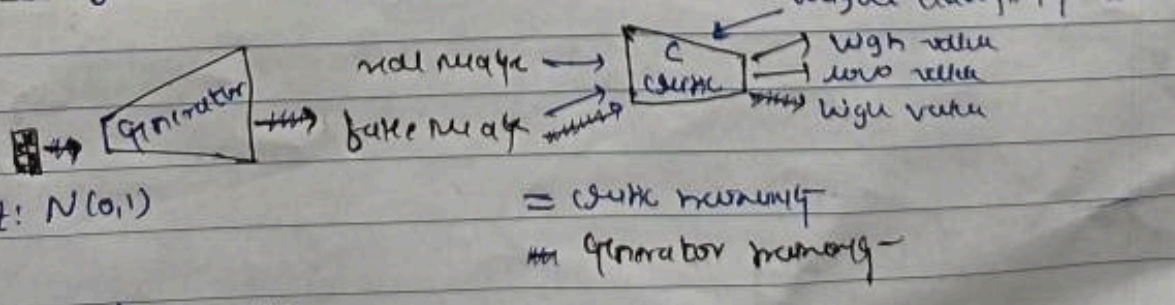


fig:- W GAN

10 Explain Denoising autoencoders in details.

One of the simpler variation of autoencoder is the denoising autoencoder, where the inputs are corrupted, and the o/p are clean; the autoencoder basically learns to clean corrupted samples. Such denoising autoencoders can generate more robust representation which improves classification.

We are using it to subtract the noise and produce the underlying meaningful data. This is called denoising autoencoder.

> Basic autoencoder learns to minimize the loss b/w x and the reconstruction $g(f(x))$, denoising autoencoders learn to minimize the loss b/w x and $g(f(x+w))$, where w → random noise.

denoising autoencoder cannot simply memorize I/p, o/p relationship.

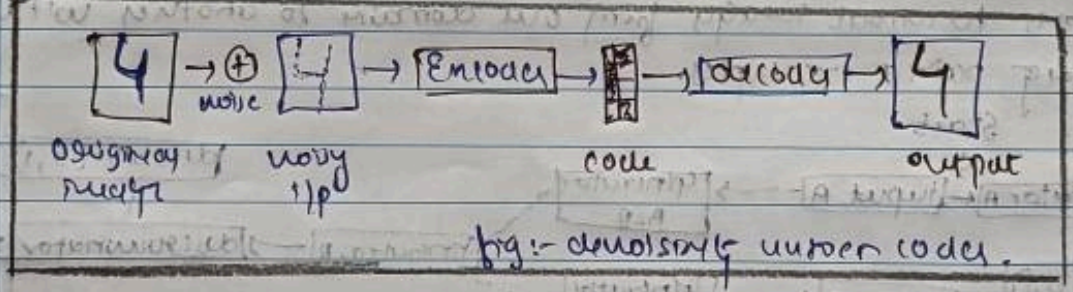


fig:- denoising autoencoder.

> advantage of denoising autoencoder:

- simpler to implement.
- requires adding 1/2 lines of code to regular autoencoder
- there is no need to compute Jacobians of hidden layer.

1. Explain transfer learning with its different approaches.

Transfer learning is a ML technique where a model trained on one task is reused as the starting point for a model on a second task.

Feature extractor:

In this approach, the pre-trained model's weights are frozen, and only the final layers are replaced and trained on new task. The pre-trained model serves as a feature extractor, and the new layers learn task-specific features.

