GROUP – A

Assignment No: 1

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Title:- Linear regression by using Deep Neural network: Implement Boston housing price. Prediction problem by Linear regression using Deep Neural network. Use Boston House price prediction dataset.

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Objective:-

-To learn about Deep Neural Network.

-To understand the concept of linear regressing in Deep Learning.

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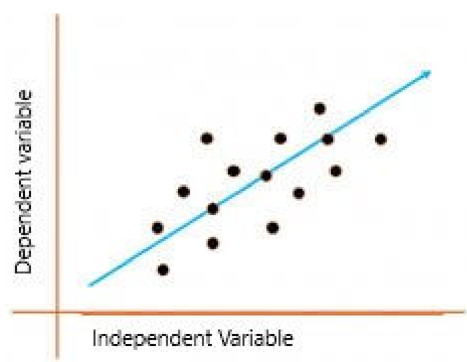
Theory:-

- **What is Linear Regression?**
  - Linear regression is useful for finding relationship between two continuous variables.
  - Linear regression shows the linear relationship between the independent (predictor) variable i.e. X-axis and the dependent (output) variable i.e. Y-axis, called linear regression.



  - The above graph presents the linear relationship between the output(y) variable and predictor(X) variables. The blue line is referred to as the best fit straight line.
  - Linear regression using deep neural networks combines the principles of linear regression with the power of deep learning algorithms.
  - In this approach, the input features are passed through one or more layers of neurons to extract features and then a linear regression model is applied to the output of the last layer to make predictions. The weights and biases of the neural network are adjusted during training to optimize the performance of the model.

- This approach can be used for a variety of tasks, including predicting numerical values, such as stock prices or housing prices, and classifying data into categories, such as detecting whether an image contains a particular object or not. It is often used in fields such as finance, healthcare, and image recognition.

- **What is Deep Neural Network?**
  - A deep neural network is a type of machine learning algorithm that is modeled after the structure and function of the human brain. It consists of multiple layers of interconnected nodes, or artificial neurons that process data and learn from it to make predictions or classifications.
  - Each layer of the network performs a specific type of processing on the data, such as identifying patterns or correlations between features, and passes the results to the next layer. The layers closest to the input are known as the "input layer", while the layers closest to the output are known as the "output layer".
  - The intermediate layers between the input and output layers are known as "hidden layers". These layers are responsible for extracting increasingly complex features from the input data, and can be deep (i.e., containing many hidden layers) or shallow (i.e., containing only a few hidden layers).
  - Deep neural networks are trained using a process known as back propagation, which involves adjusting the weights and biases of the nodes based on the error between the predicted output and the actual output.
  - This process is repeated for multiple iterations until the model reaches an optimal level of accuracy.

- **How Deep Neural Network works in Boston house price prediction**
  - Boston House Price Prediction is a common example used to illustrate how a deep neural network can work for regression tasks. The goal of this task is to predict the price of a house in Boston based on various features such as the number of rooms, crime rate, and accessibility to public transportation.
  - Here's how a deep neural network can work for Boston House Price Prediction:

  1. <u>Data preprocessing:</u> The first step is to preprocess the data. This involves normalizing the input features to have a mean of 0 and a standard deviation of 1, which helps the network learn more efficiently. The dataset is then split into training and testing sets.
  2. <u>Model architecture:</u> A deep neural network is then defined with multiple layers. The first layer is the input layer, which takes in the normalized features. This is followed by several hidden layers, which can be deep or shallow. The last layer is the output layer, which predicts the house price.
  3. <u>Model training:</u> The model is then trained using the training set. During training, the weights and biases of the nodes are adjusted based on the error between the predicted

output and the actual output. This is done using an optimization algorithm such as stochastic gradient descent.

4. Model evaluation: Once the model is trained, it is evaluated using the testing set. The performance of the model is measured using metrics such as mean squared error or mean absolute error.
5. Model prediction: Finally, the trained model can be used to make predictions on new data, such as predicting the price of a new house in Boston based on its features.
6. By using a deep neural network for Boston House Price Prediction, we can obtain accurate predictions based on a large set of input features. This approach is scalable and can be used for other regression tasks as well.

- **Boston House Price Prediction Dataset**
  - Boston House Price Prediction is a well-known dataset in machine learning and is often used to demonstrate regression analysis techniques. The dataset contains information about 506 houses in Boston, Massachusetts, USA. The goal is to predict the median value of owner-occupied homes in thousands of dollars.
  - The dataset includes 13 input features, which are:
    - **CRIM:** per capita crime rate by town
    - **ZN:** proportion of residential land zoned for lots over 25,000 sq.ft.
    - **INDUS:** proportion of non-retail business acres per town
    - **CHAS:** Charles River dummy variable (1 if tract bounds river; 0 otherwise)
    - **NOX:** nitric oxides concentration (parts per 10 million)
    - **RM:** average number of rooms per dwelling
    - **AGE:** proportion of owner-occupied units built prior to 1940
    - **DIS:** weighted distances to five Boston employment centers
    - **RAD:** index of accessibility to radial highways
    - **TAX:** full-value property-tax rate per $10,000
    - **PTRATIO:** pupil-teacher ratio by town
    - **B:** 1000(Bk - 0.63)^2 where Bk is the proportion of black people by town
    - **LSTAT:** % lower status of the population

  - The output variable is the median value of owner-occupied homes in thousands of dollars (MEDV).
  - To predict the median value of owner-occupied homes, a regression model is trained on the dataset. The model can be a simple linear regression model or a more complex model, such as a deep neural network.
  - After the model is trained, it can be used to predict the median value of owner-occupied homes based on the input features. The model's accuracy can be evaluated using metrics such as mean squared error or mean absolute error.

- Boston House Price Prediction is an example of regression analysis and is often used to teach machine learning concepts. The dataset is also used in research to compare the performance of different regression models.

- **Explanation of Code**

#Importing the pandas for data processing and numpy for numerical computing

```
import numpy as np

import pandas as pd
```

 # Importing the Boston Housing dataset from the sklearn

```
from sklearn.datasets import load_boston

boston = load_boston()
```

#Converting the data into pandas dataframe

```
data = pd.DataFrame(boston.data)
```

#First look at the data

```
data.head()
```

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

#Adding the feature names to the dataframe

```
data.columns = boston.feature_names
```

#Adding the target variable to the dataset

```
data['PRICE'] = boston.target
```

