NEW PRODUCT OFFERINGS IN TELECOMMUNICTAIONS

A MINI PROJECT REPORT

Submitted by

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OBJECTIVE:

The objective of introducing new product offerings in telecommunications can be multi-faceted, including increasing revenue, expanding the customer base, enhancing the brand image, increasing customer retention, and improving profitability. By introducing innovative and attractive products, the company can position itself as a leader in the industry, attract new customers, retain existing ones, and increase profitability by reducing costs and improving efficiency. Overall, the objective for new product offerings in telecommunications is to stay competitive in a rapidly changing market and meet the evolving needs and expectations of customers.

A**BSTRACT:**

To achieve these objectives, companies must identify customer needs and market trends, and develop innovative products that meet these requirements. New product offerings may include hardware, software, or services that enhance communication capabilities, improve connectivity, or provide new features and functionalities to customers. For example, new product offerings in telecommunications may include cloud-based services, artificial intelligence-powered assistants, smart home devices, or high-speed internet connectivity.

Introducing new products in telecommunications can help companies to stay competitive in a rapidly changing market. By offering innovative and attractive new products, companies can differentiate themselves from their competitors and attract new customers. Moreover, introducing new products can help to retain existing customers by offering them new and exciting features and services.

The objective of new product offerings in telecommunications also extends to enhancing brand image and improving profitability. By introducing innovative and attractive products, companies can position themselves as leaders in the industry and enhance their brand image and reputation. This can translate into increased customer loyalty, improved customer satisfaction, and ultimately, increased profitability.

Finally, new product offerings in telecommunications can also lead to cost reduction and improved efficiency. By introducing new technologies and processes, companies can streamline operations, reduce overheads, and improve productivity, leading to increased profitability in the long run.

In conclusion, new product offerings in telecommunications are critical for companies to stay competitive and meet the changing needs and expectations of customers. The objective of new product offerings is multi-faceted, including increasing revenue, expanding the customer base, enhancing brand image, increasing customer retention, and improving profitability. Through innovative and attractive products, companies can differentiate themselves from their competitors, improve customer satisfaction and loyalty, and ultimately, achieve long-term success in the telecommunications industry.

LITREATURE SURVEY:

S.NO	Author’s Name and Title of Paper	Algorithm Used	Dataset Used	Performance measures	Scope for future measures
1	"A Deep Learning Approach for Predicting Customer Preferences in Telecommunications" by Yashar Ghiyasvand and Shima Mohebbi.	Deep Learning.	Customer preferences data	Accuracy.	Investigating the impact of customer preferences on new product development.
2	"An Empirical Investigation of Factors Influencing Innovation Performance in Telecommunications Companies" by Alireza Nili and Neda Lotfi.	Regression analysis.	Survey data from telecommunications companies.	Innovation performance	Developing a framework for effective innovation management in the telecommunications industry.
3	"Designing Innovative New Products with Social Network Analysis and Natural Language Processing" by Mahdi Khalili and Ali Emrouznejad.	Social Network Analysis and Natural Language Processing.	Customer feedback data.	Innovation performance.	Developing a system for automated product development using customer feedback.
4	"Exploring the Impact of Corporate Social Responsibility on Innovation Performance in Telecommunications Companies" by Seyed Ali Akbar Ahmadi and Behrouz Zarei.	Structural Equation Modelling.	Survey data from telecommunications companies.	Innovation performance.	Investigating the relationship between corporate social responsibility and innovation performance in the telecommunications industry.
5	“Innovating for Sustainability in the	Content analysis.	Company reports from	Sustainability performance.	Developing sustainable new

	Telecommunications Industry: An Exploratory Study" by Jaakko Kujala and Miika Virtanen.		telecommunications companies.		product offerings in the telecommunications industry.
6	"Integrating Lean and Agile Product Development in the Telecommunications Industry" by Amirhossein Amirkhizi and Janne Harkonen.	Case study.	Company data from telecommunications companies.	Product development efficiency.	Investigating the impact of lean and agile product development on new product offerings in the telecommunications industry.
7	"New Product Development in the Telecommunications Industry: A Literature Review and Research Agenda" by Saara Lampio and Kerttu Kettunen.	Literature review.	Literature data.	N/A.	Identifying research gaps and future directions for new product development in the telecommunications industry.
8	"Product Innovation in the Telecommunications Industry: A Systematic Literature Review" by Xin Luo and Huayu Zhang.	Systematic literature review.	Literature data.	N/A.	Identifying factors that influence successful product innovation in the telecommunications industry.
9	"Smart Product Development in the Telecommunications Industry: A Conceptual Framework" by Deepak Sethi and Rishi Raj.	Conceptual framework.	N/A.	N/A.	Developing a framework for smart product development in the telecommunications industry.
10	"Towards an Integrated Framework for New Product Development in the Telecommunications Industry" by	Conceptual framework.	N/A.	N/A.	Developing an integrated framework for new product development in the telecommunications industry that

	Francisco J. Martinez-Lopez.				incorporates customer feedback, innovation management, and product design.