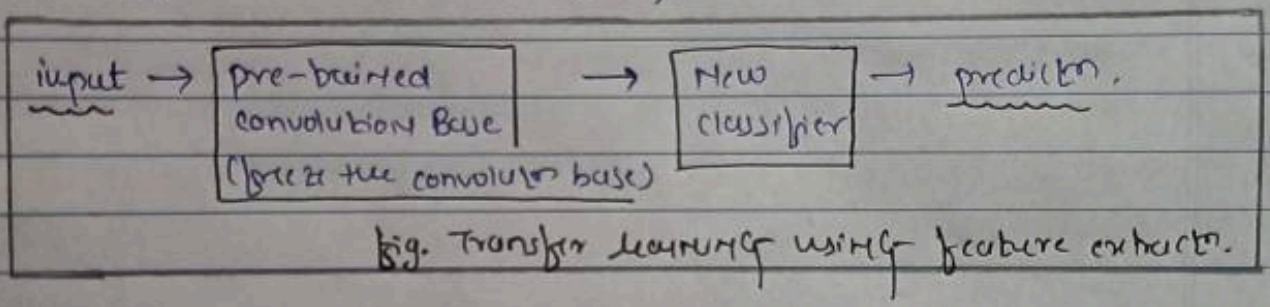


fig. Transfer learning using feature extractn.

It's called feature extractn because we use the pre-trained CNN as fixed feature-extractor, and only change the output layer.

Fine tuning:

In this approach, the pre-trained model's weights are updated during training on the new task.

The entire model, or part of it, is trained on new data to adapt to the specific task.

>techniques include: ① Train the entire architecture.

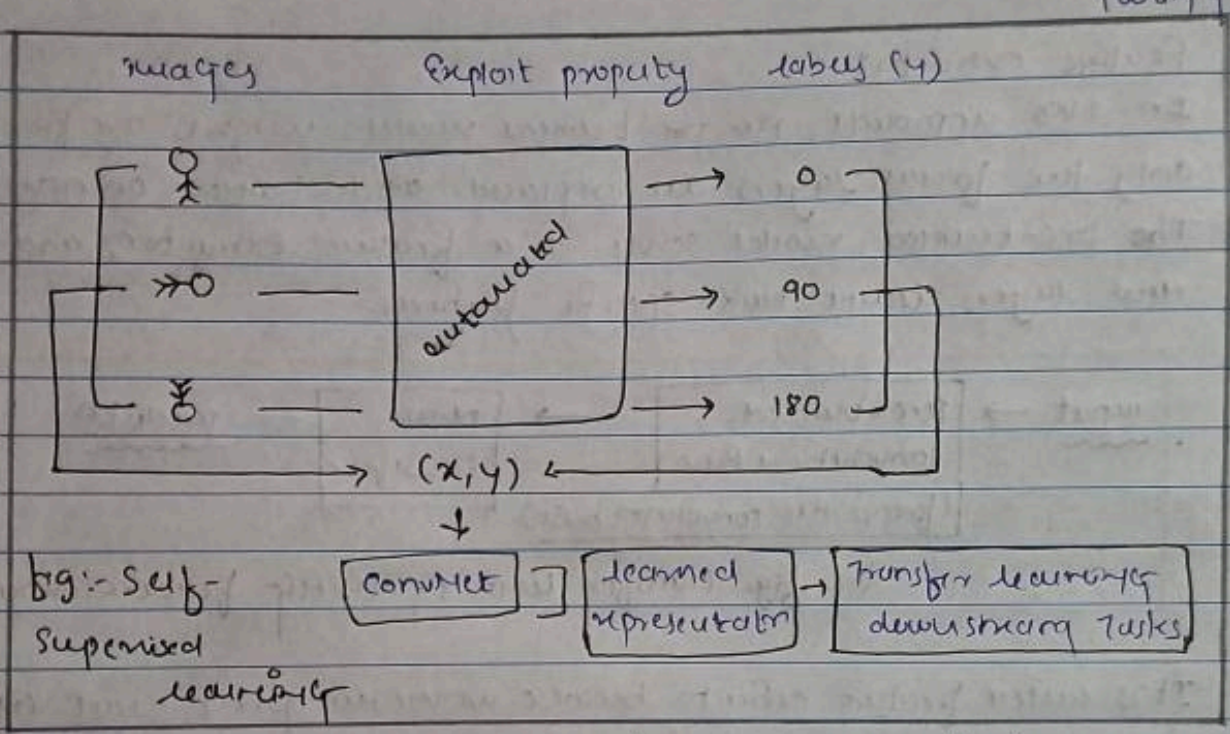
② train some layers while freezing others.

