Write-up	Correctness of Program	Documentation of Program	Viva	Timely Completion	Total	Dated Sign of Subject Teacher
4	4	4	4	4	20	

Expected Date of Completion:..... Actual Date of Completion:.....

Group B

Assignment No : 8

Title of the Assignment: Classify the email using the binary classification method. Email Spam detection has two states:
a) Normal State – Not Spam,
b) Abnormal State – Spam.
Use K-Nearest Neighbors and Support Vector Machine for classification. Analyze their performance.

Dataset Description: The csv file contains 5172 rows, each row for each email. There are 3002 columns. The first column indicates Email name. The name has been set with numbers and not recipients' name to protect privacy. The last column has the labels for prediction : 1for spam, 0 for not spam. The remaining 3000 columns are the 3000 most common words inall the emails, after excluding the non-alphabetical characters/words. For each row, thecount of each word(column) in that email(row) is stored in the respective cells. Thus,information regarding all 5172 emails are stored in a compact dataframe rather than asseparate text files.

Link:https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv

Objective of the Assignment:

Students should be able to classify email using the binary Classification and implement email spam detection technique by using K-Nearest Neighbors and Support Vector Machine algorithm.

Prerequisite:

1. Basic knowledge of Python

2. Concept of K-Nearest Neighbors and Support Vector Machine for classification.

Contents of the Theory:

1. Data Preprocessing
2. Binary Classification
3. K-Nearest Neighbours
4. Support Vector Machine
5. Train, Test and Split Procedure

Data Preprocessing:

Data preprocessing is a process of preparing the raw data and making it suitable for amachine learning model. It is the first and crucial step while creating a machine learning model.

When creating a machine learning project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean itand put in a formatted way. So for this, we use data preprocessing task.

Why do we need Data Preprocessing?

A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly used for machine learning models. Data preprocessing is required tasks for cleaning thedata and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model.

It involves below steps:

- Getting the dataset
- Importing libraries
- Importing datasets
- Finding Missing Data
- Encoding Categorical Data
- Splitting dataset into training and test set
- Feature scaling

Code :- https://www.kaggle.com/code/mfaisalqureshi/email-spam-detection-98-accuracy/notebook

Group B

Assignment No : 9

Title of the Assignment: Given a bank customer, build a neural network-based classifier that can determine whether they will leave or not in the next 6 months

Dataset Description: The case study is from an open-source dataset from Kaggle. The dataset contains 10,000 sample points with 14 distinct features such as CustomerId, CreditScore, Geography, Gender, Age, Tenure, Balance, etc.

Link for Dataset:https://www.kaggle.com/barelydedicated/bank-customer-churn-modeling

Perform the following steps:

1. Read the dataset.
2. Distinguish the feature and target set and divide the data set into training and test sets.
3. Normalize the train and test data.
4. Initialize and build the model. Identify the points of improvement and implement the same.
5. Print the accuracy score and confusion matrix (5 points).

Objective of the Assignment:

Students should be able to distinguish the feature and target set and divide the data set into training and test sets and normalize them and students should build the model on the basis of that.

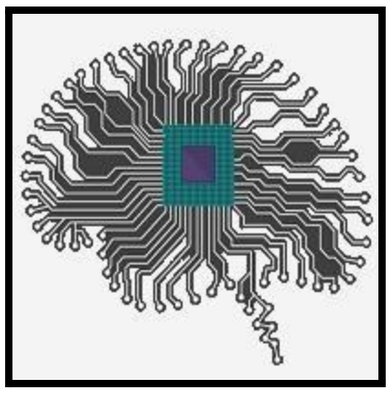
Prerequisite:

1. Basic knowledge of Python
2. Concept of Confusion Matrix

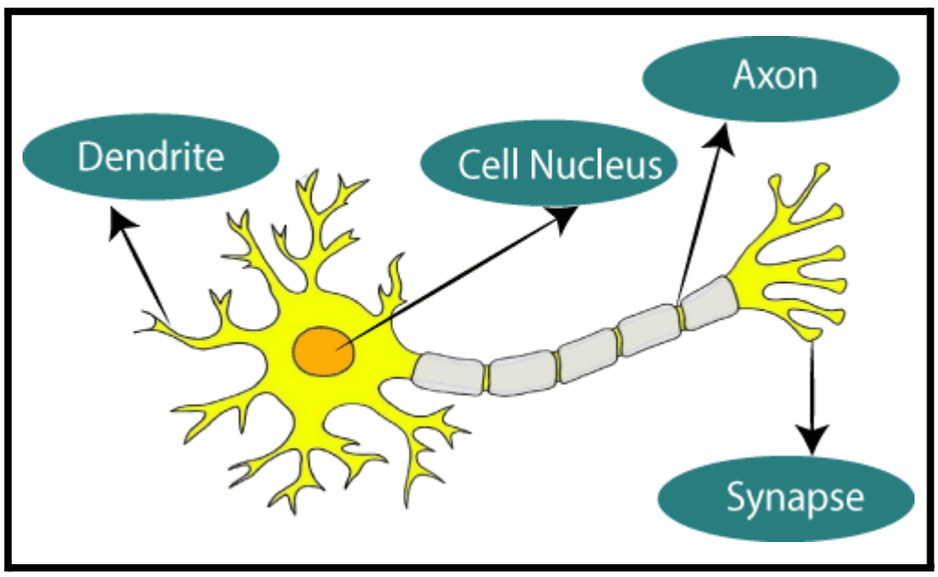
Contents of the Theory:

1. Artificial Neural Network
2. Keras
3. tensorflow
4. Normalization
5. Confusion Matrix

Artificial Neural Network:

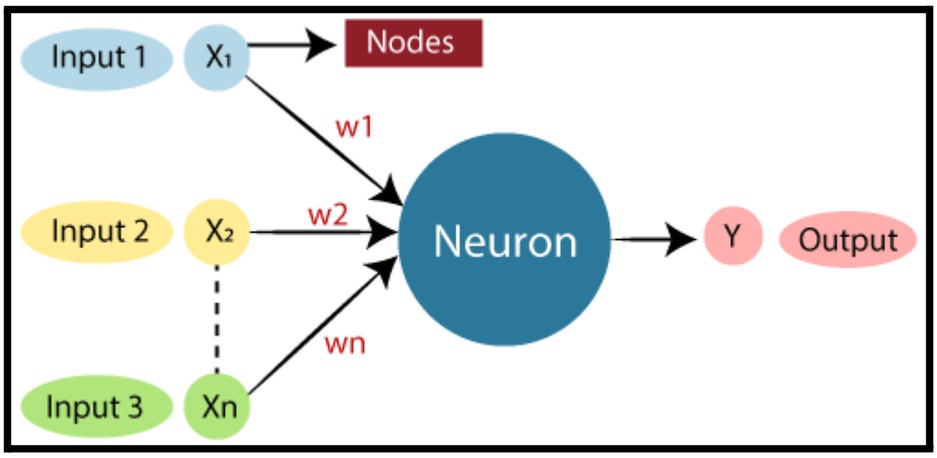


The term "Arti cial Neural Network" is derived from Biological neural networks that develop the structure of a human brain. Similar to the human brain that has neurons interconnected to one another, arti cial neural networks also have neurons that are interconnected to one another in various layers of thenetworks. These neurons are known as nodes.



The given gure illustrates the typical diagram of Biological Neural Network.

The typical Arti cial Neural Network looks something like the given gure.



Dendrites from Biological Neural Network represent inputs in Arti cial Neural Networks, cellnucleus represents Nodes, synapse represents Weights, and Axon represents Output.

