Machine Learning Final Project train the deep learning model and traditional Machine Learning Models. Compare the performance of Deep learning Algorithm and three traditional Machine Learning Models.

Imported numpy, pandas, matplot libraries, seaborn, tensorflow and all other required libraries to the project.

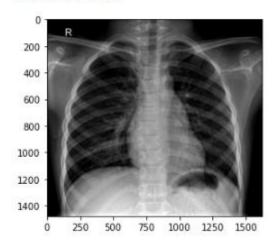
An excellent tool for image processing and computer vision work is OpenCV. It is a free library that may be used to carry out operations like face recognition, object tracking, landmark recognition, and many other things. A complete open source machine learning platform is called TensorFlow. The class concentrates on using a specific TensorFlow API to create and train machine learning models, despite the fact that TensorFlow is a robust system for managing all parts of a machine learning system.

```
In [1]: import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
    import tensorflow as tf
    import cv2
    import warnings
    warnings.filterwarnings('ignore')
    from sklearn.metrics import classification_report,confusion_matrix
In [2]: from tensorflow.keras.models import Sequential
    from tensorflow.keras.activations import softmax,sigmoid,relu
    from tensorflow.keras.optimizers import SGD,Adam
    from tensorflow.keras.layers import Conv2D,MaxPool2D,AvgPool2D,Flatten,Dropout,Dense,MaxPooling2D
    from sklearn.metrics import classification_report,confusion_matrix
```

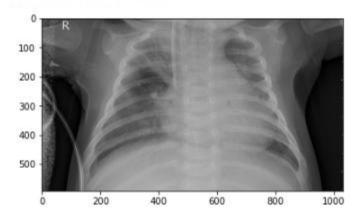
Collected the chest\_xray dataset of pneumonia effect persons and normal persons, below shown images are samples.

```
img1 =r"C:\Users\LAHARI\Downloads\chest_xray\train\Normal\IM-0764-0001.jpeg"
print("Undiseased lungs")
im = cv2.imread(img1)
plt.imshow(cv2.cvtColor(im,cv2.COLOR_BGR2RGB))
plt.show()
img2 =r"C:\Users\LAHARI\Downloads\chest_xray\train\PNEUMONIA\person253_bacteria_1155.jpeg"
print("PNEUMONIA effected lungs")
im = cv2.imread(img2)
plt.imshow(cv2.cvtColor(im,cv2.COLOR_BGR2RGB))
plt.show()
```

#### Undiseased lungs



#### PNEUMONIA effected lungs



In deep learning, a convolutional neural network (CNN) is a class of artificial neural network most commonly applied to analyze visual imagery.

```
from PIL import Image
import os
import shutil
from skimage.io import imread
from PIL import Image
training_path=r'C:\Users\LAHARI\Downloads\chest_xray\train'
testing_path =r'C:\Users\LAHARI\Downloads\chest_xray\test'
```

The original data inputs are used to feed the Keras ImageDataGenerator, which transforms the data randomly and outputs a result that only contains the newly altered data. The data are not included. In order to broaden the model's applicability, additional data is added using the Keras ImageDataGenerator module. Data augmentation uses an image data generator to conduct random operations on data, including translations, rotations, scale modifications, and vertical flips.

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
datagen = ImageDataGenerator(
   rescale=1./255,
   validation_split=0.50)
```

```
batch_size = 20
input_shape=(150,150,3)
```

```
train_datagen = datagen.flow_from_directory(
    training_path,
    target_size=input_shape[:2],
    class_mode='binary')
```

Found 1174 images belonging to 2 classes.

```
valid_datagen = datagen.flow_from_directory(
  testing_path,
  target_size=input_shape[:2],
  class_mode='binary')
```

Found 624 images belonging to 2 classes.

```
model = Sequential()
model.add(Conv2D(filters=64,kernel_size=(3,3),padding = 'same',activation = 'relu',input_shape=(150,150,3)))
model.add(MaxPool2D(pool_size = (2,2),strides = 2, padding='valid'))
model.add(Conv2D(64,(5,5),padding='SAME',activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Flatten())
model.add(Dense(units = 128, activation = 'relu'))
model.add(Dense(units = 128, activation='relu'))
model.add(Dense(1,activation='sigmoid'))
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 150, 150, 64)	1792
max_pooling2d (MaxPooling2D )	(None, 75, 75, 64)	0
conv2d_1 (Conv2D)	(None, 75, 75, 64)	102464
max_pooling2d_1 (MaxPooling 2D)	(None, 37, 37, 64)	0
flatten (Flatten)	(None, 87616)	0
dense (Dense)	(None, 128)	11214976
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

-----

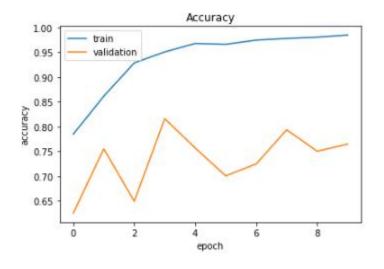
Total params: 11,319,361 Trainable params: 11,319,361 Non-trainable params: 0