③ freeze the entire architecture.

The fine-tuning strategy is to only replace and retain classifier on top of the convnet on new dataset, but to also fine-tune the weights of pre-trained NN by continuing backpropagation.

2. Explain self-supervised learning with example.

Self-Supervised learning is a learning paradigm where a model learns to make predictions about some aspect of its input data without explicit supervision.



> Self-Supervised learning is a technique used to train models in which o/p labels are part of the i/p data, thus no separate o/p labels are required. Also known as predictive learning. In this method, the unsupervised problem is changed into a supervised one using auto-generation of labels. A classic example of this would be language models.

> The language model is a word sequence predictor model trained to predict the next word based on the previous input sentence. This kind of task is a self-supervised learning task, because you are not defining separate o/p labels. Instead you're providing texts as i/p & o/p in a specific way that will help model to understand fundamentals & style of language used in dataset for the language used in the dataset.

3. Explain meta-learning with example.

Meta-learning @ learning to learn, is a subfield of ML where models are trained to learn new tasks more efficiently with minimal data.

> Meta-learning algorithms don't use directly that kind of historic data, but they learns from the o/p of ML models. This means that meta-learning algorithms require the presence of other models that have already been trained on data.

> Types of meta-learning algorithms.

- Meta-learning optimizers : optimize existing NN to learn faster with new data.
- Metric meta-learning: Goal of learning embedding for NN where distance b/w similar i/p samples becomes closer & vice-versa for dissimilar samples.

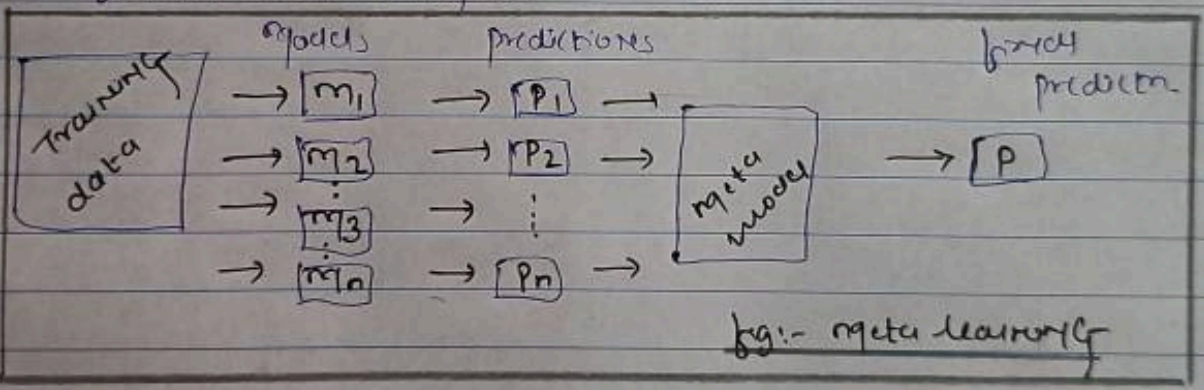


fig:- meta learning

Example: if the goal is to classify images, ML models take images as i/p and predict classes with meta-learning model taking predictions of those ML models as i/p and based on that predict classes of the images. In that sense, meta-learning occurs one level above ML.

> probably, the most popular meta-learning technique is stacking. Stacking is a type of ensemble learning algorithm that combining result of two @ more ML models.