#Looking at the data with names and target variable

```
data.head(n=10)
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33	36.2
5	0.02985	0.0	2.18	0.0	0.458	6.430	58.7	6.0622	3.0	222.0	18.7	394.12	5.21	28.7
6	0.08829	12.5	7.87	0.0	0.524	6.012	66.6	5.5605	5.0	311.0	15.2	395.60	12.43	22.9
7	0.14455	12.5	7.87	0.0	0.524	6.172	96.1	5.9505	5.0	311.0	15.2	396.90	19.15	27.1
8	0.21124	12.5	7.87	0.0	0.524	5.631	100.0	6.0821	5.0	311.0	15.2	386.63	29.93	16.5
9	0.17004	12.5	7.87	0.0	0.524	6.004	85.9	6.5921	5.0	311.0	15.2	386.71	17.10	18.9

#Shape of the data

print(data.shape)

#Checking the null values in the dataset

data.isnull().sum()

CRIM 0

ZN 0

INDUS 0

CHAS 0

NOX 0

RM 0

AGE 0

DIS 0

RAD 0

TAX 0

PTRATIO 0

B 0

LSTAT 0

PRICE 0

dtype: int64

#Checking the statistics of the data

data.describe()

 # This is sometimes very useful, for example if you look at the CRIM the max is 88.97 and 75% of the value is below 3.677083 and mean is 3.613524 so it means the max values is actually an outlier or there are outliers present in the column.

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.455534
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.164946
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.400000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.050000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.200000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000

data.info()

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 506 entries, 0 to 505

Data columns (total 14 columns):

 # Column Non-Null Count Dtype

--- ------ -------------- -----

0 CRIM 506 non-null float64

1 ZN 506 non-null float64

2 INDUS 506 non-null float64

3 CHAS 506 non-null float64

4 NOX 506 non-null float64

5 RM 506 non-null float64

6 AGE 506 non-null float64

7 DIS 506 non-null float64

8 RAD 506 non-null float64

9 TAX 506 non-null float64

10 PTRATIO 506 non-null float64

11 B 506 non-null float64

12 LSTAT 506 non-null float64

13 PRICE 506 non-null float64

dtypes: float64(14)

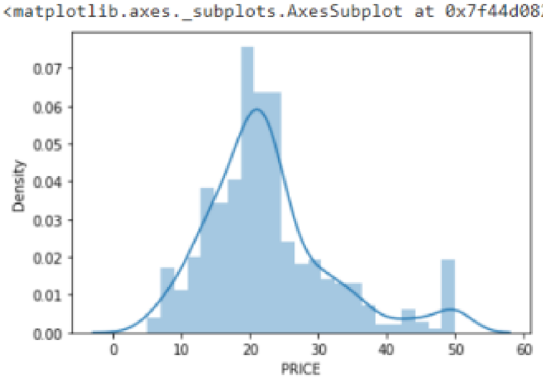
memory usage: 55.5 KB

#checking the distribution of the target variable

```
import seaborn as sns
sns.distplot(data.PRICE)
```

#The distribution seems normal, has not be the data normal we would have perform log transformation or took to square root of the data to make the data normal. Normal distribution is need for the machine learning for better predictability of the model.

<matplotlib.axes._subplots.AxesSubplot at 0x7f44d082c670>



#Distribution using box plot

```
sns.boxplot(data.PRICE)
```

#Checking the correlation of the independent feature with the dependent feature. Correlation is a statistical technique that can show whether and how strongly pairs of variables are related. An intelligent correlation analysis can lead to a greater understanding of your data. Checking correlation of the data

```
correlation = data.corr()
```

```
correlation.loc['PRICE']
CRIM -0.388305
ZN 0.360445
INDUS -0.483725
CHAS 0.175260
NOX -0.427321
RM 0.695360
AGE -0.376955
DIS 0.249929
RAD -0.381626
TAX -0.468536
PTRATIO -0.507787
B 0.333461
LSTAT -0.737663
PRICE 1.000000
Name: PRICE, dtype: float64
```

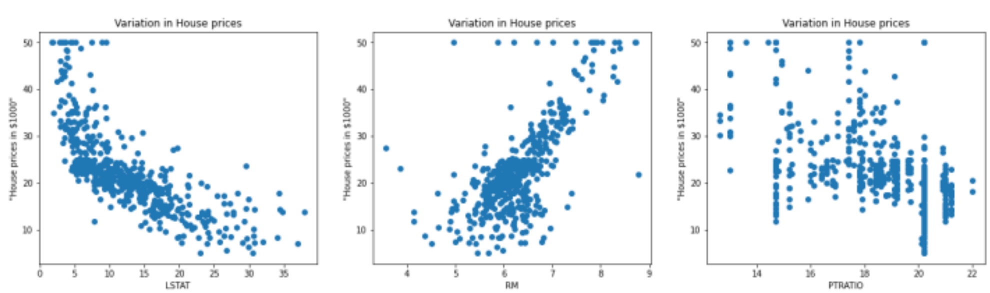
 # plotting the heatmap

```
import matplotlib.pyplot as plt
fig,axes = plt.subplots(figsize=(15,12))
sns.heatmap(correlation,square = True,annot = True)
```

 # By looking at the correlation plot LSAT is negatively correlated with -0.75 and RM is positively correlated to the price and PTRATIO is correlated negatively with -0.51.

 # Checking the scatter plot with the most correlated features

```
plt.figure(figsize = (20,5))
features = ['LSTAT','RM','PTRATIO']
for i, col in enumerate(features):
plt.subplot(1, len(features) , i+1)
x = data[col]
y = data.PRICE
plt.scatter(x, y, marker='o')
plt.title("Variation in House prices")
plt.xlabel(col)
plt.ylabel('"House prices in $1000"')
```



 # Splitting the dependent feature and independent feature

#X = data[['LSTAT','RM','PTRATIO']]

```
X = data.iloc[:,:-1]
y= data.PRICE
```

 # In order to provide a standardized input to our neural network, we need the perform the normalization of our dataset. This can be seen as an step to reduce the differences in scale that may arise from the existent features. We perform this normalization by subtracting the mean from our data and dividing it by the standard deviation. One more time, this normalization should only be performed by using the mean and standard deviation from the training set, in order to avoid any information leak from the test set.

```
mean = X_train.mean(axis=0)
std = X_train.std(axis=0)
X_train = (X_train - mean) / std
X_test = (X_test - mean) / std
```

#Linear Regression

```
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
```

#Fitting the model

```
regressor.fit(X_train,y_train)
```

 # Model Evaluation

#Prediction on the test dataset

```
y_pred = regressor.predict(X_test)
```

 # Predicting RMSE the Test set results

```
from sklearn.metrics import mean_squared_error
rmse = (np.sqrt(mean_squared_error(y_test, y_pred)))
print(rmse)
from sklearn.metrics import r2_score
r2 = r2_score(y_test, y_pred)
print(r2)
```

 # Neural Networks

#Scaling the dataset

```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()

X_train = sc.fit_transform(X_train)

X_test = sc.transform(X_test)
```

 # Due to the small amount of presented data in this dataset, we must be careful to not create an overly complex model, which could lead to overfitting our data. For this, we are going to adopt an architecture based on two Dense layers, the first with 128 and the second with 64 neurons, both using a ReLU activation function. A dense layer with a linear activation will be used as output layer. In order to allow us to know if our model is properly learning, we will use a mean squared error loss function and to report the performance of it we will adopt the mean average error metric. By using the summary method from Keras, we can see that we have a total of 10,113 parameters, which is acceptable for us.

#Creating the neural network model

```
import keras

from keras.layers import Dense, Activation,Dropout

from keras.models import Sequential

model = Sequential()

model.add(Dense(128,activation = 'relu',input_dim =13))

model.add(Dense(64,activation = 'relu'))

model.add(Dense(32,activation = 'relu'))

model.add(Dense(16,activation = 'relu'))

model.add(Dense(1))
```

#model.compile(optimizer='adam', loss='mse', metrics=['mae'])

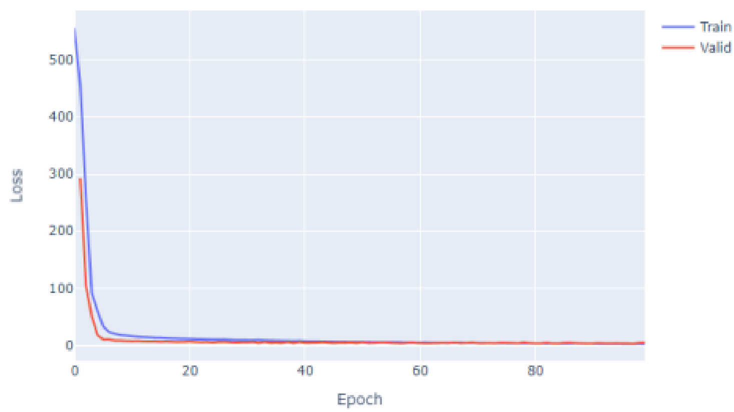
```
model.compile(optimizer = 'adam',loss ='mean_squared_error',metrics=['mae'])