Relationship between Biological neural network and arti cial neural network:

Biological Neural Network	**Artificial Neural Network**
Dendrites	Inputs
Cell nucleus	Nodes
Synapse	Weights
Axon	Output

An**Arti cial Neural Network**in the eld of**Arti cial intelligence**where it attempts to mimic the network of neurons makes up a human brain so that computers will have an option tounderstand things and make decisions in a human-like manner. The arti cial neural networkis designed by programming computers to behave simply like interconnected brain cells.

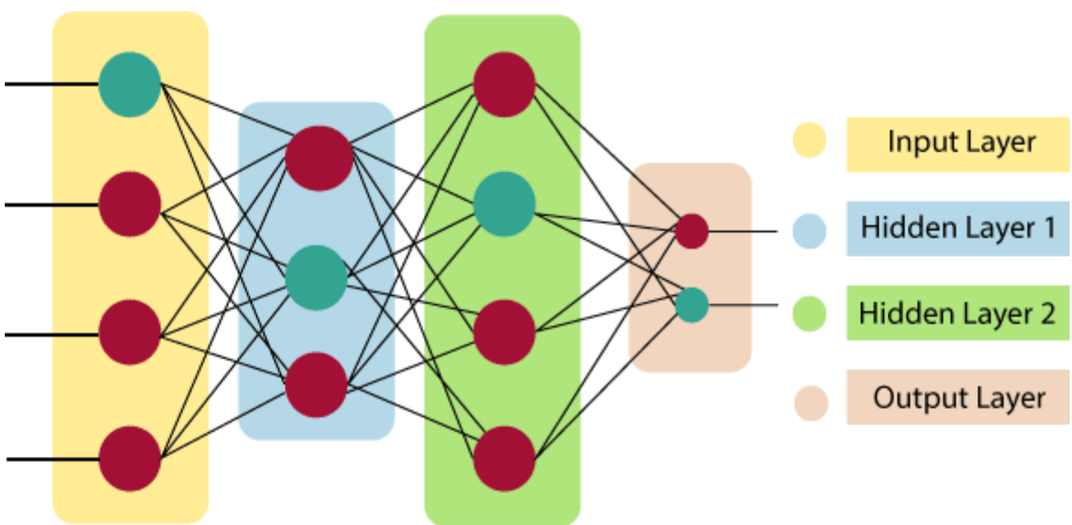
There are around 1000 billion neurons in the human brain. Each neuron has an association point somewhere in the range of 1,000 and 100,000. In the human brain, data is stored in such a manner as to be distributed, and we can extract more than one piece of this data when necessary from our memory parallelly. We can say that the human brain is made up ofincredibly amazing parallel processors.

We can understand the artificial neural network with an example, consider an example of adigital logic gate that takes an input and gives an output. "OR" gate, which takes two inputs. If one or both the inputs are "On," then we get "On" in output. If both the inputs are "Off," thenwe get "Off" in output. Here the output depends upon input. Our brain does not perform the same task. The outputs to inputs relationship keep changing because of the neurons in our brain, which are "learning."

The architecture of an artificial neural network:

To understand the concept of the architecture of an artificial neural network, we have to understand what a neural network consists of. In order to define a neural network that consists of a large number of artificial neurons, which are termed units arranged in a sequence of layers. Lets us look at various types of layers available in an artificial neural network.

Artificial Neural Network primarily consists of three layers:



Input Layer:

As the name suggests, it accepts inputs in several different formats provided by the programmer.

Hidden Layer:

The hidden layer presents in-between input and output layers. It performs all the calculationsto nd hidden features and patterns.

Output Layer:

The input goes through a series of transformations using the hidden layer, which nally results in output that is conveyed using this layer.

The arti cial neural network takes input and computes the weighted sum of the inputs andincludes a bias. This computation is represented in the form of a transfer function.

$$\sum_{i=1}^{n} Wi * Xi + b$$

It determines weighted total is passed as an input to an activation function to produce the output. Activation functions choose whether a node should re or not. Only those who are red make it to the output layer. There are distinctive activation functions available that canbe applied upon the sort of task we are performing.

