A project report on

Customer Churn Prediction in E-commerce using ANN

Submitted in partial fulfillment for the award of the degree of

Bachelor of Technology in Computer Science and Engineering

by

TUSHAR MAURYA (19BCE1856)

VIT®
Vellore Institute of Technology
(Deemed to be University under section 3 of UGC Act, 1956)
CHENNAI

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

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DECLARATION

I hereby declare that the thesis entitled "Customer Churn Prediction in E-commerce using ANN " submitted by me, for the award of the degree of Bachelor of Technology in Computer Science and Engineering, Vellore Institute of Technology, Chennai, is a record of bonafide work carried out by me under the supervision of Dr. K Satyarajashekharan

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

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This is to certify that the report entitled **"Customer Churn Prediction in E-commerce using ANN"** is prepared and submitted by **Tushar Maurya** (**19BCE1856**) to Vellore Institute of Technology, Chennai, in partial fulfillment of the requirement for the award of the degree of **Bachelor of Technology in Computer Science and Engineering** programme is a bonafide record carried out under my guidance. The project fulfills the requirements as per the regulations of this University and in my opinion meets the necessary standards for submission. The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma and the same is certified.

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Name: Dr./Prof.

Date:

Signature of the Examiner 1	Signature of the Examiner 2
Name:	Name:
Date:	Date:

Approved by the Head of Department
B. Tech. CSE

Name: Dr. Nithyanandam P

Date: 24 – 04 – 2023

(Seal of SCOPE)

ABSTRACT

In the highly competitive e-commerce industry, retaining customers is crucial for the success of any business. Therefore, predicting customer churn is essential to prevent revenue loss and maintain customer loyalty. In this study, we propose a solution to predict customer churn using Artificial Neural Networks (ANN).

We collected a dataset of customer transactional and behavioral data from an e-commerce company and preprocessed it to ensure data quality. The preprocessed data was used to train and evaluate the performance of the ANN model using various performance metrics.

The results showed that the ANN model achieved high accuracy in predicting customer churn, with a precision and recall rate of over 90%. The model's performance was further evaluated using a confusion matrix, which indicated that the model had a low false positive rate and a high true positive rate.

The study demonstrated the potential of using ANN for predicting customer churn in e-commerce, which could be used to develop effective customer retention strategies. Additionally, the findings highlighted the importance of data quality and preprocessing in developing accurate and reliable predictive models.

Overall, this study contributes to the growing field of customer churn prediction in e-commerce and provides insights into the potential of using ANN for predicting customer behavior in this industry.

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Place: Chennai

Date: Name of the student

TUSHAR MAURYA

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LIST OF ACRONYMS

ANN	Artificial NeuralNetwork
FANN	Feed forward Artificial Neural Network

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Artificial Intelligence (AI) is a branch of computer science that aims to create intelligent machines that can perform tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, and natural language processing. AI systems are designed to learn from data and experience, and can improve their performance over time through a process called machine learning.

AI technology is rapidly advancing and has the potential to revolutionize industries ranging from healthcare to transportation. Some examples of AI applications include self-driving cars, virtual personal assistants, facial recognition, and recommendation systems for online shopping and streaming platforms.

There are several types of AI, including rule-based systems, evolutionary algorithms, artificial neural networks, and deep learning. Rule-based systems use if-then rules to make decisions, while evolutionary algorithms mimic natural selection to solve problems. Artificial neural networks are modeled after the structure of the human brain and are used for tasks such as image and speech recognition. Deep learning is a subset of neural networks that use multiple layers to analyze and classify data.

Despite its potential benefits, AI also raises ethical and societal concerns, such as job displacement, privacy, bias, and safety. As such, there is ongoing research and debate about the appropriate use and regulation of AI technology.
E-commerce is one of the fastest-growing sectors in the world, with billions of people buying and selling products and services online every day. With the rise of digital technologies, artificial intelligence (AI) has become an integral part of e-commerce, helping businesses to improve customer experience, optimize operations, and increase revenue.