4. what is the difference blw Bagging & Boosting algorithms

Criteria	Bagging	Boosting
Type of Ensemble	parallel ensemble	sequential ensemble
Base learners	Trained independently on bootstrapped samples	Trained sequentially, each correcting errors of the previous one
Data sampling	Bootstraped samples with replacement	weighted sampling based on errors.
model complexity	low bias, high variance	low bias, low variance (with high potential @ for overfitting)
weighting of models	Equal weights	weighted by performance
Training strategy	independent learners	Sequential learning.
Error correction	Models are averaged to reduce variance	Errors are corrected by subsequent models.
Examples	Random forest	AdaBoost, Gradient Boosting

5. How does the AdaBoost algorithm work?

AdaBoost (adaptive Boosting) is a boosting algorithm that works by iteratively training weak learning and adjusting weight of training examples based on the errors of previous models. It assign higher weights to misclassified examples, allowing subsiquent models to focus more on correcting those mistakes.

working:

① Assigning weights: first of all, datapoints will be assigning some weights. Initially, all the weights will be equal.

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the formula to calculate the sample weights is:

$$w(x_i, y_i) = 1/N, \quad i = 1, 2, \ldots n$$ { N → total no. of data points

② Classify the samples:
Classify the samples & see how variables classify samples. We'll create decision stump for each of feature & then calculate gini index of each tree. Tree with lower gini index will our first stump.

③ Calculate the influence: we'll now calculate 'influence' or 'amount of say' or 'importance' for classifying in classifying data points using formula: $\frac{1}{2} \log \frac{1 - \text{Total Error}}{\text{Total Error}}$

Total Error → Summation of all sample weights of misclassified data points.
Total Error will always be b/w 0 and 1

④ Calculate TE and performance: updating weights.

$$\text{New sample weights} = \text{old weight} * e^{\pm d}$$ ..d → amount of say

d → Negative ... when sample correctly classified
d → positive ... when sample misclassified

⑤ Decrease errors: Make new dataset to see if mos decreased or not. We will remove 'sample weights' & 'new sample weights' columns & then based on 'New sample weights' divide our datapoints into buckets.

⑥ New dataset: Select random no. b/w 0-1. Since incorrectly classified records have higher sample weight, prob. of selecting these records are in the new dataset is very high.

⑦ Repeat previous steps: New dataset & repeat all above steps...
i) Assign equal weights
ii) Find stump that does the best job classifying
iii) calculate 'amount of say' and 'total error'
iv) normalize new sample weights.

• Iterate through these steps until and unless a low training error is achieved.

6. What is Ensemble learning

Ensemble learning is a ML technique where multiple models are combined to improve performance.

Explain the techniques Bagging & Random forest..

Bagging: Bootstraping aggregating

Bagging is an ensemble technique mainly used to reduce the variance of our predictn by combining result of multiple classifiers modelled on different sub-samples of the same dataset.

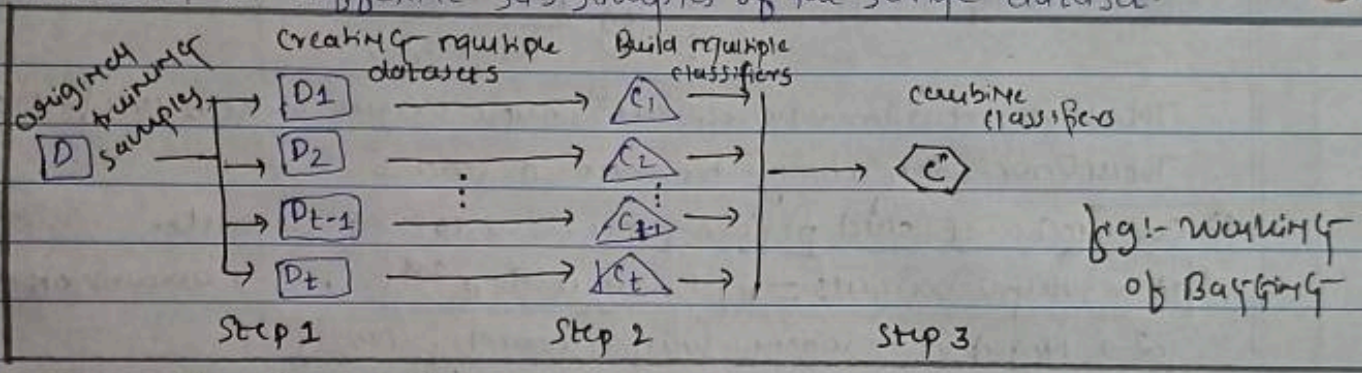

fig:- working of Bagging

main steps involved:

> creating multiple datasets: replacement of original dataset and the new datasets formed from original dataset

> Building multiple classifier: on each of these smaller dataset, a classifier is built, usually same classifier is built on all dataset

> combining classifiers: all individual classifiers are now combined to give a better classifier, usually with very less variance compared to before.

- Bagging is similar to Divide and conquer.

Random forest: It is an ensemble learning method that is used to collection of decision trees, where each tree is trained on a random subset of the features and data.

> The Random forest classification algorithm consist of many decision trees, & it uses bagging & feature randomness when building each individual tree.

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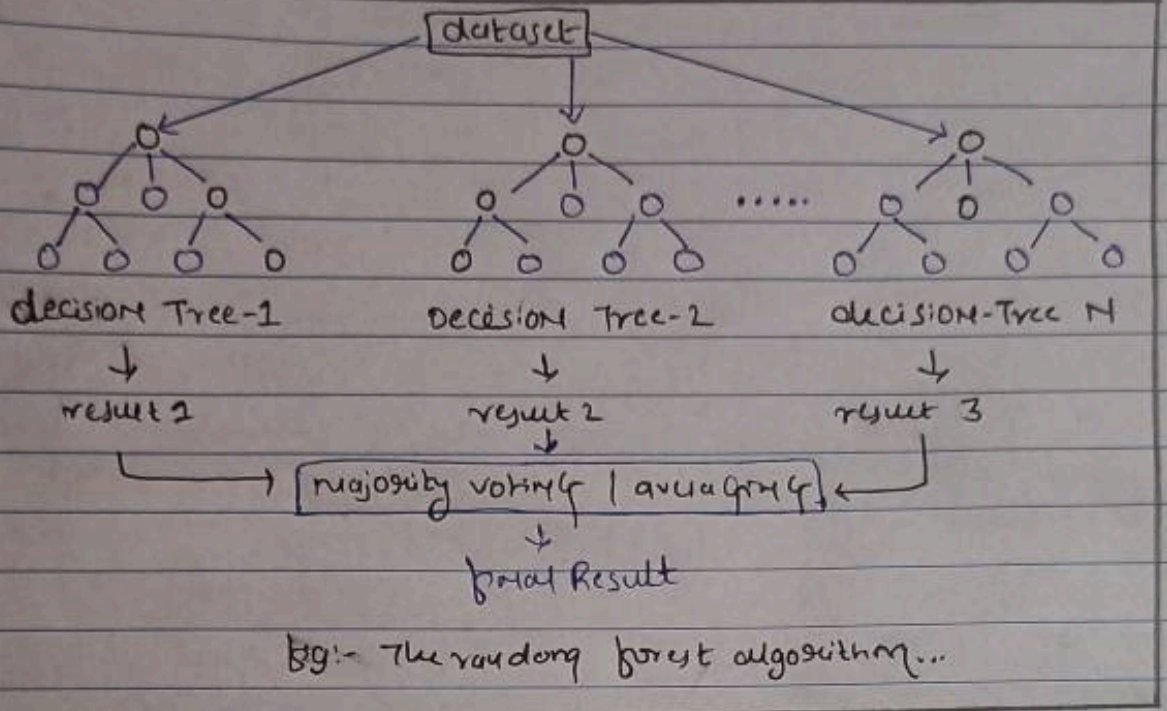

fig:- The random forest algorithm...