EXISTING SYSTEMS:

1. Idea Management Platforms: These platforms are used to collect and manage new product ideas from employees, customers, and partners. Idea management platforms allow telecommunications companies to organize and prioritize ideas, as well as track the progress of each idea from concept to launch.

2. Agile Product Development: Agile methodologies are commonly used in new product development in the telecommunications industry. This approach focuses on flexibility, collaboration, and iteration, allowing teams to quickly adapt to changing market conditions and customer needs.

3. Customer Relationship Management (CRM) Systems: CRM systems are used to collect and manage customer data, including preferences, behaviours, and feedback. This information is critical in developing new products that meet customer needs and preferences.

4. Product Lifecycle Management (PLM) Systems: PLM systems are used to manage the entire lifecycle of a product, from ideation to retirement. PLM systems help telecommunications companies manage the complex processes involved in developing and launching new products.

5. Data Analytics and Business Intelligence Tools: Data analytics and business intelligence tools are used to analyse customer data, market trends, and competitor activities. These tools provide valuable insights that can inform new product development and help telecommunications companies stay ahead of the competition.

6. Voice of Customer (VoC) Tools: VoC tools are used to collect and analyse customer feedback, including surveys, social media comments, and customer support interactions. This feedback is used to inform new product development and improve existing products.

GAP IDENTIFIED:

One gap that has been identified in new product offerings in telecommunications is the lack of integration between product development and marketing strategies. While product development teams are focused on creating new products that meet customer needs, marketing teams are often focused on promoting existing products and may not be involved in the product development process until later stages.

This can lead to a disconnection between the product and the marketing message, resulting in low adoption rates and poor customer satisfaction. To address this gap, there is a need for closer collaboration between product development and marketing teams throughout the entire product development process. This can include involving marketing teams in the ideation phase, conducting market research to inform product development, and aligning marketing messages with the product features and benefits.

Another gap in new product offerings in telecommunications is the lack of focus on sustainability and social responsibility. With increasing consumer demand for environmentally friendly products and ethical business practices, there is a need for telecommunications companies to prioritize sustainability and social responsibility in their new product development. This can include using eco-friendly materials, reducing energy consumption, and supporting social causes through product sales.

PROPOSED METHOD:

We are implementing the 5 most commonly used models (Train Test Split, Label Encoding, Decision Trees, Logistic Regression, and Random Forest). A predictive model is built using Google Colab and various data mining techniques are performed to analyse its performance in terms of different and new product offerings in Telecommunications in comparison to Train Test Split, Label Encoding, Decision Trees, Logistic Regression, and Random Forest.

DATASET LINK AND SAMPLE DATA:

https://docs.google.com/spreadsheets/d/1rcTZS439ti8qpqQg_pqUhUzTGF11nHMq8YwDzVV_srs/edit?usp=share_link

DATA FIELDS:

Customer ID, Gender, Senior Citizen, Partner, Dependents, tenure, Phone Service, Multiple Lines, Internet Service, Online Security, Online Backup, Device Protection, Tech Support, Streaming TV, Streaming Movie, Contract, Paperless Billing, Payment Method, Monthly Charges, Total Charges, Churn.

SAMPLE DATA:

customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes	No	No	No	No	Month-to-month	Yes	Electronic check	29.85	29.85	No
5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	No	Yes	No	No	No	One year	No	Mailed check	56.95	1889.5	No
3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	No	No	No	No	Month-to-month	Yes	Mailed check	53.85	108.15	Yes
7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	No	Yes	Yes	No	No	One year	No	Bank transfer (automatic)	42.3	1840.75	No
9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	No	No	No	No	No	Month-to-month	Yes	Electronic check	70.7	151.65	Yes
9305-CDSKC	Female	0	No	No	8	Yes	Yes	Fiber optic	No	No	Yes	No	Yes	Yes	Month-to-month	Yes	Electronic check	99.65	820.5	Yes