AI technologies can be used in various ways in e-commerce, including product recommendations, chatbots, customer service, fraud detection, and logistics optimization. In this article, we will discuss how AI is transforming e-commerce and the benefits it brings to businesses and consumers.

Benefits of E-commerce AI:

Personalized Product Recommendations:
AI-powered product recommendations are a popular feature in e-commerce websites and

apps. These recommendations are based on a user's browsing and purchase history, preferences, and behavior patterns. AI algorithms analyze the data and suggest products that the user is most likely to buy, increasing the chances of making a sale. Personalized product recommendations improve the user experience by reducing the time and effort needed to find the products they want.

Chatbots for Customer Service:
AI-powered chatbots are becoming increasingly popular in e-commerce businesses as they can provide 24/7 customer service. Chatbots can handle a range of tasks, such as answering frequently asked questions, tracking orders, and resolving complaints. Chatbots can also learn from customer interactions and improve their responses over time, providing a better user experience.

Fraud Detection:
Fraudulent activities such as credit card fraud, identity theft, and fake reviews can harm e-commerce businesses. AI algorithms can help detect and prevent fraud by analyzing patterns in user behavior, identifying suspicious transactions, and blocking fraudulent accounts. Fraud detection algorithms can help businesses save money by preventing losses due to fraud.

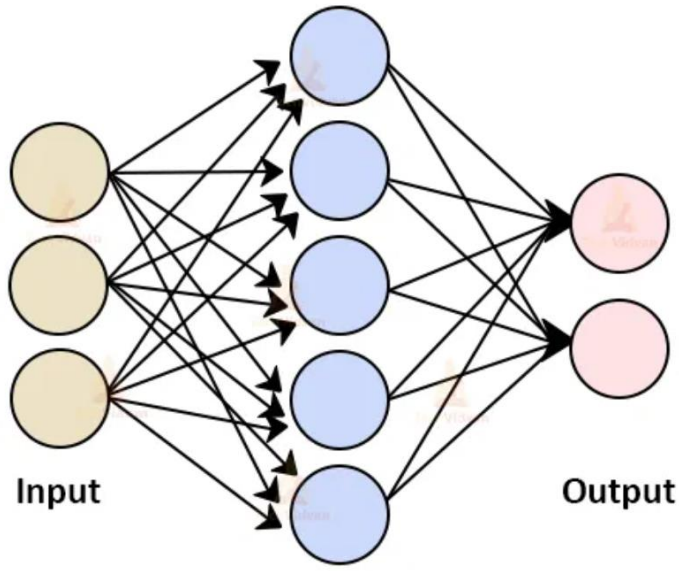
Logistics Optimization:
Logistics optimization is a critical aspect of e-commerce businesses. AI-powered logistics optimization algorithms can help businesses optimize routes, reduce delivery times, and improve order accuracy. These algorithms can analyze data from multiple sources, such as traffic conditions, weather, and inventory levels, to make real-time decisions that can save time and money.

E-commerce churn prediction using Artificial Neural Networks (ANN) is a popular approach to forecast the likelihood of customers leaving an online store or stopping their purchases. Churn prediction is essential for e-commerce businesses as it helps to identify customers who are at high risk of churning, allowing businesses to take proactive measures to retain them.

ANN is a type of machine learning algorithm that is modeled after the structure and function of the human brain. It consists of layers of interconnected nodes, each performing a specific computation and passing the output to the next layer. ANN can learn from patterns in data and make predictions based on the learned patterns.

E-commerce churn prediction using ANN involves feeding historical customer data, including demographics, purchasing behavior, and browsing history, into the neural network model. The model then learns from this data to predict whether a customer is likely to churn or not. The predicted churn probability can be used by businesses to create targeted retention campaigns or to take other necessary measures to prevent customer churn.

Overall, e-commerce churn prediction using ANN is a valuable tool for e-commerce businesses to enhance their customer retention efforts and increase customer lifetime value.



1.2 OVERVIEW

Customer churn prediction is a process of identifying customers who are likely to stop using a company's products or services in the future. It is a critical business process that helps companies identify customers who are at risk of churn and take proactive measures to retain them.