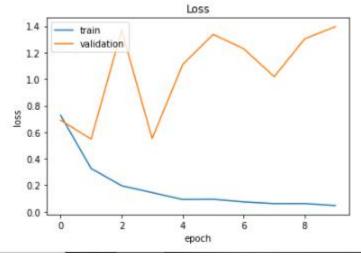
model.compile(optimizer ='adam',loss='binary\_crossentropy',metrics = ['accuracy'])

```
Epoch 1/10
50
Epoch 2/10
37/37 [====
          =========] - 157s 4s/step - loss: 0.3262 - accuracy: 0.8612 - val_loss: 0.5480 - val_accuracy: 0.75
48
Epoch 3/10
37/37 [======
       90
Epoch 4/10
         =========] - 149s 4s/step - loss: 0.1443 - accuracy: 0.9506 - val_loss: 0.5522 - val_accuracy: 0.81
37/37 [===
57
Epoch 5/10
       37/37 [====
Epoch 6/10
37/37 [================] - 147s 4s/step - loss: 0.0941 - accuracy: 0.9659 - val_loss: 1.3367 - val_accuracy: 0.70
Epoch 7/10
       37/37 [======
Epoch 8/10
37/37 [====
       00
Epoch 10/10
37/37 [=====
          =========] - 148s 4s/step - loss: 0.0472 - accuracy: 0.9847 - val_loss: 1.3949 - val_accuracy: 0.76
44
```

```
hist
plt.title('Accuracy')
plt.plot(hist.history['accuracy'])
plt.plot(hist.history['val_accuracy'])
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()

plt.title('Loss')
plt.plot(hist.history['loss'])
plt.plot(hist.history['val_loss'])
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```





```
from sklearn import metrics
from sklearn.metrics import classification report
y_pred = (model.predict(valid_datagen) > 0.505).astype(int)
y test = valid datagen.classes
print(classification_report(y_test, y_pred))
20/20 [======] - 24s 1s/step
             precision
                        recall f1-score
                                           support
                 0.29
          0
                           0.11
                                    0.16
                                              234
                 0.61
                           0.84
                                    0.71
                                              390
          1
```

0.47

0.57

0.45

0.49

```
train_datagen.class_indices
{'NORMAL': 0, 'PNEUMONIA': 1}
```

0.57

0.43

0.50

624

624

624

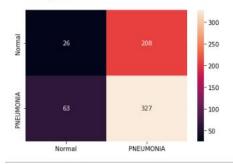
sns.heatmap(metrics.confusion\_matrix(y\_test,y\_pred),annot=True,xticklabels=['Normal','PNEUMONIA'],yticklabels=['Normal','PNEUMONIA']



accuracy

macro avg

weighted avg



Conclusion for CNN model: Accuracy is 60%.

# Traditional Machine learning models:

```
import pandas as pd
from sklearn import svm
import os
import matplotlib.pyplot as plt
from skimage.transform import resize
from skimage, io import imread
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,accuracy_score,confusion_matrix
import pickle
Efftype = ['Normal','Pneumonia']
training_path=r'C:\Users\LAHARI\Downloads\chest_xray\train'
testing_path = r'C:\Users\LAHARI\Downloads\chest_xray\test'
```

```
flat data arr=[]
 target arr=[]
 # Loading training data of NORMAL and PNEUMONIA LUNGS chestx-ray
 datadir=training path
 for i in Efftype:
     print(f'lungs type: {i}')
     path=os.path.join(datadir,i)
     for img in os.listdir(path):
         img array=imread(os.path.join(path,img))
         img resized=resize(img array,(150,150,3))
         flat data arr.append(img resized.flatten())
         target arr.append(Efftype.index(i))
     print(f'lungs type:{i} lungs data loaded successfully')
 flat data=np.array(flat data arr)
 target=np.array(target arr)
 df=pd.DataFrame(flat_data)
 df['Target']=target
 df
```

```
lungs type: Normal
   lungs type:Normal lungs data loaded successfully
  lungs type: Pneumonia
  lungs type:Pneumonia lungs data loaded successfully
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  1174 rows × 67501 columns
4
```

```
flat data arr=[]
target_arr=[]
# Loading testing data of NORMAL and PNEUMONIA LUNGS chestx-ray
datadir=testing path
for i in Efftype:
   print(f'lungs type : {i}')
   path=os.path.join(datadir,i)
   for img in os.listdir(path):
        img_array=imread(os.path.join(path,img))
        img_resized=resize(img_array,(150,150,3))
        flat_data_arr.append(img_resized.flatten())
        target_arr.append(Efftype.index(i))
   print(f'lungs type:{i} lungs data loaded successfully')
flat data=np.array(flat data arr)
target=np.array(target arr)
df2=pd.DataFrame(flat data)
df2['Target']=target
df2.head()
```