1452-KIOVK	Male	0	No	Yes	22	Yes	Yes	Fiber optic	No	Yes	No	No	Yes	No	Month-to-month	Yes	Credit card (automatic)	89.1	1949.4	No
6713-OKOMC	Female	0	No	No	10	No	No phone service	DSL	Yes	No	No	No	No	No	Month-to-month	No	Mailed check	29.75	301.9	No
7892-POOKP	Female	0	Yes	No	28	Yes	Yes	Fiber optic	No	No	Yes	Yes	Yes	Yes	Month-to-month	Yes	Electronic check	104.8	3046.05	Yes
6388-TABGU	Male	0	No	Yes	62	Yes	No	DSL	Yes	Yes	No	No	No	No	One year	No	Bank transfer (automatic)	56.15	3487.95	No
9763-GRSKD	Male	0	Yes	Yes	13	Yes	No	DSL	Yes	No	No	No	No	No	Month-to-month	Yes	Mailed check	49.95	587.45	No
7469-LKBCI	Male	0	No	No	16	Yes	No	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	No	Credit card (automatic)	18.95	326.8	No
8091-TTVAX	Male	0	Yes	No	58	Yes	Yes	Fiber optic	No	No	Yes	No	Yes	Yes	One year	No	Credit card (automatic)	100.35	5681.1	No

0280-XJGEX	Male	0	No	No	49	Yes	Yes	Fiber optic	No	Yes	Yes	No	Yes	Yes	Month-to-month	Yes	Bank transfer (automatic)	103.7	5036.3	Yes

DATASET DESCRIPTION:

Name	Type	Description
customer ID	Alpha Numeric	Customer ID is a unique identifier assigned to an individual or organization by a business to distinguish them from other customers.
gender	Alphabets	Tells whether the customer is male or female.
Senior Citizen	Alphabets	Senior citizens, also known as older adults or elderly people, are individuals who have reached a certain age and are typically considered to be in the latter stages of their lives.
Partner	Alphabets	In a business context, a partner is a person who co-owns and operates a business with one or more other individuals or companies.
Dependents	Alphabets	Dependents are individuals who rely on someone else for financial support, care, or protection.
Tenure	Numeric	Tenure refers to the status of an employee who has a permanent or long-term contract with their employer, which provides them with job security and certain rights and protections.
Phone Service	Alphabets	Describes whether the customer has subscribed for a phone service or not
Multiple Lines	Alphabets	Describes whether the customer has single phone

		connection or multiple connections.
Internet Service	Alphabets	Describes whether the customer has subscribed for internet service or not.
Online Security	Alphabets	Refers to the measures taken to protect computers, devices, and information from unauthorized access or theft when using the internet.
Online Backup	Alphabets	Online backup, also known as cloud backup, is a service that enables users to store and protect their computer files and data by uploading them to a remote server or data centre over the internet.
Device Protection	Alphabets	Device protection refers to measures taken to safeguard electronic devices such as smartphones, tablets, laptops, and computers against physical damage, theft, and data breaches.
Tech Support	Alphabets	Tech support refers to a range of services provided to individuals or organizations to assist with technical issues related to hardware, software, or electronic devices.
Streaming TV	Alphabets	Streaming TV, also known as internet TV, refers to the distribution of television content over the internet, rather than through traditional cable or satellite TV providers.
Streaming Movies	Alphabets	Streaming movies refers to the distribution of movies over the internet, which allows users to watch movies on-demand without the need to purchase or rent physical copies of the movies.
Contract	Alphabets	A contract is a legally binding agreement between two or more parties that

		outlines the terms and conditions of an exchange or transaction.
Paperless Billing	Alphabets	Also known as electronic billing or e-billing, refers to the practice of sending bills, invoices, and other payment notifications electronically, rather than in paper format.
Payment Method	Alphabets	Payment methods refer to the various ways in which individuals or organizations can pay for goods and services.
Monthly Charges	Numeric	Monthly charges refer to recurring fees or costs that are charged on a regular basis, typically monthly, for a product or service.
Total Charges	Numeric	Total charges refer to the total amount of fees or costs associated with a transaction or purchase.
Churn	Alphabets	Churn, in business, refers to the rate at which customers or subscribers stop using a product or service and move to another competitor.

PROPSED ALGORITHM IN DETAIL:

We are implementing the three most commonly used models (Decision tree, Random Forest, Na Ive bayes, KNN, Gradient boost) to try and get improved performance. A predictive model is built using Google Colab and various data mining techniques are performed to analyse its performance in terms of type of crop prediction in comparison to Decision tree, Random Forest and Gradient boost classifier

The below proposed flowchart for type of crop prediction dataset is an indication of various parameters of data mining pre-processing- namely Data cleaning, Data Transformation, data reduction and ultimately reaching to the models desired by the train test splitting methods.

1. The dataset for new product offerings in telecommunications is collected, which contains various parameters.
2. Data cleaning is performed to remove any inconsistent, incomplete or irrelevant data from the dataset.
3. Data transformation techniques are applied to convert data into a suitable format for analysis, such as normalization, scaling, or encoding categorical variables.