Keras:

Keras is an open-source high-level Neural Network library, which is written in Python is capable enough to run on Theano, TensorFlow, or CNTK. It was developed by one of the Google engineers, Francois Chollet. It is made user-friendly, extensible, and modular for facilitating faster experimentation with deep neural networks. It not only supports Convolutional Networks and Recurrent Networks individually but also their combination.

It cannot handle low-level computations, so it makes use of the**Backend**library to resolve it.The backend library act as a high-level API wrapper for the low-level API, which lets it run onTensorFlow, CNTK, or Theano.

Initially, it had over 4800 contributors during its launch, which now has gone up to 250,000 developers. It has a 2X growth ever since every year it has grown. Big companies like Microsoft, Google, NVIDIA, and Amazon have actively contributed to the development of Keras. It has an amazing industry interaction, and it is used in the development of popular rms likes Net ix, Uber, Google, Expedia, etc.

Tensor□ow:

TensorFlow is a Google product, which is one of the most famous deep learning tools widelyused in the research area of machine learning and deep neural network. It came into the market on 9th November 2015 under the Apache License 2.0. It is built in such a way that it can easily run on multiple CPUs and GPUs as well as on mobile operating systems. It consists of various wrappers in distinct languages such asJava, C++, or Python.

Normalization:

Normalization is a scaling technique in Machine Learning applied during data preparation tochange the values of numeric columns in the dataset to use a common scale. It is not necessary for all datasets in a model. It is required only when features of machine learning models have different ranges.

Mathematically, we can calculate normalization with the below formula:Xn = (X -

Xminimum) / (Xmaximum - Xminimum)

Where,

- Xn = Value of Normalization
- Xmaximum = Maximum value of a feature
- Xminimum = Minimum value of a feature

Example: Let's assume we have a model dataset having maximum and minimum values of feature as mentioned above. To normalize the machine learning model, values are shiftedand rescaled so their range can vary between 0 and 1. This technique is also known asMin-Max scaling. In this scaling technique, we will change the feature values as follows:

Case1-If the value of X is minimum, the value of Numerator will be 0; hence Normalizationwill also be 0.

Xn = (X - Xminimum) / (Xmaximum - Xminimum) ---------- formula

Put X =Xminimum in above formula, we get;

Xn = Xminimum- Xminimum/ (Xmaximum - Xminimum)Xn = 0

Case2-If the value of X is maximum, then the value of the numerator is equal to the denominator; hence Normalization will be 1.

Xn = (X - Xminimum) / (Xmaximum - Xminimum)Put X

=Xmaximum in above formula, we get;

Xn = Xmaximum - Xminimum/ (Xmaximum - Xminimum)Xn = 1

Case3-On the other hand, if the value of X is neither maximum nor minimum, then values of normalization will also be between 0 and 1.

Hence, Normalization can be de nēd as a scaling method where values are shifted and rescaled to maintain their ranges between 0 and 1, or in other words; it can be referred to as Min-Max scaling technique.

Normalization techniques in Machine Learning

Although there are so many feature normalization techniques in Machine Learning, few of them are most frequently used. These are as follows:

- **Min-Max Scaling:**This technique is also referred to as scaling. As we have already discussed above, the Min-Max scaling method helps the dataset to shift and rescalethe values of their attributes, so they end up ranging between 0 and 1.
- **Standardization scaling:**

Standardization scaling is also known as**Z-score**normalization, in which values are centered around the mean with a unit standard deviation, which means the attributebecomes zero and the resultant distribution has a unit standard deviation. Mathematically,we can calculate the standardization by subtracting the feature value from the mean anddividing it by standard deviation.

Hence, standardization can be expressed as follows:

$$X' = \frac{X - \mu}{\sigma}$$

Here,**μ**represents the mean of feature value, and**σ**represents the standard deviation offeature values.