Steps:- ① Select random sample from dataset using bootstrap aggregating
② construct a decision tree for each sample & save predicted result for each Tree.
③ calculate a vote for each predicted result.
④ determine which predicted result has most votes.
• This is becomes your final predict.

7. Explain Stacking & Blending models with examples.

Stacking: Stacking is an ensemble learning method that combines multiple ML algorithms via meta learning.

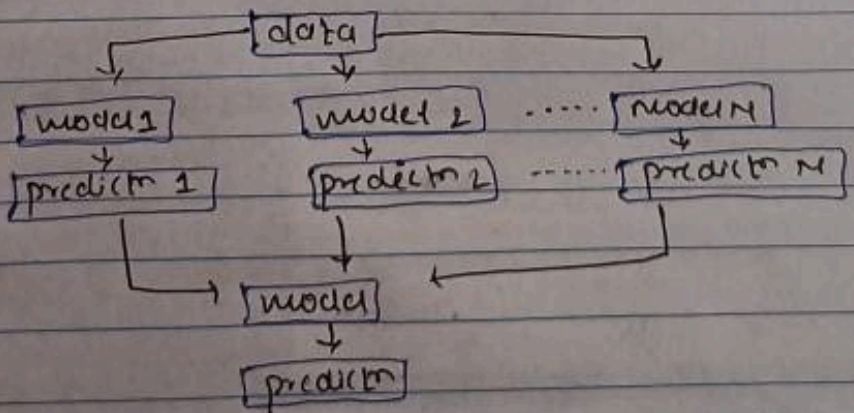

fig:- visual visualization of stacked generator.

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Example: Suppose we have three base models: Random forest, SVM and Gradient Boosting machine. We train each of these models on training data. Then we use their predictions as features to train meta-model, such as logistic regression, which combines these predictions to make final prediction.
advantage: improves the model prediction accuracy. Using predictions of not so good models & then using those predictions as ip/p features for better model.

Blending: Blending is similar to stacking but involves using a holdout set to train meta-model instead of cross-validation.
Steps: ① train_data is split into base_train_data & holdout_set.
② Base models are fitted on base_train_data, & predictions are made on holdout_set and test_data. These will create new prediction features.
③ A new meta-model is then fit on holdout_set with new prediction features. Both original & meta features from holdout_set will be used.
④ The trained meta-model is used to make final prediction on the test data using both original & new meta features.

Example: we divide training data in two parts: one for training Base models and other for training meta-model. We train several base models on the first part of the training data and make predictions on holdout_set. Then, we use these predictions as features along with original features to train the meta-model.

8. Explain XGBoost classification and Regression in detail.
XG Boost (Extreme Gradient Boosting) is an implement of gradient boosting ML machines designed for speed & performance.
It can be used for both classification and regression tasks.
XGBoost builds a series of decision trees sequentially, where each subsequent tree corrects the errors of the previous ones.

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XGBoost can be used in a variety of applications including Kaggle competitions, recommender systems, and click-through rate prediction among others. It is also highly customizable and allows for fine-tuning of various model parameters to optimize performance.