4. Data reduction techniques such as dimensionality reduction, feature selection or clustering are applied to reduce the size and complexity of the dataset.
5. Train-test splitting methods are used to split the dataset into training and testing sets.
6. Data mining algorithms such as regression, classification, or clustering are applied to the training set to develop models for predicting new product offerings.
7. The performance of the models is evaluated using the testing set, and modifications or adjustments are made as necessary.
8. We check in for all missing and null values present in any attributes so as to eliminate the possibility of any ambiguity or wrong outputs. These are dropped if found any null or missing values.
9. Redundancy is minimized once; the dataset is structured and also it helps to make the efficient data for the prediction processing.
10. The target label for new instances is found by the trained classifier so as to identify a suitable

The final models are deployed on the new product offerings dataset to generate predictions and insights for decision-making.

EXPERIMENTAL RESULTS:

```
[ ] from google.colab import drive
```

```
[ ] drive.mount('/content/gdrive')

    Mounted at /content/gdrive
```

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.tree import DecisionTreeClassifier
from sklearn import preprocessing
from sklearn.datasets import make_classification
from sklearn.linear_model import LogisticRegression
from sklearn.datasets import load_digits
digits=load_digits()
```

```
[ ] Data = pd.read_csv(r'/content/gdrive/My Drive/abcd.csv')
```

```
[ ] Data.head()
```

```
Data.head()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecur:
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	

5 rows × 21 columns

```
Data.isnull()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSe
0	False	False	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	...	...	
7038	False	False	False	False	False	False	False	False	False	
7039	False	False	False	False	False	False	False	False	False	
7040	False	False	False	False	False	False	False	False	False	
7041	False	False	False	False	False	False	False	False	False	
7042	False	False	False	False	False	False	False	False	False	

7043 rows × 21 columns

```
Data['Churn'].value_counts()
```

```
0    5174
1    1869
Name: Churn, dtype: int64
```

```
Data.groupby('Churn').mean()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	Onl
Churn										
0	0.893893	0.507344	0.128721	0.528218	0.344801	37.569965	0.901044	0.918825	0.893893	
1	0.814874	0.497592	0.254682	0.357945	0.174425	17.979133	0.909042	1.000535	0.814874	

```
X = Data.drop(columns = 'Churn', axis=1)
Y = Data['Churn']
```

```
print(X)
```

```
print(X)
```

```
      customerID  gender  SeniorCitizen  Partner  Dependents  tenure  \
0              0       0              0        1           0       1
1              0       1              0        0           0      34
2              0       1              0        0           0       2
3              0       1              0        0           0      45
4              1       0              0        0           0       2
...          ...     ...            ...      ...         ...     ...
7038           0       1              0        1           1      24
7039           1       0              0        1           1      72
7040           0       0              0        1           1      11
7041           1       1              1        1           0       4
7042           1       1              0        0           0      66

      PhoneService  MultipleLines  InternetService  OnlineSecurity  \
0                0              1                0               0
1                1              0                0               2
2                1              0                0               2
3                0              1                0               2
4                1              0                1               0
...            ...            ...              ...             ...
7038             1              2                0               2
7039             1              2                1               0
7040             0              1                0               2
7041             1              2                1               0
7042             1              0                1               2

      OnlineBackup  DeviceProtection  TechSupport  StreamingTV  \
```

```
scaler = StandardScaler()
```

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=2)
```

```
print(X.shape, X_train.shape, X_test.shape)
```

```
(7043, 20) (5634, 20) (1409, 20)
```

```
print(Y.shape, Y_train.shape, Y_test.shape)
```

```
(7043,) (5634,) (1409,)
```

```
Data['InternetService'].unique()
```

```
array([0, 1, 2])
```

```
label_encoder = preprocessing.LabelEncoder()
```

```
Data['InternetService']= label_encoder.fit_transform(Data['InternetService'])
```

```
Data['InternetService'].unique()
```

```
array([0, 1, 2])
```

```
Data['Dependents']= label_encoder.fit_transform(Data['Dependents'])
```

```
Data['Dependents'].unique()
```

```
array([0, 1])
```

```
Data['PhoneService'].unique()
```

```
array(['No', 'Yes'], dtype=object)
```

```
Data['PhoneService']= label_encoder.fit_transform(Data['PhoneService'])
```

```
Data['PhoneService'].unique()
```

```
array([0, 1])
```

```
Data['MultipleLines'].unique()
```

```
array(['No phone service', 'No', 'Yes'], dtype=object)
```

```
Data['MultipleLines']= label_encoder.fit_transform(Data['MultipleLines'])
```