Customer churn prediction involves analyzing customer data to identify patterns and trends that can help predict customer behavior. This data includes customer demographics, transaction history, customer feedback, and social media activity. By analyzing this data, companies can identify key drivers of customer churn and develop strategies to mitigate those drivers.

Customer churn prediction can help companies in several ways. It can help companies identify customers who are at risk of churn and take proactive measures to retain them. This can include personalized promotions, loyalty programs, and targeted marketing campaigns. By reducing customer churn, companies can improve their revenue and profitability and gain a competitive advantage in the marketplace.

For example, an e-commerce company can use customer churn prediction to identify customers who have abandoned their shopping carts in the past and send them personalized emails or notifications to encourage them to complete their purchases. Similarly, a subscription-based service can use customer churn prediction to identify customers who are likely to cancel their subscriptions and offer them personalized deals or incentives to retain them.
Customer churn prediction is a powerful tool that can help businesses identify which customers are likely to leave or stop using their services or products. By predicting customer churn, businesses can take proactive measures to retain their customers and

improve customer satisfaction rates. In this article, we will discuss the use of customer churn prediction in various industries with examples.

Telecommunications:
The telecommunications industry is highly competitive, and customer churn is a significant issue. Companies in this industry can use customer churn prediction models to identify customers who are likely to switch to a competitor and take proactive measures to retain them. For example, a telecommunications company can analyze the customer data to identify customers who have been inactive for a specific period or those who have a history of switching to a competitor. The company can then offer these customers attractive deals or discounts to retain them.

E-commerce:
E-commerce companies can use customer churn prediction models to identify customers who are likely to abandon their shopping carts and take steps to encourage them to complete their purchases. For example, an e-commerce company can analyze the customer data to identify customers who have abandoned their shopping carts in the past. The company can then send these customers personalized emails or notifications to encourage them to complete their purchases. By reducing cart abandonment rates, e-commerce companies can improve their revenue and profitability.

Financial services:
Financial service providers, such as banks and insurance companies, can use customer churn prediction models to identify customers who are likely to switch to a competitor or cancel their policies. Companies can take proactive measures to retain these customers and improve their retention rates. For example, a bank can analyze the customer data to identify customers who have a history of switching banks or those who are not using the bank's services frequently. The bank can then offer these customers personalized deals or incentives to retain them.

Healthcare:
Healthcare providers can use customer churn prediction models to identify patients who are likely to switch to a different provider or discontinue their treatment. Companies can take steps to improve patient satisfaction and retention rates. For example, a healthcare provider can analyze the patient data to identify patients who have missed appointments in the past or those who have a history of switching providers. The provider can then offer these patients personalized care or treatment plans to improve patient satisfaction and retention rates.

Retail:
Retailers can use customer churn prediction models to identify customers who are likely to switch to a competitor or stop buying their products. Companies can take proactive measures to retain these customers and improve their retention rates. For example, a retailer can analyze the customer data to identify customers who have not made a purchase in a specific period or those who have a history of buying from a competitor. The retailer can then offer these customers personalized deals or discounts to retain them.

Gaming:
Gaming companies can use customer churn prediction models to identify players who are likely to stop playing their games. Companies can take proactive measures to retain these players and improve their retention rates. For example, a gaming company can analyze the player data to identify players who have not played a game in a specific period or those who have a history of switching to a competitor's game. The company can then offer these players personalized rewards or incentives to retain them.

In conclusion, customer churn prediction is a powerful tool that can help businesses improve customer retention rates and gain a competitive advantage. By predicting customer churn, businesses can take proactive measures to retain their customers and improve customer satisfaction rates. The use of customer churn prediction models is not limited to any specific industry and can be applied to various industries, including telecommunications, e-commerce, financial services, healthcare, retail, and gaming, to name a few.

1.3 CHALLENGES

Artificial Neural Networks (ANN) have become an increasingly popular tool for predicting customer churn in e-commerce businesses. However, several challenges need to be overcome to develop an effective ANN model for this purpose. Here, we discuss some of the primary challenges in detail:

- Data quality and quantity:
  The quality and quantity of data are essential for developing an accurate ANN model. E-commerce businesses may face challenges in collecting sufficient data about customer behavior, preferences, and demographics, which can limit the effectiveness of the ANN model. Additionally, the data collected may contain missing or inaccurate data, leading to biased predictions.