!pip install ann_visualizer

!pip install graphviz

from ann_visualizer.visualize import ann_viz;
```

#Build your model here

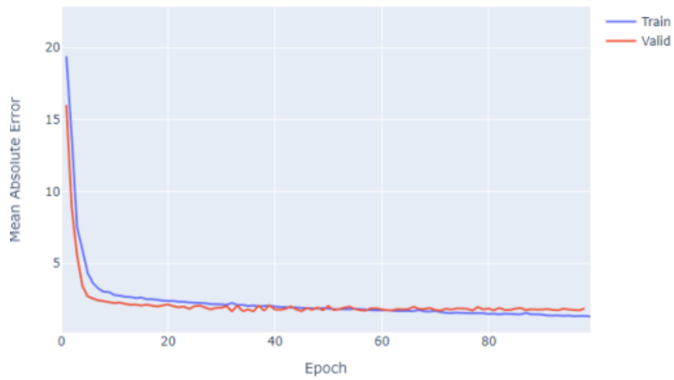
```
ann_viz(model, title="DEMO ANN");

history = model.fit(X_train, y_train, epochs=100, validation_split=0.05)
```

 # By plotting both loss and mean average error, we can see that our model was capable of learning patterns in our data without overfitting taking place (as shown by the validation set curves)

```
from plotly.subplots import make_subplots
import plotly.graph_objects as go
fig = go.Figure()
fig.add_trace(go.Scattergl(y=history.history['loss'],
name='Train'))
fig.add_trace(go.Scattergl(y=history.history['val_loss'],
name='Valid'))
fig.update_layout(height=500, width=700,
xaxis_title='Epoch',
yaxis_title='Loss')
fig.show()
```




```
fig = go.Figure()
fig.add_trace(go.Scattergl(y=history.history['mae'], name='Train'))
fig.add_trace(go.Scattergl(y=history.history['val_mae'], name='Valid'))
fig.update_layout(height=500, width=700,
xaxis_title='Epoch',
yaxis_title='Mean Absolute Error')
fig.show()
```



#Evaluation of the model

y_pred = model.predict(X_test)

mse_nn, mae_nn = model.evaluate(X_test, y_test)

print('Mean squared error on test data: ', mse_nn)

print('Mean absolute error on test data: ', mae_nn)

4/4 [==============================] - 0s 4ms/step - loss: 10.5717 - mae: 2.2670

Mean squared error on test data: 10.571733474731445

Mean absolute error on test data: 2.2669904232025146

#Comparison with traditional approaches

#First let's try with a simple algorithm, the Linear Regression:

from sklearn.metrics import mean_absolute_error

lr_model = LinearRegression()

lr_model.fit(X_train, y_train)

y_pred_lr = lr_model.predict(X_test)

mse_lr = mean_squared_error(y_test, y_pred_lr)

mae_lr = mean_absolute_error(y_test, y_pred_lr)

print('Mean squared error on test data: ', mse_lr)

print('Mean absolute error on test data: ', mae_lr)

from sklearn.metrics import r2_score

r2 = r2_score(y_test, y_pred)

```
print(r2)
0.8812832788381159
```

 # Predicting RMSE the Test set results

```
from sklearn.metrics import mean_squared_error
rmse = (np.sqrt(mean_squared_error(y_test, y_pred)))
print(rmse)
3.320768607496587
```

 # Make predictions on new data