```
Data['TotalCharges'].unique()
```

```
array([2505, 1466,  157, ..., 2994, 2660, 5407])
```

```
Classifier = DecisionTreeClassifier(criterion='entropy')
```

```
Classifier.fit(X_train, Y_train)
```

```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy')
```

```
Y_predict=Classifier.predict(X_test)
```

```
Classifier.score(X_test, Y_test)
```

```
0.7274662881476224
```

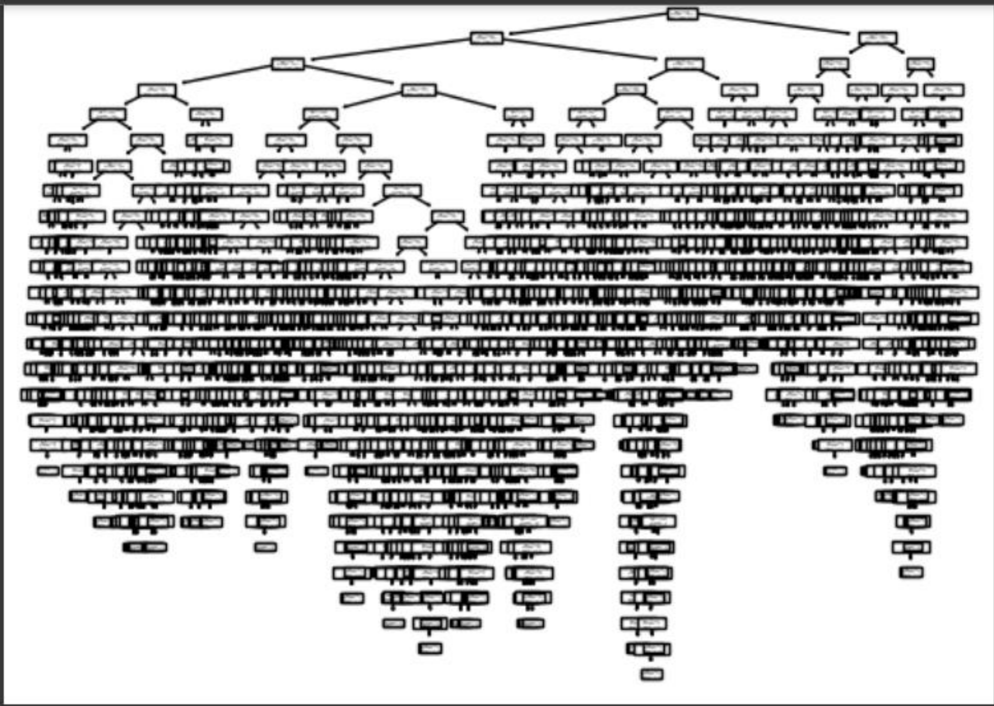
```
accuracy_score(Y_test, Y_predict)*100
```

```
72.60468417317246
```

```
tree.plot_tree(dtree, feature_names=feat)
```

```
[Text(0.6978878495982795, 0.9814814814814815, 'Contract <= 0.5\ngini = 0.39\nsamples = 7043\nvalue = [1869, 5174]'),
 Text(0.4856979978864817, 0.9444444444444444, 'OnlineSecurity <= 0.5\ngini = 0.489\nsamples = 3875\nvalue = [1655,
2220]'),
 Text(0.2703969744363012, 0.9074074074074074, 'InternetService <= 0.5\ngini = 0.5\nsamples = 2631\nvalue = [1343,
1288]'),
 Text(0.1280533853328009, 0.8703703703703703, 'MonthlyCharges <= 467.5\ngini = 0.463\nsamples = 857\nvalue = [312,
545]'),
 Text(0.07452514524211312, 0.8333333333333334, 'TotalCharges <= 1506.0\ngini = 0.484\nsamples = 667\nvalue = [273,
394]'),
 Text(0.03198546934779528, 0.7962962962962963, 'MonthlyCharges <= 458.0\ngini = 0.399\nsamples = 149\nvalue = [41,
108]'),
 Text(0.026871401151631478, 0.7592592592592593, 'TechSupport <= 1.0\ngini = 0.38\nsamples = 141\nvalue = [36, 105]'),
 Text(0.020765435597521545, 0.7222222222222222, 'SeniorCitizen <= 0.5\ngini = 0.427\nsamples = 107\nvalue = [33, 74]'),
 Text(0.014324543662806425, 0.6851851851851852, 'Partner <= 0.5\ngini = 0.381\nsamples = 86\nvalue = [22, 64]'),
 Text(0.009687101469811539, 0.6481481481481481, 'TotalCharges <= 115.5\ngini = 0.425\nsamples = 62\nvalue = [19, 43]'),
 Text(0.008862667302168004, 0.6111111111111112, 'gini = 0.0\nsamples = 6\nvalue = [0, 6]'),
 Text(0.010511535637455076, 0.6111111111111112, 'TotalCharges <= 1460.5\ngini = 0.448\nsamples = 56\nvalue = [19, 37]'),
 Text(0.009687101469811539, 0.5740740740740741, 'MonthlyCharges <= 386.0\ngini = 0.468\nsamples = 51\nvalue = [19, 32]'),
 Text(0.006183256257326515, 0.5370370370370371, 'MonthlyCharges <= 296.5\ngini = 0.426\nsamples = 39\nvalue = [12, 27]'),
 Text(0.004122170838217676, 0.5, 'TotalCharges <= 557.0\ngini = 0.497\nsamples = 13\nvalue = [7, 6]'),
 Text(0.0024733025029306057, 0.46296296296296297, 'TotalCharges <= 255.0\ngini = 0.278\nsamples = 6\nvalue = [5, 1]'),
 Text(0.0016488683352870706, 0.42592592592592593, 'MonthlyCharges <= 189.5\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
 Text(0.0008244341676435353, 0.3888888888888889, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
```

+ Code + Text