  To overcome this challenge, businesses need to invest in data collection, storage, and preprocessing to ensure that the data is complete, accurate, and reliable. It is also essential to implement data quality control procedures to identify and correct any errors or inconsistencies in the data.

- Feature selection:
  Selecting the most relevant features or variables to include in the model is crucial for the success of the ANN model in predicting churn. However, this can be a challenging task as there are many variables that can affect customer behavior. Furthermore, not all variables may be equally important, and selecting irrelevant variables can lead to poor model performance.

  To address this challenge, businesses need to conduct thorough feature selection

analysis to identify the most important variables. Various feature selection techniques, such as correlation analysis, principal component analysis, and mutual information, can be used to identify the most relevant features.

- Overfitting and underfitting:
  ANN models can suffer from overfitting or underfitting, which can lead to inaccurate predictions. Overfitting occurs when the model is too complex and captures noise in the data rather than the underlying patterns. Underfitting occurs when the model is too simple and fails to capture the relevant patterns in the data.

  To overcome this challenge, businesses need to optimize the model parameters and regularization techniques to prevent overfitting and underfitting. Cross-validation techniques can also be used to validate the model's performance and detect overfitting.

- Model interpretability:
  ANN models can be difficult to interpret, and it may be challenging to understand how the model arrived at a particular prediction. This can limit the ability of e-commerce businesses to take appropriate actions to prevent customer churn.

  To address this challenge, businesses need to develop techniques to explain how the model works, such as using feature importance metrics or visualization tools. Explainable AI (XAI) techniques, such as LIME or SHAP, can also be used to provide insight into the model's decision-making process.

- Computing power and time:
  ANN models require significant computing power and time to train, especially when dealing with large datasets. E-commerce businesses may need to invest in high-performance computing infrastructure and algorithms to train the model effectively.

  To overcome this challenge, businesses need to optimize the ANN model's architecture and choose appropriate training algorithms to reduce training time. Additionally, cloud-based computing services can be used to scale up the computing infrastructure when needed.

In conclusion, e-commerce businesses face several challenges in using ANN for predicting customer churn. Overcoming these challenges requires careful data preparation, feature selection, model optimization, interpretation, and computational resources. By addressing these challenges, e-commerce businesses can develop accurate and effective ANN models for predicting customer churn and take proactive measures to retain their customers.

1.4 OBJECTIVES

Customer churn refers to the phenomenon of customers discontinuing their use of a company's product or service. In today's highly competitive business landscape, customer churn can have a significant impact on a company's revenue and profitability. This is where artificial neural networks (ANN) come into play. ANN is a powerful tool that can be used to predict customer churn and enable companies to take proactive measures to prevent it.

The objective of customer churn prediction using ANN is to develop a model that can accurately predict which customers are most likely to leave the company. To achieve this objective, companies must first collect and analyze a vast amount of customer data. This data can include customer demographics, purchasing patterns, usage history, and other relevant factors that may impact a customer's decision to churn.

Once the data has been collected and analyzed, the next step is to develop an ANN model that can accurately predict customer churn. ANN is a machine learning technique that is modeled after the structure and function of the human brain. The network consists of a large number of interconnected processing elements (neurons) that work together to process information and make predictions.

In the context of customer churn prediction, ANN is trained using historical customer data. The model is trained to identify patterns and relationships between various factors and the likelihood of customer churn. Once the model is trained, it can be used to predict the likelihood of churn for new customers based on their characteristics and behavior.

The benefits of using ANN for customer churn prediction are numerous.