```
import sklearn
new_data = sklearn.preprocessing.StandardScaler().fit_transform(([[0.1, 10.0,
5.0, 0, 0.4, 6.0, 50, 6.0, 1, 400, 20, 300, 10]]))
prediction = model.predict(new_data)
print("Predicted house price:", prediction)
1/1 [==============================] - 0s 70ms/step
Predicted house price: [[11.104753]]
```

#new_data = sklearn.preprocessing.StandardScaler().fit_transform(([[0.1, 10.0, 5.0, 0, 0.4, 6.0, 50, 6.0, 1, 400, 20, 300, 10]])) is a line of code that standardizes the input features of a new data point. In this specific case, we have a new data point represented as a list of 13 numeric values ([0.1, 10.0, 5.0, 0, 0.4, 6.0, 50, 6.0, 1, 400, 20, 300, 10]) that represents the values for the 13 features of the Boston House Price dataset. The StandardScaler() function from the sklearn.preprocessing module is used to standardize the data. Standardization scales each feature to have zero mean and unit variance, which is a common preprocessing step in machine learning to ensure that all features contribute equally to the model. The fit_transform() method is used to fit the scaler to the data and apply the standardization transformation. The result is a new data point with standardized feature values.

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Conclusion:- In this way we can Predict the Boston House Price using Deep Neural Network.

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GROUP – A

Assignment No: 2

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Title:- Binary classification using Deep Neural Networks Example: Classify movie reviews into positive" reviews and "negative" reviews, just based on the text content of the reviews. Use IMDB dataset.

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Objective:-

-To learn about Deep Neural Network.

-To understand the concept of classification using Deep Learning.

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Theory:-

- **What is Classification?**
  - The act or method of distributing into a class or category according to characteristics.
  - The model tries to predict the correct label of a given input data. In classification, the model is fully trained using the training data, and then it is evaluated on test data before being used to perform prediction on new unseen data.

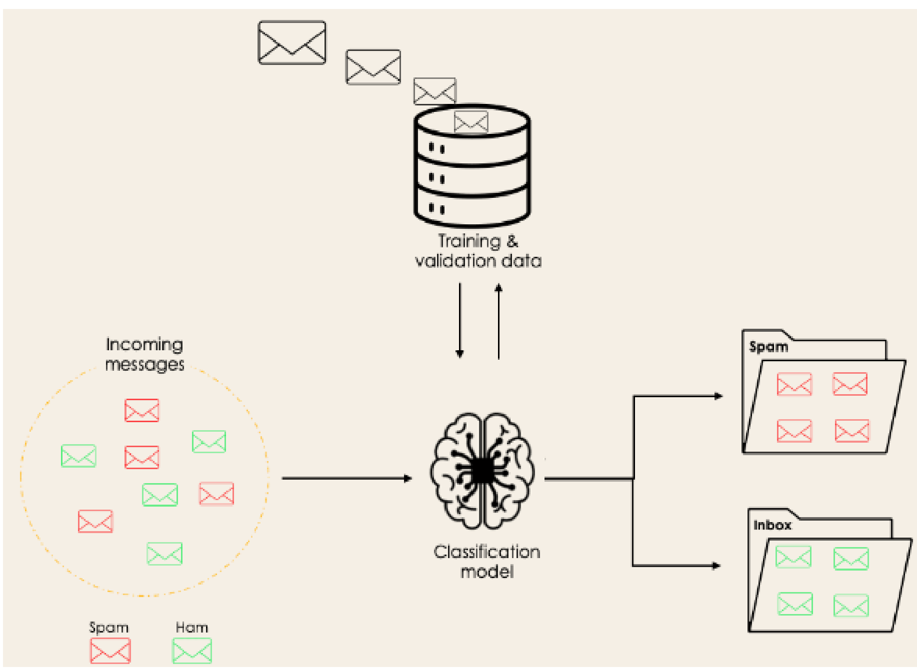


Figure 1: Classification

- **What is Deep Neural Network?**
    - A deep neural network is a type of machine learning algorithm that is modeled after the structure and function of the human brain. It consists of multiple layers of interconnected nodes, or artificial neurons that process data and learn from it to make predictions or classifications.

- **How Deep Neural Network works in classification?**
    - Deep neural networks are commonly used for classification tasks because they can automatically learn to extract relevant features from raw input data and map them to the correct output class.
    - The basic architecture of a deep neural network for classification consists of three main parts: an input layer, one or more hidden layers, and an output layer. The input layer receives the raw input data, which is usually preprocessed to a fixed size and format. The hidden layers are composed of neurons that apply linear transformations and nonlinear activations to the input features to extract relevant patterns and representations. Finally, the output layer produces the predicted class labels, usually as a probability distribution over the possible classes.
    - During training, the deep neural network learns to adjust its weights and biases in each layer to minimize the difference between the predicted output and the true labels. This is typically done by optimizing a loss function that measures the discrepancy between the predicted and true labels, using techniques such as gradient descent or stochastic gradient descent.
    - One of the key advantages of deep neural networks for classification is their ability to learn hierarchical representations of the input data.
    - In a deep neural network with multiple hidden layers, each layer learns to capture more complex and abstract features than the previous layer, by building on the representations learned by the earlier layers. This hierarchical structure allows deep neural networks to learn highly discriminative features that can separate different classes of input data, even when the data is highly complex or noisy.
    - Overall, the effectiveness of deep neural networks for classification depends on the choice of architecture, hyperparameters, and training procedure, as well as the quality and quantity of the training data. When trained properly, deep neural networks can achieve state-of-the-art performance on a wide range of classification tasks, from image recognition to natural language processing.

- **IMDB Dataset**
    - The IMDB dataset is a large collection of movie reviews collected from the IMDB. website, which is a popular source of user-generated movie ratings and reviews. The dataset consists of 50,000 movie reviews, split into 25,000 reviews for training and 25,000 reviews for testing.

- Each review is represented as a sequence of words, where each word is represented by an integer index based on its frequency in the dataset. The labels for each review are binary, with 0 indicating a negative review and 1 indicating a positive review.
- The IMDB dataset is commonly used as a benchmark for sentiment analysis and text classification tasks, where the goal is to classify the movie reviews as either positive or negative based on their text content.
- The dataset is challenging because the reviews are often highly subjective and can contain complex language and nuances of meaning, making it difficult for traditional machine learning approaches to accurately classify them.
- Deep learning approaches, such as deep neural networks, have achieved state-of-the-art performance on the IMDB dataset by automatically learning to extract relevant features from the raw text data and map them to the correct output class. The IMDB dataset is widely used in research and education for natural language processing and machine learning, as it provides a rich source of labeled text data for training and testing deep learning models.

- **Explanation of Code**

  # The IMDB sentiment classification dataset consists of 50,000 movie reviews from IMDB users that are labeled as either positive (1) or negative (0). The reviews are preprocessed and each one is encoded as a sequence of word indexes in the form of integers. The words within the reviews are indexed by their overall frequency within the dataset. For example, the integer "2" encodes the second most frequent word in the data. The 50,000 reviews are split into 25,000 for training and 25,000 for testing. Text Process word by word at different timestamp. Convert input text to vector represent input text.

  # DOMAIN: Digital content and entertainment industry

  # CONTEXT: The objective of this project is to build a text classification model that analyses the customer's sentiments based on their reviews in the IMDB database. The model uses a complex deep learning model to build an embedding layer followed by a classification algorithm to analyses the sentiment of the customers.

  # DATA DESCRIPTION: The Dataset of 50,000 movie reviews from IMDB, labeled by sentiment (positive/negative).

  # Reviews have been preprocessed, and each review is encoded as a sequence of word indexes (integers).

  # For convenience, the words are indexed by their frequency in the dataset, meaning thr for that has index 1 is the most frequent word.

  # Use the first 20 words from each review to speed up training, using a max vocabulary size of 10,000.

  # As a convention, "0" does not stand for a specific word, but instead is used to encode any unknown word.

 # PROJECT OBJECTIVE: Build a sequential NLP classifier which can use input text parameters to determine the customer sentiments.

import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
#loading imdb data with most frequent 10000 words
from keras.datasets import imdb
(X_train, y_train), (X_test, y_test) = imdb.load_data(num_words=10000)
 # you may take top 10,000 word frequently used review of movies other are discarded
#consolidating data for EDA Exploratory data analysis (EDA) is used by data scientists to analyze and investigate data sets and summarize their main characteristics
data = np.concatenate((X_train, X_test), axis=0) # axis 0 is first running vertically downwards across
rows (axis 0), axis 1 is second running horizontally across columns (axis 1),
label = np.concatenate((y_train, y_test), axis=0)
X_train.shape
(25000,)
X_test.shape
(25000,)
y_train.shape
(25000,)
y_test.shape
(25000,)
print("Review is ",X_train[0]) # series of no converted word to vocabulory associated with index
print("Review is ",y_train[0])
Review is [1, 194, 1153, 194, 8255, 78, 228, 5, 6, 1463, 4369, 5012, 134, 26, 4, 715, 8, 118, 1634, 14, 394, 20, 13, 119, 954, 189, 102, 5, 207, 110, 3103, 21, 14, 69, 188, 8, 30, 23, 7, 4, 249, 126, 93, 4, 114, 9, 2300, 1523, 5, 647, 4, 116, 9, 35, 8163, 4, 229, 9, 340, 1322, 4, 118, 9, 4, 130, 4901, 19, 4, 1002, 5, 89, 29, 952, 46, 37, 4, 455, 9, 45, 43, 38, 1543, 1905, 398, 4, 1649, 26, 6853, 5, 163, 11, 3215, 2, 4, 1153, 9, 194, 775, 7, 8255, 2, 349, 2637, 148, 605, 2, 8003, 15, 123, 125, 68, 2, 6853, 15, 349, 165, 4362, 98, 5, 4, 228, 9, 43, 2, 1157, 15, 299, 120, 5, 120, 174, 11, 220, 175, 136, 50, 9, 4373, 228, 8255, 5, 2, 656, 245, 2350, 5, 4, 9837, 131, 152, 491, 18, 2, 32, 7464, 1212, 14, 9, 6, 371, 78, 22, 625, 64, 1382, 9, 8, 168, 145, 23, 4, 1690, 15, 16, 4, 1355, 5, 28, 6, 52, 154, 462, 33, 89, 78, 285, 16, 145, 95]
Review is 0
vocab=imdb.get_word_index()

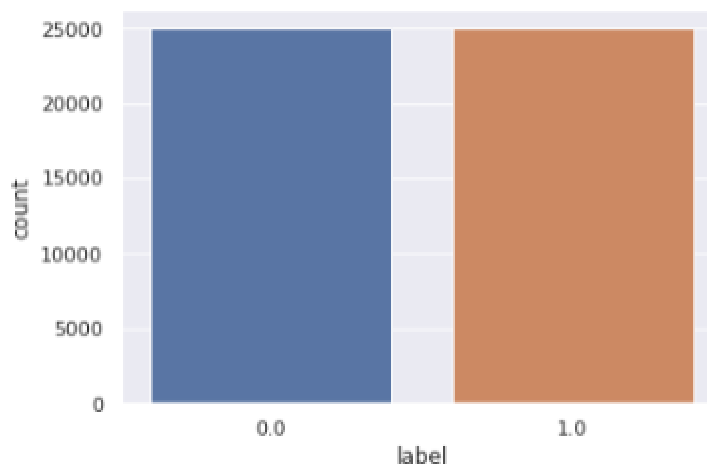
# Retrieve the word index file mapping words to indices
print(vocab)
{'fawn': 34701, 'tsukino': 52006, 'nunnery': 52007, 'sonja': 16816, 'vani': 63951, 'woods': 1408, 'spiders':
16115,
y_train
array([1, 0, 0, ..., 0, 1, 0])
y_test
array([0, 1, 1, ..., 0, 0, 0])
 # Function to perform relevant sequence adding on the data
 # Now it is time to prepare our data. We will vectorize every review and fill it with zeros so that it contains exactly 10000 numbers. That means we fill every review that is shorter than 500 with zeros. We do this because the biggest review is nearly that long and every input for our neural network needs to have the same size.
 # We also transform the targets into floats.
 # sequences is name of method the review less than 10000 we perform padding overthere binary vectorization code:
 # VECTORIZE as one cannot feed integers into a NN
 # Encoding the integer sequences into a binary matrix - one hot encoder basically
 # From integers representing words, at various lengths - to a normalized one hot encoded tensor (matrix) of 10k columns
def vectorize(sequences, dimension = 10000):
 # We will vectorize every review and fill it with zeros so that it contains exactly 10,000 numbers.
 # Create an all-zero matrix of shape (len(sequences), dimension)
results = np.zeros((len(sequences), dimension))
for i, sequence in enumerate(sequences):
results[i, sequence] = 1
return results
 # Now we split our data into a training and a testing set.
 # The training set will contain reviews and the testing set
 # # Set a VALIDATION set
test_x = data[:10000]
test_y = label[:10000]
train_x = data[10000:]
train_y = label[10000:]
test_x.shape
(10000,)
test_y.shape
(10000,)

train_x.shape
(40000,)
train_y.shape
(40000,)
print("Categories:", np.unique(label))
print("Number of unique words:", len(np.unique(np.hstack(data))))
 # The hstack() function is used to stack arrays in sequence horizontally (column wise).
Categories: [0 1]
Number of unique words: 9998
length = [len(i) for i in data]
print("Average Review length:", np.mean(length))
print("Standard Deviation:", round(np.std(length)))
 # The whole dataset contains 9998 unique words and the average review length is 234 words, with a standard deviation of 173 words.
Average Review length: 234.75892
Standard Deviation: 173
 # If you look at the data you will realize it has been already pre-processed.
 # All words have been mapped to integers and the integers represent the words sorted by their frequency.
 # This is very common in text analysis to represent a dataset like this.
 # So 4 represents the 4th most used word,
 # 5 the 5th most used word and so on...
 # The integer 1 is reserved for the start marker,
 # the integer 2 for an unknown word and 0 for padding.
 # Let's look at a single training example:
print("Label:", label[0])
Label: 1
print("Label:", label[1])
Label: 0
print(data[0])
 # Retrieves a dict mapping words to their index in the IMDB dataset.
index = imdb.get_word_index() # word to index
 # Create inverted index from a dictionary with document ids as keys and a list of terms as values for each document
reverse_index = dict([(value, key) for (key, value) in index.items()]) # id to word
decoded = " ".join([reverse_index.get(i - 3, "#") for i in data[0]])
 # The indices are offset by 3 because 0, 1 and 2 are reserved indices for "padding", "start of sequence" and "unknown".
print(decoded)

 # this film was just brilliant casting location scenery story direction everyone's really suited the part they played and you could just imagine being there robert # is an amazing actor and now the same being
director # father came from the same scottish island as myself so i loved the fact there was a real connection with this film the witty remarks throughout the film
#Adding sequence to data
 # Vectorization is the process of converting textual data into numerical vectors and is a process that is usually applied once the text is cleaned.