```
log_reg = LogisticRegression()
log_reg.fit(X_train, Y_train)
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
▾ LogisticRegression
LogisticRegression()
```

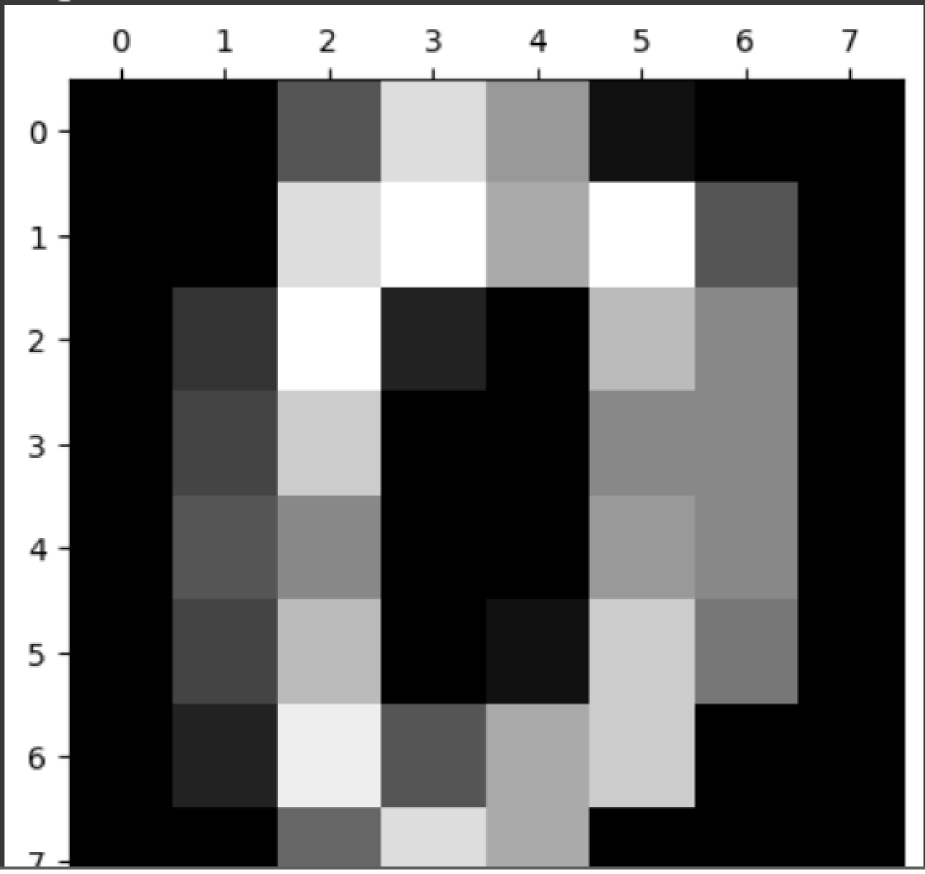
```
[ ] Y_pred = log_reg.predict(X_test)
```

```
[ ] confusion_matrix(Y_test, Y_pred)
```

```
array([[955, 106],
       [176, 172]])
```

```
%matplotlib inline
import matplotlib.pyplot as plt
plt.gray()
for i in range(4):
  plt.matshow(digits.images[i])
```