```
lungs type : Normal
lungs type:Normal lungs data loaded successfully
lungs type : Pneumonia
lungs type:Pneumonia lungs data loaded successfully
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# 1)SVC model

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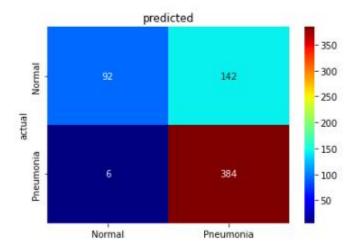
Support Vector Classification (SVC), which is a supervised machine learning algorithm used for classification tasks. It belongs to the family of linear and nonlinear classifiers, and it works by finding the best hyperplane that separates the data into different classes.

```
from sklearn.svm import SVC
svm_model = SVC()
svm_model.fit(x_train,y_train)

SVC()

y_pred_svm=svm_model.predict(x_test)
print(classification_report(y_test,y_pred_svm))
cm = confusion_matrix(y_test,y_pred_svm)
sns.heatmap(cm,annot=True,cmap='jet',fmt="1",xticklabels={'Normal': 0, 'Pneumonia': 1},yticklabels={'Normal': 0, 'Pneumonia': 1}
plt.title("predicted")
plt.ylabel('actual')
plt.show()
```

	precision	recall	f1-score	support
0	0.94	0.39	0.55	234
1	0.73	0.98	0.84	390
accuracy			0.76	624
macro avg	0.83	0.69	0.70	624
weighted avg	0.81	0.76	0.73	624



Conclusion for SVC model: Accuracy is 76%.

## 2)Decision tree classifier

Decision Tree Classifier models are known for their interpretability, as the decision tree structure can be visualized and analyzed to understand how the model is making its predictions. However, decision trees can be prone to overfitting, particularly if the tree is allowed to grow to its full depth. Techniques such as pruning and setting a maximum depth can help to prevent overfitting. Decision trees can also be sensitive to the choice of splitting criterion and can struggle with complex datasets with many features.

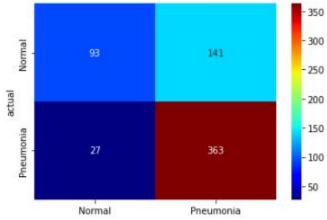
```
from sklearn.tree import DecisionTreeClassifier
dct model = DecisionTreeClassifier()
dct_model.fit(x_train,y_train)

DecisionTreeClassifier()

y_pred_dct=dct_model.predict(x_test)
print(classification_report(y_test,y_pred_dct))
```

```
y_pred_dct=dct_model.predict(x_test)
print(classification_report(y_test,y_pred_dct))
cm = confusion_matrix(y_test,y_pred_dct)
sns.heatmap(cm,annot=True,cmap='jet',fmt="1",xticklabels={'Normal': 0, 'Pneumonia': 1},yticklabels={'Normal': 0, 'Pneumonia': 1}
plt.ylabel('actual')
plt.show()
```

	precision	recall	f1-score	support	
0	0.78	0.40	0.53	234	
1	0.72	0.93	0.81	390	
accuracy			0.73	624	
macro avg	0.75	0.66	0.67	624	
weighted avg	0.74	0.73	0.70	624	



Conclusion for DTC model: Accuracy is 73%.

# 3) k-Nearest Neighbors (k-NN)

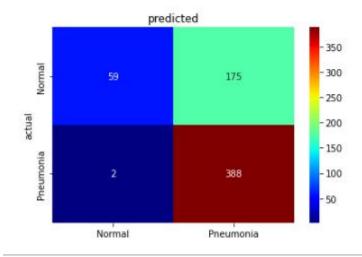
The k-NN algorithm is a type of lazy learning algorithm that is used for both classification and regression tasks. It works by finding the k data points in the training set that are closest to a new data point and using their labels to make a prediction.

```
from sklearn.neighbors import KNeighborsClassifier
knn_model = KNeighborsClassifier()
knn_model.fit(x_train,y_train)

KNeighborsClassifier()

y_pred_knn=knn_model.predict(x_test)
print(classification_report(y_test,y_pred_knn))
cm = confusion_matrix(y_test,y_pred_knn))
sns.heatmap(cm,annot=True,cmap='jet',fmt="1",xticklabels={'Normal': 0, 'Pneumonia': 1},yticklabels={'Normal': 0, 'Pneumonia': 1};
plt.title("predicted")
plt.ylabel('actual')
plt.show()
```

	precision	recall	f1-score	support	
0	0.97	0.25	0.40	234	
1	0.69	0.99	0.81	390	
accuracy			0.72	624	
macro avg	0.83	0.62	0.61	624	
weighted avg	0.79	0.72	0.66	624	



Conclusion for K-NN model: Accuracy is 72%.

### Conclusion:

The process for conclusion of traditional machine learning models is similar to that of deep learning models, but the difference lies in the algorithms used and the complexity of the models. Deep learning models can handle more complex tasks and larger datasets, while traditional machine learning models are simpler and can handle smaller datasets.