```
data = vectorize(data)
label = np.array(label).astype("float32")
labelDF=pd.DataFrame({'label':label})
sns.countplot(x='label', data=labelDF)
```

```
<AxesSubplot:xlabel='label', ylabel='count'>
```



 # Creating train and test data set

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(data,label, test_size=0.20, random_state=1)
X_train.shape
(40000, 10000)
X_test.shape
(10000, 10000)
```

 # Let's create sequential model

```
from keras.utils import to_categorical
from keras import models
from keras import layers
model = models.Sequential()
```

 # Input - Layer
 # Note that we set the input-shape to 10,000 at the input-layer because our reviews are 10,000 integers long.
 # The input-layer takes 10,000 as input and outputs it with a shape of 50.
model.add(layers.Dense(50, activation = "relu", input_shape=(10000,)))
 # Hidden - Layers
 # Please note you should always use a dropout rate between 20% and 50%. # here in our case 0.3 means 30% dropout we are using dropout to prevent overfitting.
 # By the way, if you want you can build a sentiment analysis without LSTMs, then you simply need to replace it by a flatten layer:
model.add(layers.Dropout(0.3, noise_shape=None, seed=None))
model.add(layers.Dense(50, activation = "relu"))
model.add(layers.Dropout(0.2, noise_shape=None, seed=None))
model.add(layers.Dense(50, activation = "relu"))
 # Output- Layer
model.add(layers.Dense(1, activation = "sigmoid"))
model.summary()

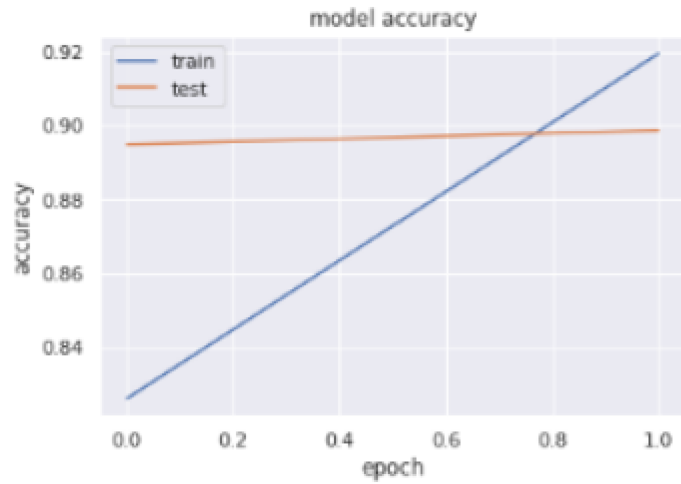
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 50)                500050

 dropout (Dropout)           (None, 50)                0

 dense_1 (Dense)             (None, 50)                2550

 dropout_1 (Dropout)         (None, 50)                0

 dense_2 (Dense)             (None, 50)                2550

 dense_3 (Dense)             (None, 1)                 51

=================================================================
```

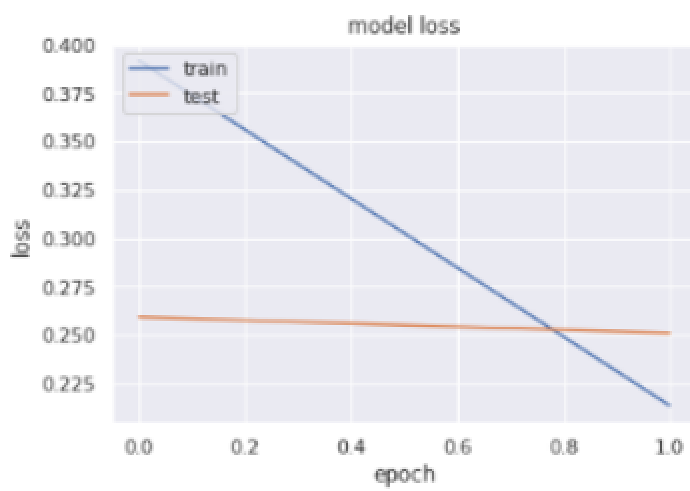
Total params: 505,201
Trainable params: 505,201
Non-trainable params: 0
#For early stopping
 # Stop training when a monitored metric has stopped improving.