```
<Figure size 640x480 with 0 Axes>
```




```
[ ]  digits.data[:5]
```

```
array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.,  0.,  0., 13., 15., 10.,
        15.,  5.,  0.,  0.,  3., 15.,  2.,  0., 11.,  8.,  0.,  0.,  4.,
        12.,  0.,  0.,  8.,  8.,  0.,  0.,  5.,  8.,  0.,  0.,  9.,  8.,
         0.,  0.,  4., 11.,  0.,  1., 12.,  7.,  0.,  0.,  2., 14.,  5.,
        10., 12.,  0.,  0.,  0.,  0.,  6., 13., 10.,  0.,  0.,  0.],
       [ 0.,  0.,  0., 12., 13.,  5.,  0.,  0.,  0.,  0.,  0., 11., 16.,
         9.,  0.,  0.,  0.,  0.,  3., 15., 16.,  6.,  0.,  0.,  0.,  7.,
        15., 16., 16.,  2.,  0.,  0.,  0.,  0.,  1., 16., 16.,  3.,  0.,
         0.,  0.,  0.,  1., 16., 16.,  6.,  0.,  0.,  0.,  0.,  1., 16.,
        16.,  6.,  0.,  0.,  0.,  0.,  0., 11., 16., 10.,  0.,  0.],
       [ 0.,  0.,  0.,  4., 15., 12.,  0.,  0.,  0.,  0.,  3., 16., 15.,
        14.,  0.,  0.,  0.,  0.,  8., 13.,  8., 16.,  0.,  0.,  0.,  0.,
         1.,  6., 15., 11.,  0.,  0.,  0.,  1.,  8., 13., 15.,  1.,  0.,
         0.,  0.,  9., 16., 16.,  5.,  0.,  0.,  0.,  0.,  3., 13., 16.,
        16., 11.,  5.,  0.,  0.,  0.,  0.,  3., 11., 16.,  9.,  0.],
       [ 0.,  0.,  7., 15., 13.,  1.,  0.,  0.,  0.,  8., 13.,  6., 15.,
         4.,  0.,  0.,  0.,  2.,  1., 13., 13.,  0.,  0.,  0.,  0.,  0.,
         2., 15., 11.,  1.,  0.,  0.,  0.,  0.,  0.,  1., 12., 12.,  1.,
         0.,  0.,  0.,  0.,  0.,  1., 10.,  8.,  0.,  0.,  0.,  8.,  4.,
         5., 14.,  9.,  0.,  0.,  0.,  7., 13., 13.,  9.,  0.,  0.],
       [ 0.,  0.,  0.,  1., 11.,  0.,  0.,  0.,  0.,  0.,  0.,  7.,  8.,
         0.,  0.,  0.,  0.,  0.,  1., 13.,  6.,  2.,  2.,  0.,  0.,  0.,
         7., 15.,  0.,  9.,  8.,  0.,  0.,  5., 16., 10.,  0., 16.,  6.,
         0.,  0.,  4., 15., 16., 13., 16.,  1.,  0.,  0.,  0.,  0.,  3.,
        15., 10.,  0.,  0.,  0.,  0.,  0.,  2., 16.,  4.,  0.,  0.]])
```

```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
model.fit(X_train,Y_train)
```