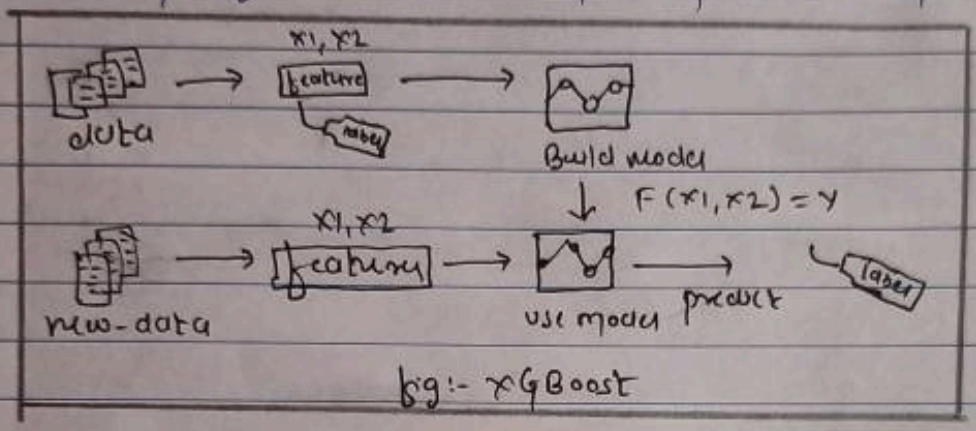

fig:- XGBoost

> Regression predictive modeling problem involves predicting a numerical value such as dollar amount or a height.
XGBoost can also be used directly for regression predictive modeling

> The very first step of fitting XGBoost to the training data is to make an initial prediction. This prediction can be anything, but by default it's 0.5, regardless of whether you are using XGBoost for
> Regression or classification.
Calculating: Quality score, Similarity score, for the Residuals.
λ(lamda) is regularization parameter & the output value will be the sum of residual divided by no. of residuals + λ. (for regression)
> When using XGBoost for classification, we have to be aware that min. no. of Residuals in leaf related to method called cover, which is denominator of the similarity score, minus λ(lamda) → for classification.

9. Explain the concept of : 1) Augmented Reality
2) Quantum Computing

PTO

Augmented Reality: (AR): AR is a technology that overlays digital information (such as images, videos, or 3D models) onto the real world, usually viewed through a device like a smartphones or the AR glasses.

properties/Rules: (1) it must be combine virtual & real information with the real world as primary place of action.
(2) must be interactive with real-time updates.
(3) it must be virtual information registered in 3D space, in the physical environment.

Applications of AR:
(1) Entertainment: in Gaming
(2) Education: interactive content
(3) Navigation: provide direction
(4) Healthcare: assist surgeons real-time
(5) marketing: interactive campaigns
(6) Design: facilitate 3D visualization.

Quantum computing: AI & quantum computing are two rapidly advancing fields with the potential to mutually benefit each other. Quantum computing, based on principles of Quantum mechanics, offers the promise of solving certain complex problems exponentially faster than classical computers. when appod to AI, quantum computing can enhance various aspects of AI research & application. Heres a dataset exploration of AI in realm of emerging QC:
(1) Quantum ML (QML): combining with classical ML
(2) Quantum NN: version of ANN, uses Quantum bits for data.
(3) Quantum-enhanced optimization: well-suited for solving optimization prob.
(4) Quantum data processing: process & analyze large dataset more efficiently

10. What is metaverse?
The metaverse refers to a collective virtual shared space, created by convergence of virtual reality, augmented reality, and the internet.

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Characteristics:

① Immersive Experience: Users can immerse themselves in virtual envs that simulate real-world experience, often through VR (or) AR. These experience can include realistic visual, sounds & interaction.

② persistant virtual worlds: metaverse consist of interconnected virtual worlds (or) space that persist over time, allowing users to explore, interact and create within these digital envs. These worlds can be vast & diverse.

③ Diverse range of activities: Users can engage in wide range of activities within metaverse, including socializing with others, gaming, attending virtual events (or) concerts, shopping, learning, creating & sharing content.

Components:

① Digital continuity: allowing users to move seamlessly b/w spaces.

② interoperability: data can flow b/w diff. virtual worlds & platforms.

③ User Agency: control over digital presence, including avatars, data.

④ persistant: virtual env continously exist & evolve, when user not active.

⑤ Economy & commerce: user can buy, sell, trade digital assets, virtual services.

⑥ immersive interaction: through AR, VR, haptic feedback, voice communication.

⑦ socialization & collaboration: core component, user connecting in digital spaces.

challenges:

① privacy & security: managing personal data, digital identity & cyber security

② moderation (contents): Ensuring safety and preventing harmful content.

③ Digital Divide: Accessibility, affordability & equal participation in the metaverse.