```
# monitor: Quantity to be monitored.
# patience: Number of epochs with no improvement after which training will be
stopped.
import tensorflow as tf
callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=3)
# We use the "adam" optimizer, an algorithm that changes the weights and biases
during training. We also choose binary-crossentropy as loss (because we deal with
binary classification) and accuracy as our evaluation metric.
model.compile(
optimizer = "adam",
loss = "binary_crossentropy",
metrics = ["accuracy"]
)
from sklearn.model_selection import train_test_split
results = model.fit(
X_train, y_train,
epochs= 2,
batch_size = 500,
validation_data = (X_test, y_test),
callbacks=[callback]
)
# Let's check mean accuracy of our model
print(np.mean(results.history["val_accuracy"]))
# Evaluate the model
score = model.evaluate(X_test, y_test, batch_size=500)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
20/20 [==============================] - 1s 24ms/step - loss: 0.2511 -
accuracy:
0.8986
Test loss: 0.25108325481414795
Test accuracy: 0.8985999822616577
#Let's plot training history of our model.
# list all data in history
print(results.history.keys())
# summarize history for accuracy
plt.plot(results.history['accuracy'])
plt.plot(results.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
```

plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
 # summarize history for loss
plt.plot(results.history['loss'])
plt.plot(results.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```





plt.show()

===

Conclusion:- In this way we can Classify the Movie Reviews by using DNN.===
=====

GROUP – A

Assignment No: 3

==

Title:- Convolutional neural network (CNN): Use MNIST Fashion Dataset and create a classifier to classify fashion clothing into categories.

==

Objective:-

-To learn about Convolutional Neural Network.

-To understand the concept of classification.

==

Theory:-

- **What is Classification?**
    - The act or method of distributing into a class or category according to characteristics.
    - The model tries to predict the correct label of a given input data. In classification, the model is fully trained using the training data, and then it is evaluated on test data before being used to perform prediction on new unseen data.

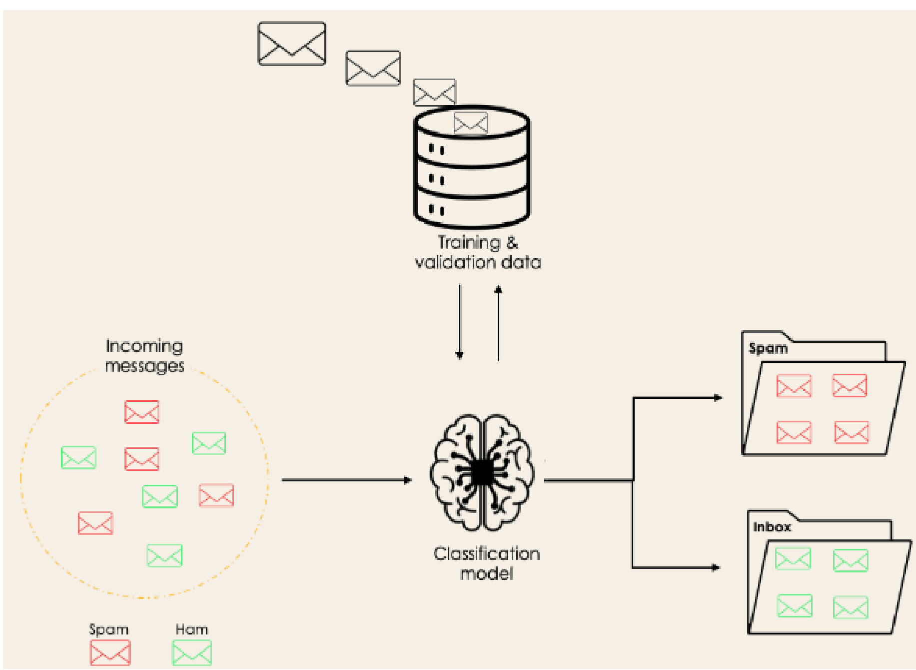


Figure 1: Classification

- **What is Convolution Neural Network?**
  - A Convolutional Neural Network (CNN) is a type of Deep Learning neural network architecture commonly used in Computer Vision. Computer vision is a field of Artificial Intelligence that enables a computer to understand and interpret the image or visual data.
  - Convolutional Neural Network consists of Convolutional layer, Pooling layer, and fully connected layers.

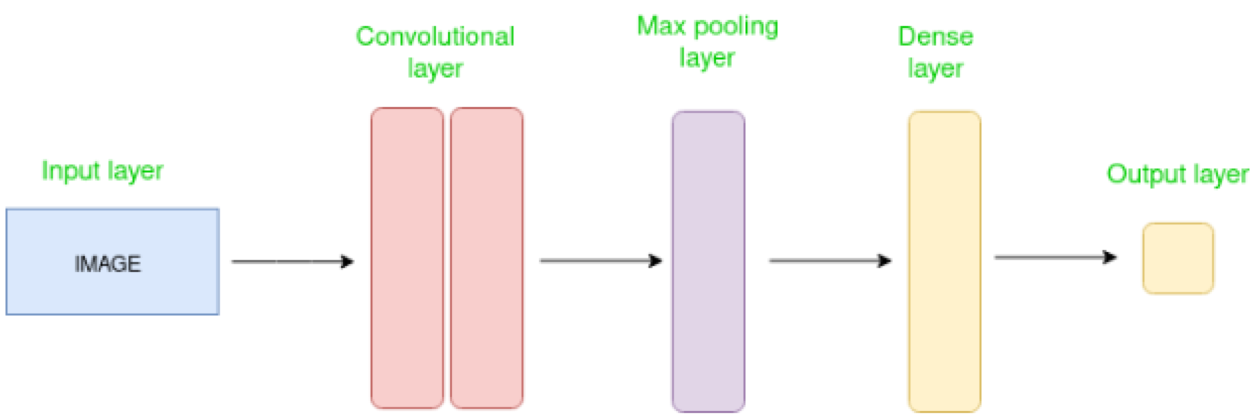


Figure 1: CNN Architecture

  - The Convolutional layer applies filters to the input image to extract features, the Pooling layer down samples the image to reduce computation, and the fully connected layer makes the final prediction. The network learns the optimal filters through backpropagation and gradient descent.

- **How DL works on classification using CNN?**
  - Deep neural networks using CNNs work on classification tasks by learning to automatically extract features from input images and using those features to make predictions.
  - Here's how it works:
    1. Input layer: The input layer of the network takes in the image data as input.

    Convolutional layers: The convolutional layers apply filters to the input images to extract relevant features. Each filter produces a feature map that highlights areas of the image that match the filter.

    2. Activation functions: An activation function is applied to the output of each convolutional layer to introduce non-linearity into the network.
    3. Pooling layers: The pooling layers down sample the feature maps to reduce the spatial dimensions of the data.

4. Dropout layer: Dropout is used to prevent overfitting by randomly dropping out a percentage of the neurons in the network during training.
5. Fully connected layers: The fully connected layers take the flattened output from the last pooling layer and perform a classification task by outputting a probability distribution over the possible classes.
6. Softmax activation function: The softmax activation function is applied to the output of the last fully connected layer to produce a probability distribution over the possible classes.
7. Loss function: A loss function is used to compute the difference between the predicted probabilities and the actual labels.
8. Optimization: An optimization algorithm, such as stochastic gradient descent, is used to minimize the loss function by adjusting the values of the network parameters.
9. Training: The network is trained on a large dataset of labeled images, adjusting the values of the parameters to minimize the loss function.
10. Prediction: Once trained, the network can be used to classify new images by passing them through the network and computing the output probability distribution.

- **MNIST Dataset**
  - The MNIST Fashion dataset is a collection of 70,000 grayscale images of 28x28 pixels, representing 10 different categories of clothing and accessories. The categories include T-shirts/tops, trousers, pullovers, dresses, coats, sandals, shirts, sneakers, bags, and ankle boots.
  - The dataset is often used as a benchmark for testing image classification algorithms, and it is considered a more challenging version of the original MNIST dataset which contains handwritten digits. The MNIST Fashion dataset was released by Zalando Research in 2017 and has since become a popular dataset in the machine learning community.
  - MNIST Fashion dataset is a collection of 70,000 grayscale images of 28x28 pixels each. These images represent 10 different categories of clothing and accessories, with each category containing 7,000 images.
  - The categories are as follows:

    T-shirt/tops

    Trousers

    Pullovers

    Dresses

    Coats

Sandals

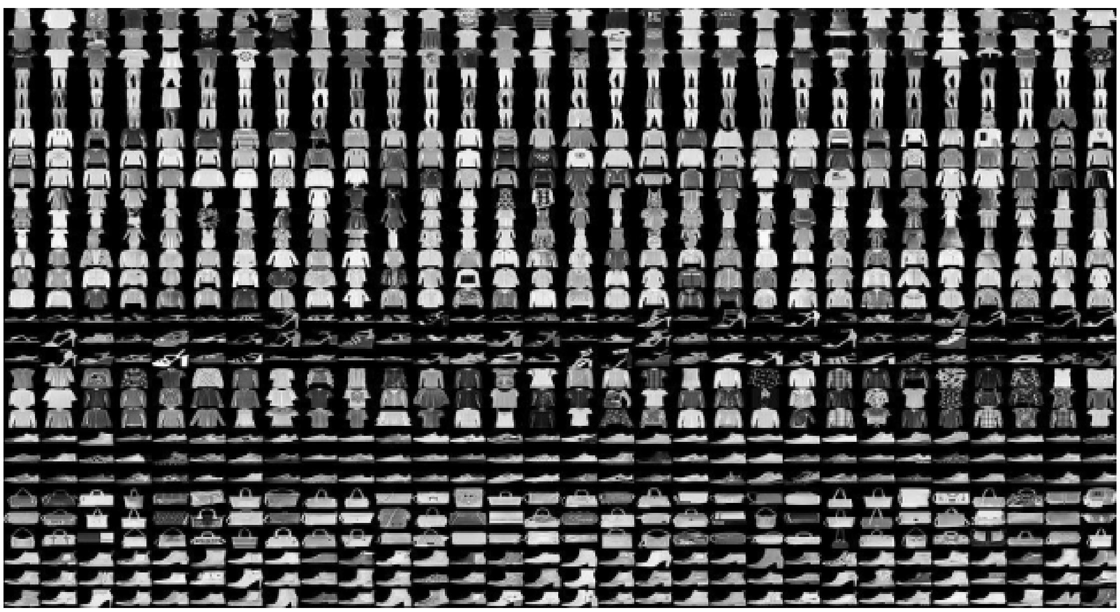
Shirts

Sneakers

Bags

Ankle boots

- The images were obtained from Zalando's online store and are preprocessed to be normalized and centered. The training set contains 60,000 images, while the test set contains 10,000 images. The goal of the dataset is to accurately classify the images into their respective categories.
- The MNIST Fashion dataset is often used as a benchmark for testing image classification algorithms, and it is considered a more challenging version of the original MNIST dataset which contains handwritten digits. The dataset is widely used in the machine learning community for research and educational purposes.



- Here are the general steps to perform Convolutional Neural Network (CNN) on the MNIST Fashion dataset:
    - ➢ Import the necessary libraries, including TensorFlow, Keras, NumPy, and Matplotlib.
    - ➢ Load the dataset using Keras' built-in function, keras.datasets.fashion_mnist.load_data(). This will provide the training and testing sets, which will be used to train and evaluate the CNN.
    - ➢ Preprocess the data by normalizing the pixel values between 0 and 1, and reshaping the images to be of size (28, 28, 1) for compatibility with the CNN.

- Define the CNN architecture, including the number and size of filters, activation functions, and pooling layers. This can vary based on the specific problem being addressed.
- Compile the model by specifying the loss function, optimizer, and evaluation metrics. Common choices include categorical cross-entropy, Adam optimizer, and accuracy metric.
- Train the CNN on the training set using the fit() function, specifying the number of epochs and batch size.