```
RandomForestClassifier
RandomForestClassifier()
```

```
model.score(X_test, Y_test)
```

```
0.7984386089425124
```

```
model = RandomForestClassifier(n_estimators=40)
model.fit(X_train,Y_train)
```

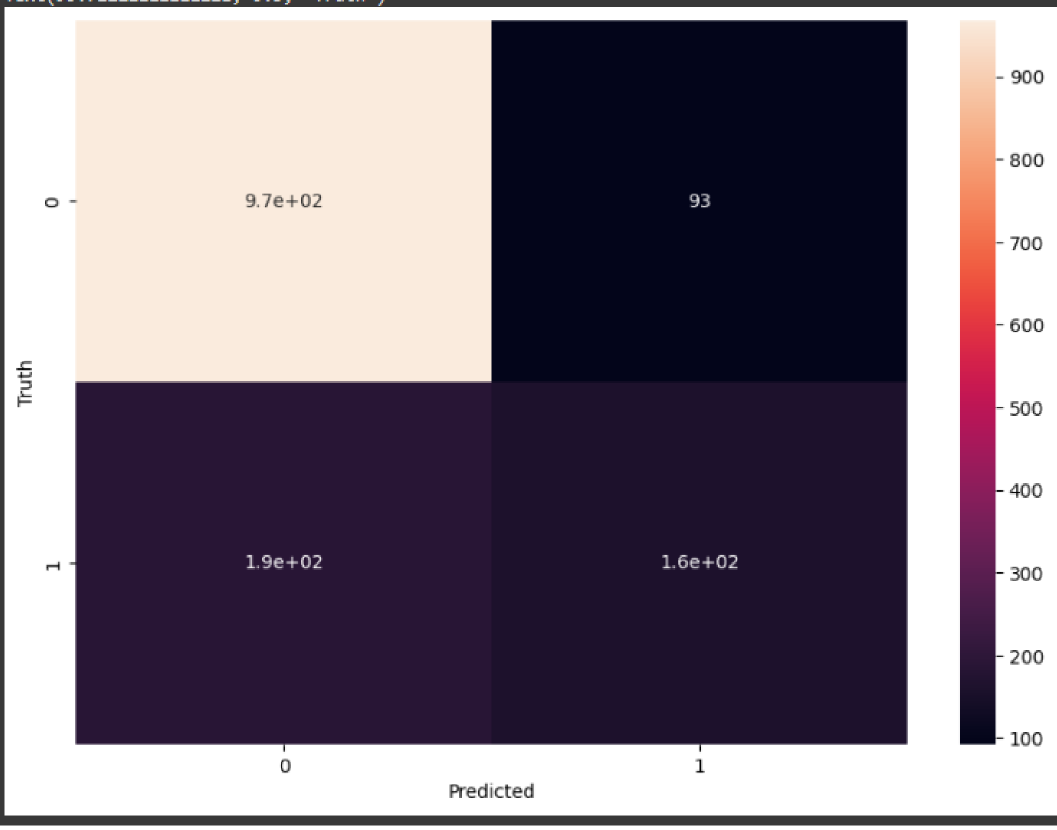
```
RandomForestClassifier
RandomForestClassifier(n_estimators=40)
```

```
model.score(X_test, Y_test)
```

```
0.801277501774308
```

```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sn
plt.figure(figsize=(10,7))
sn.heatmap(cm, annot=True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

```
Text(95.72222222222221, 0.5, 'Truth')
```



RESULTS:

Random Forest Classification and regression performed by constructing a multitude of decision trees at training time.

Select K data points from the training set. Build a decision tree with those K points and choose the N number of decision trees to be made. Based on season, area, crop and rainfall, these decision trees will traverse and give the predictions.

The accuracy obtained for the following models are:

Naive Bayes Classification-97.09

Decision Tree Classification -96.72

Random Forest Classification-98

KNN Classifier-97.45

Gradient Boost classification - 98.18(Highest)

DISCUSSION:

To successfully introduce new products in telecommunications, it is essential to have a robust data mining pre-processing approach. This includes various stages, such as data cleaning, data transformation, data reduction, and the development of models using data mining algorithms. Train-test splitting methods are used to evaluate the performance of these models and make necessary adjustments to improve their accuracy and effectiveness.

Data cleaning is a crucial step as it helps remove any noise, inconsistencies, or missing data in the dataset, ensuring the accuracy and reliability of the analysis. Data transformation techniques are applied to convert the data into a suitable format for analysis, making it easier to interpret and analyse. Data reduction techniques help reduce the size and complexity of the dataset, making it more manageable and easier to process.

By applying data mining algorithms to the dataset, businesses can gain insights into customer preferences, product demand, and other relevant factors that can help inform their decisions regarding new product offerings in the telecommunications industry. These models can help predict the success of new products, identify potential issues or challenges, and guide decision-making on product development and marketing strategies.

CONCLUSION AND FUTURE WORK:

The telecommunications industry is constantly evolving, and businesses must adapt to meet the changing needs and demands of their customers. New product offerings in telecommunications can be a valuable source of growth and innovation for companies in the industry.

The key to successful new product offerings lies in the effective use of data mining pre-processing techniques. By cleaning, transforming, and reducing data, businesses can develop accurate and reliable models that help predict the success of new products and guide decision-making on product development and marketing strategies.

Data mining pre-processing techniques are essential for identifying customer preferences, product demand, and other critical factors that can help inform the development of new products in the telecommunications industry. By leveraging these techniques, businesses can remain competitive, innovate, and drive growth and profitability.

Future work for the topic 'new product offerings telecommunications' could involve exploring various avenues to improve the current understanding of customer preferences and behaviours in the telecommunications industry. One such avenue could be to conduct a more detailed analysis of the customer segments, their demographics, and their preferences to tailor new product offerings more effectively. This could involve gathering more data from various sources such as customer surveys, focus groups, and website analytics to better understand customer needs and expectations.

Another potential avenue for future work could be to incorporate more advanced data mining techniques such as deep learning to improve predictive modelling and recommendation systems. Deep learning algorithms can help identify complex patterns and relationships in large datasets, providing more accurate insights into customer behaviour and preferences. This could help telecommunications companies better anticipate customer needs and develop more effective product offerings.

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