④ Legal & Regulatory framework: for virtual property, intellectual, etc.

11. application of Variational Autoencoder, architecture...

VAEs consist of an encoder NN that maps input data to a latent space representation and a decoder NN that reconstructs the i/p

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data from the latent space.
The encoder produces the mean & variance of the latent space distribution, which is then sampled to generate latent vectors.

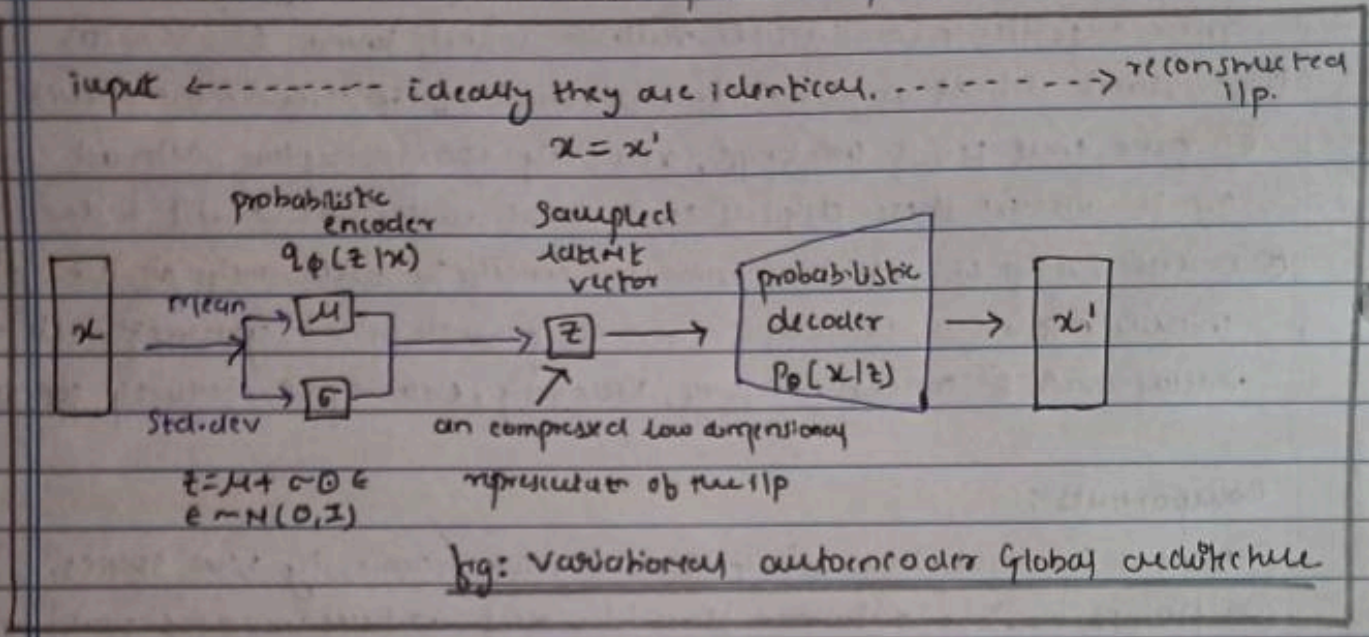

fig: Variational autoencoder Global architecture

VAEs work:
> map an i/p to distribution over the latent space
> pick a point from distribution in the latent space
> decode sampled point and compute reconstruction and KL divergence error.
- The reconstruction error is same as one used in standard autoencoders. KL divergence error regulates the distance btw distribution of generated and the original image.
- VAEs are constrained in normal distribution during training.

You can, ∴ pick a point in normal distribution & the NN will create new image based on the training data.

Application of VAEs in Image Generation: An autoencoder takes an i/p image & creates a low-dimensional representation, ie. a latent vector. This vector is then used to reconstruct original image. Regular autoencoder gets an image as i/p & o/p the same image. However VAEs generate new images with the same distribution as the training images..