- Evaluate the performance of the model on the testing set using the evaluate() function. This will provide metrics such as accuracy and loss on the test set.
- Use the trained model to make predictions on new images, if desired, using the predict() function.

- **Explanation of Code**

import tensorflow as tf

import matplotlib.pyplot as plt

from tensorflow import keras

import numpy as np

(x_train, y_train), (x_test, y_test) = keras.datasets.fashion_mnist.load_data()

 # There are 10 image classes in this dataset and each class has a mapping corresponding to the following labels:

#0 T-shirt/top

#1 Trouser

#2 pullover

#3 Dress

#4 Coat

#5 sandals

#6 shirt

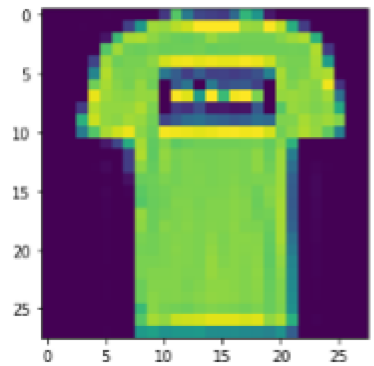
#7 sneaker

#8 bag

#9 ankle boot

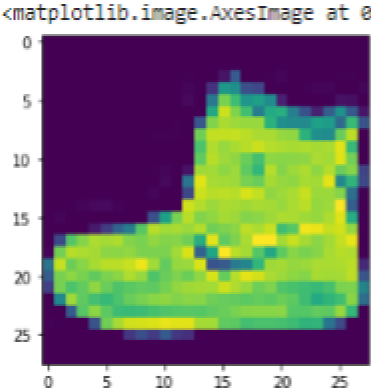
plt.imshow(x_train[1])

<matplotlib.image.AxesImage at 0x7f85874f3a00>



plt.imshow(x_train[0])

<matplotlib.image.AxesImage at 0x7f8584b93d00>



 # Next, we will preprocess the data by scaling the pixel values to be between 0 and 1, and then reshaping the images to be 28x28 pixels.

x_train = x_train.astype('float32') / 255.0

x_test = x_test.astype('float32') / 255.0

x_train = x_train.reshape(-1, 28, 28, 1)

x_test = x_test.reshape(-1, 28, 28, 1)

 # 28, 28 comes from width, height, 1 comes from the number of channels

 # -1 means that the length in that dimension is inferred.

 # This is done based on the constraint that the number of elements in an ndarray or Tensor when reshaped must remain the same. Each image is a row vector (784 elements) and there are lots of such rows (let it be n, so there are 784n elements). So

TensorFlow can infer that -1 is n. converting the training_images array to 4 dimensional array with sizes 60000, 28, 28, 1 for 0th to 3rd dimension.

x_train.shape

(60000, 28, 28)

x_test.shape

(10000, 28, 28, 1)

y_train.shape

(60000,)

y_test.shape

(10000,)

 # We will use a convolutional neural network (CNN) to classify the fashion items.

 # The CNN will consist of multiple convolutional layers followed by max pooling,

 # dropout, and dense layers. Here is the code for the model:

model = keras.Sequential([

keras.layers.Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1)),

 # 32 filters (default), randomly initialized

 # 3*3 is Size of Filter

 # 28,28,1 size of Input Image

 # No zero-padding: every output 2 pixels less in every dimension

 # in Paramter shwon 320 is value of weights: (3x3 filter weights + 32 bias) * 32 filters

 # 32*3*3=288(Total)+32(bias)= 320

keras.layers.MaxPooling2D((2,2)),

 # It shown 13 * 13 size image with 32 channel or filter or depth.

keras.layers.Dropout(0.25),

 # Reduce Overfitting of Training sample drop out 25% Neuron

keras.layers.Conv2D(64, (3,3), activation='relu'),

 # Deeper layers use 64 filters

 # 3*3 is Size of Filter

 # Observe how the input image on 28x28x1 is transformed to a 3x3x64 feature map

 # 13(Size)-3(Filter Size)+1(bias)=11 Size for Width and Height with 64 Depth or filtter or channel

 # in Paramter shwon 18496 is value of weights: (3x3 filter weights + 64 bias) * 64 filters

 # 64*3*3=576+1=577*32 + 32(bias)=18496

keras.layers.MaxPooling2D((2,2)),

 # It shown 5 * 5 size image with 64 channel or filter or depth.

keras.layers.Dropout(0.25),

keras.layers.Conv2D(128, (3,3), activation='relu'),

 # Deeper layers use 128 filters

 # 3*3 is Size of Filter

 # Observe how the input image on 28x28x1 is transformed to a 3x3x128 feature map. It show 5(Size)-3(Filter Size)+1(bias)=3 Size for Width and Height with 64 Depth or filtter or channel.

 # 128*3*3=1152+1=1153*64 + 64(bias)= 73856

 # To classify the images, we still need a Dense and Softmax layer.

 # We need to flatten the 3x3x128 feature map to a vector of size 1152

keras.layers.Flatten(),

keras.layers.Dense(128, activation='relu'),

 # 128 Size of Node in Dense Layer

 # 1152*128 = 147584

keras.layers.Dropout(0.25),

keras.layers.Dense(10, activation='softmax')

 # 10 Size of Node another Dense Layer

 # 128*10+10 bias= 1290

])

model.summary()Layer (type) Output Shape Param #

===

conv2d (Conv2D) (None, 26, 26, 32) 320

max_pooling2d (MaxPooling2D (None, 13, 13, 32) 0

)

dropout (Dropout) (None, 13, 13, 32) 0

conv2d_1 (Conv2D) (None, 11, 11, 64) 18496

max_pooling2d_1 (MaxPooling (None, 5, 5, 64) 0 2D)

dropout_1 (Dropout) (None, 5, 5, 64) 0

conv2d_2 (Conv2D) (None, 3, 3, 128) 73856

flatten (Flatten) (None, 1152) 0

dense (Dense) (None, 128) 147584

dropout_2 (Dropout) (None, 128) 0

dense_1 (Dense) (None, 10) 1290

Total params: 241,546

Trainable params: 241,546

Non-trainable params: 0

 # Compile and Train the Model. After defining the model, we will compile it and train it on the training data.

model.compile(optimizer='adam',loss='sparse_categorical_crossentropy',
metrics=['accuracy'])

history = model.fit(x_train, y_train, epochs=10, validation_data=(x_test, y_test))

 # 1875 is a number of batches. By default batches contain 32 samles.60000 / 32 = 1875. Finally, we will evaluate the performance of the model on the test data.

test_loss, test_acc = model.evaluate(x_test, y_test)

print('Test accuracy:', test_acc)

313/313 [==============================] - 3s 10ms/step - loss: 0.2606 - accuracy: 0.9031

Test accuracy: 0.9031000137329102

==

Conclusion:- In this way we can Classify fashion clothing into categories using CNN.

==

GROUP – A

Assignment No: 4 (Mini Project)

===

Title:- Implement Gender and Age Detection: predict if a person is a male or female and also their age. Gender and Age Detection on UTKFace dataset

===

Objective:-

-To build a deep neural network model that can recognize Gender and Age Detection on UTKFace dataset.

===

Theory:-

- Collect and prepare the dataset
  - In this case, we can use the "UTKFace" dataset which contains images of faces with their corresponding gender and age labels. We need to preprocess the data, like resizing the images to a uniform size, shuffling the dataset, and limit the age to a certain value (like 100 years).
  - Split the dataset: Split the dataset into training, validation, and testing sets. The usual split ratio is 80%, 10% and 10%, respectively.

- Define data generators
  - Define data generators for training, validation, and testing sets using the "ImageDataGenerator" class in Keras. This class provides data augmentation techniques that can improve the model's performance, such as rotation, zoom, and horizontal flip.
  - Define the neural network model: Define a convolutional neural network (CNN) model that takes the face images as input and outputs two values - the probability of being male and the predicted age.
  - The model can have multiple convolutional and pooling layers followed by some dense layers.
- Compile the model
  - Compile the model with appropriate loss and metrics for each output (gender and age).
  - In this case, we can use binary cross-entropy loss for gender and mean squared error (MSE) for age.
- Train the model

  - Train the model using the fit method of the model object. We need to pass the data generators for the training and validation sets, as well as the number of epochs and batch size.
- Evaluate the model
  - Evaluate the model's performance on the testing set using the evaluate method of the model object. This will give us the accuracy and mean absolute error (MAE) of the model.
  - Predict the gender and age of a sample image: Load a sample image and preprocess it. We can use the "cv2" library to read the image, resize it to the same size as the training images, and normalize it. Then, we can use the "predict" method of the model object to get the predicted gender and age.

- Explanation of Source Code