However, unlike Min-Max scaling technique, feature values are not restricted to a speci□crange in the standardization technique.

This technique is helpful for various machine learning algorithms that use distance measures such as**KNN, K-means clustering, and Principal component analysis**, etc. Further,it is also important that themodel is built on assumptions and data is normally distributed.

When to use Normalization or Standardization?

Which is suitable for our machine learning model, Normalization or Standardization? This is probably a big confusion among all data scientists as well as machine learning engineers. Although both terms have the almost same meaning choice of using normalization or standardization will depend on your problem and the algorithm you are using in models.

1. Normalization is a transformation technique that helps to improve the performance as well as the accuracy of your model better. Normalization of a machine learning model is useful when you don't know feature distribution exactly. In other words, the feature distribution of data does not follow a**Gaussian**(bell curve) distribution. Normalization must

have an abounding range, so if you have outliers in data, they will be affected by Normalization.

Further, it is also useful for data having variable scaling techniques such as**KNN, arti□cial neural network**s. Hence, you can't use assumptions for the distribution of data.

2. Standardization in the machine learning model is useful when you are exactly aware of the feature distribution of data or, in other words, your data follows a Gaussian distribution. However, this does not have to be necessarily true. Unlike Normalization, Standardization does not necessarily have a bounding range, so if you have outliers in your data, they will notbe affected by Standardization.

Further, it is also useful when data has variable dimensions and techniques such as**linear regression, logistic regression, and linear discriminant analysis**.

Example: Let's understand an experiment where we have a dataset having two attributes, i.e., age and salary. Where the age ranges from 0 to 80 years old, and the income varies from 0 to 75,000 dollars or more. Income is assumed to be 1,000 times that of age. As a result, the ranges of these two attributes are much different from one another.

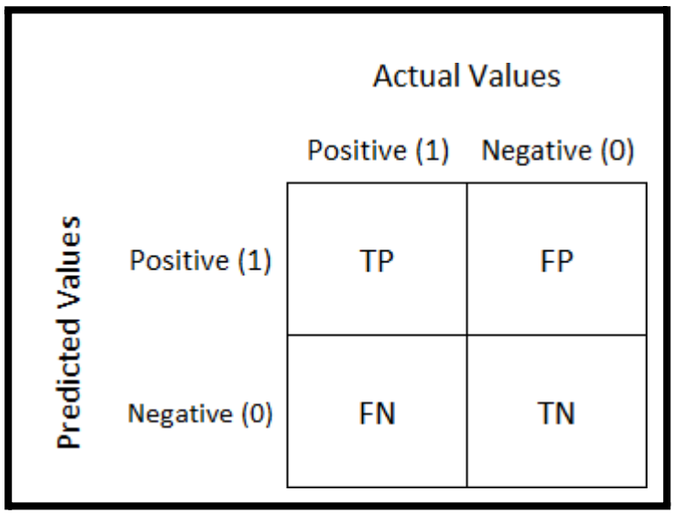
Because of its bigger value, the attributed income will organically in uēnce the conclusion more when we undertake further analysis, such as multivariate linear regression. However, this does not necessarily imply that it is a better predictor. As a result, we normalize the dataso that all of the variables are in the same range.

Further, it is also helpful for the prediction of credit risk scores where normalization isapplied to all numeric data except the class column. It uses the**tanh transformation** technique, which converts all numeric features into values of range between 0 to 1.