```
import tensorflow as tf

from tensorflow.keras.models import Sequential

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

from tensorflow.keras.preprocessing.image import ImageDataGenerator

import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import cv2

# Define constants

img_height = 128

img_width = 128

batch_size = 32

epochs = 10

# Load the "UTKFace" dataset

df = pd.read_csv('UTKFace.csv')

df['age'] = df['age'].apply(lambda x: min(x, 100)) # limit age to 100

df = df.sample(frac=1).reset_index(drop=True) # shuffle the dataset
```

```
df['image_path'] = 'UTKFace/' + df['image_path']
df_train = df[:int(len(df)*0.8)] # 80% for training
df_val = df[int(len(df)*0.8):int(len(df)*0.9)] # 10% for validation
df_test = df[int(len(df)*0.9):] # 10% for testing
# Define data generators for training, validation, and testing sets
train_datagen = ImageDataGenerator(rescale=1./255)
val_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)
train_generator = train_datagen.flow_from_dataframe(
dataframe=df_train,
x_col='image_path',
y_col=['male', 'age'],
target_size=(img_height, img_width),
batch_size=batch_size,
class_mode='raw')
val_generator = val_datagen.flow_from_dataframe(
dataframe=df_val,
x_col='image_path',
y_col=['male', 'age'],
target_size=(img_height, img_width),
batch_size=batch_size,
class_mode='raw')
test_generator = test_datagen.flow_from_dataframe(
dataframe=df_test,
x_col='image_path',
```

y_col=['male', 'age'],

target_size=(img_height, img_width),

batch_size=batch_size,

class_mode='raw')

 # Define the neural network model

model = Sequential([

Conv2D(32, (3,3), activation='relu', input_shape=(img_height, img_width, 3)),

MaxPooling2D((2,2)),

Conv2D(64, (3,3), activation='relu'),

MaxPooling2D((2,2)),

Conv2D(128, (3,3), activation='relu'),

MaxPooling2D((2,2)),

Conv2D(128, (3,3), activation='relu'),

MaxPooling2D((2,2)),

Flatten(),

Dropout(0.5),

Dense(512, activation='relu'),

Dense(2)

])

 # Compile the model

model.compile(optimizer='adam',

loss={'dense_1': 'binary_crossentropy', 'dense_2': 'mse'},

metrics={'dense_1': 'accuracy', 'dense_2': 'mae'})

Train the model

history = model.fit(train_generator

```
epochs=epochs,
validation_data=val_generator)
# Evaluate the model on the test set
loss, accuracy, mae = model.evaluate(test_generator)
print("Test accuracy:", accuracy)
print("Test MAE:", mae)
# Predict the gender and age of a sample image
img = cv2.imread('sample_image.jpg')
img
```

==

Conclusion:- In this way Gender Age Detection Implemented.

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