Confusion Matrix:

The confusion matrix is a matrix used to determine the performance of the classi catiōn models for a given set of test data. It can only be determined if the true values for test data are known. The matrix itselfcan be easily understood, but the related terminologies may beconfusing. Since it shows the errors in the model performance in the form of a matrix, hence also known as an**error matrix**. Some features of Confusion matrix are given below:

- For the 2 prediction classes of classi ērs, the matrix is of 2*2 table, for 3 classes, it is3*3 table, and so on.
- The matrix is divided into two dimensions, that are**predicted values**and**actual values**along with the total number of predictions.
- Predicted values are those values, which are predicted by the model, and actualvalues are the true values for the given observations.
- It looks like the below table:



The above table has the following cases:

- **True Negative:**Model has given prediction No, and the real or actual value was alsoNo.
- **True Positive:**The model has predicted yes, and the actual value was also true.
- **False Negative:**The model has predicted no, but the actual value was Yes, it is alsocalled as**Type-II error**.
- **False Positive:**The model has predicted Yes, but the actual value was No. It is alsocalled a**Type-I error.**

Need for Confusion Matrix in Machine learning

- It evaluates the performance of the classi cation models, when they makepredictions on test data, and tells how good our classi cation model is.
- It not only tells the error made by the classi ers but also the type of errors such as itis either type-I or type-II error.
- With the help of the confusion matrix, we can calculate the different parameters forthe model, such as accuracy, precision, etc.

Example: We can understand the confusion matrix using an example.

Suppose we are trying to create a model that can predict the result for the disease that iseither a person has that disease or not. So, the confusion matrix for this is given as:

n = 100	Actual: No	Actual: Yes	
Predicted: No	TN: 65	FP: 3	68
Predicted: Yes	FN: 8	TP: 24	32
	73	27	

From the above example, we can conclude that:

- The table is given for the two-class classifier, which has two predictions "Yes" and "NO." Here, Yes defines that patient has the disease, and No defines that patient doesnot has that disease.
- The classifier has made a total of **100 predictions**. Out of 100 predictions, **89 are true predictions**, and **11 are incorrect predictions**.
- The model has given prediction "yes" for 32 times, and "No" for 68 times. Whereas theactual "Yes" was 27, and actual "No" was 73 times.

Calculations using Confusion Matrix:

We can perform various calculations for the model, such as the model's accuracy, using thismatrix. These calculations are given below:

- **Classification Accuracy:** It is one of the important parameters to determine the accuracy of the classification problems. It defines how often the model predicts thecorrect output. It can be calculated as the ratio of the number of correct predictionsmade by the classifier to all number of predictions made by the classifiers. The formula is given below:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN}$$

- **Misclassification rate:** It is also termed as Error rate, and it defines how often the model gives the wrong predictions. The value of error rate can be calculated as thenumber of incorrect predictions to all number of the predictions made by the classifier. The formula is given below:

$$\text{Error rate} = \frac{FP+FN}{TP+FP+FN+TN}$$

- **Precision:** It can be defined as the number of correct outputs provided by the model or out of all positive classes that have predicted correctly by the model, how many ofthem were actually true. It can be calculated using the below formula:

$$\text{Precision} = \frac{TP}{TP+FP}$$

- **Recall:** It is defined as the out of total positive classes, how our model predictedcorrectly. The recall must be as high as possible.

$$\text{Recall} = \frac{TP}{TP+FN}$$

- **F-measure:** If two models have low precision and high recall or vice versa, it is difficult to compare these models. So, for this purpose, we can use F-score. This score helps us to evaluate the recall and precision at the same time. The F-score is maximum if the recall is equal to the precision. It can be calculated using the belowformula:

$$\text{F-measure} = \frac{2*Recall*Precision}{Recall+Precision}$$

Other important terms used in Confusion Matrix:

- **Null Error rate:** It defines how often our model would be incorrect if it always predicted the majority class. As per the accuracy paradox, it is said that "*the bestclassifier has a higher error rate than the null error rate.*"

- **ROC Curve:** The ROC is a graph displaying a classifier's performance for all possible thresholds. The graph is plotted between the true positive rate (on the Y-axis) and thefalse Positive rate (on the x-axis).

Code :- https://www.kaggle.com/code/jaysadguru00/starter-bank-customer-churn-modeling-6dbfe05e-a

Conclusion:

In this way we build a a neural network-based classifier that can determine whether they willleave or not in the next 6 months