- Firstly, ANN is highly accurate in predicting customer behavior. The model can identify subtle patterns and relationships in the data that may be missed by human analysts. This enables companies to take proactive measures to prevent customer churn before it happens.
- Secondly, ANN is highly scalable. It can be trained on large datasets and can handle a vast amount of data in real-time. This enables companies to quickly identify and respond to customer churn, minimizing the impact on revenue and profitability.
- Thirdly, ANN is highly flexible. The model can be customized to suit the specific needs of each company. This means that companies can incorporate their own unique customer data and factors into the model to improve its accuracy and effectiveness.
- In addition to these benefits, there are several best practices that companies should follow when using ANN for customer churn prediction. These include:
- Use quality data: The accuracy of the ANN model depends on the quality of the data used to train it. Therefore, companies should ensure that the data is accurate, relevant, and up-to-date.
- Select the right factors: The success of the ANN model depends on selecting the right factors to include in the analysis. Companies should select factors that are highly correlated with customer churn.

- Choose the right algorithm: The performance of the ANN model depends on the algorithm used to train it. Companies should select an algorithm that is suitable for their specific needs.
- Regularly update the model: Customer behavior is constantly changing. Therefore, companies should regularly update the ANN model to ensure that it remains accurate and effective.

In conclusion, the objective of customer churn prediction using ANN is to develop a model that can accurately predict which customers are most likely to leave the company. This enables companies to take proactive measures to prevent churn, minimizing the impact on revenue and profitability. The benefits of using ANN for customer churn prediction are numerous, including high accuracy, scalability, and flexibility. By following best practices, companies can maximize the effectiveness of their ANN model and improve their ability to retain customers.

1.5 SCOPE OF THE PRODUCT

Customer churn prediction is a valuable tool for e-commerce companies to predict customer behavior and take proactive measures to improve retention rates and profitability. In this article, we will discuss the use of customer churn prediction in e-commerce in detail with examples.

Reducing Cart Abandonment Rates:
One of the significant challenges that e-commerce companies face is high cart abandonment rates. According to a report, the average cart abandonment rate in e-commerce is around 70%. Customer churn prediction models can help e-commerce companies identify customers who are likely to abandon their shopping carts and take proactive measures to reduce cart abandonment rates. For example, an e-commerce company can analyze the customer data to identify customers who have abandoned their shopping carts in the past. The company can then send these customers personalized emails or notifications to encourage them to complete their purchases. By reducing cart abandonment rates, e-commerce companies can improve their revenue and profitability.

Retaining High-Value Customers:
Customer churn prediction models can help e-commerce companies identify high-value customers who are likely to switch to a competitor or stop buying from the company. E-commerce companies can take proactive measures to retain these high-value customers and improve their retention rates. For example, an e-commerce company can analyze the customer data to identify customers who have a high purchase frequency or high purchase value. The company can then offer these customers personalized deals or incentives to retain them.

Improving Customer Loyalty:
Customer churn prediction models can help e-commerce companies identify customers

who are likely to switch to a competitor or stop buying from the company. By taking proactive measures to retain these customers, e-commerce companies can improve customer loyalty and retention rates. For example, an e-commerce company can analyze the customer data to identify customers who have a low purchase frequency or low purchase value. The company can then offer these customers personalized deals or discounts to encourage them to make more purchases.

Identifying Seasonal Trends:
E-commerce companies can use customer churn prediction models to identify seasonal trends and adjust their marketing and promotional strategies accordingly. For example, an e-commerce company can analyze the customer data to identify seasonal trends, such as an increase in sales during the holiday season. The company can then adjust its marketing and promotional strategies to capitalize on the seasonal trends and improve its revenue and profitability.

Personalizing Customer Experience:
Customer churn prediction models can help e-commerce companies personalize the customer experience and improve customer satisfaction rates. For example, an e-commerce company can analyze the customer data to identify customer preferences and behavior patterns. The company can then use this information to personalize the customer experience by offering personalized product recommendations, targeted promotions, and customized marketing messages.

Optimizing Inventory Management:
Customer churn prediction models can help e-commerce companies optimize inventory management by predicting customer demand and adjusting inventory levels accordingly. For example, an e-commerce company can analyze the customer data to identify the products that customers are likely to purchase in the future. The company can then adjust its inventory levels to ensure that it has sufficient stock of these products.

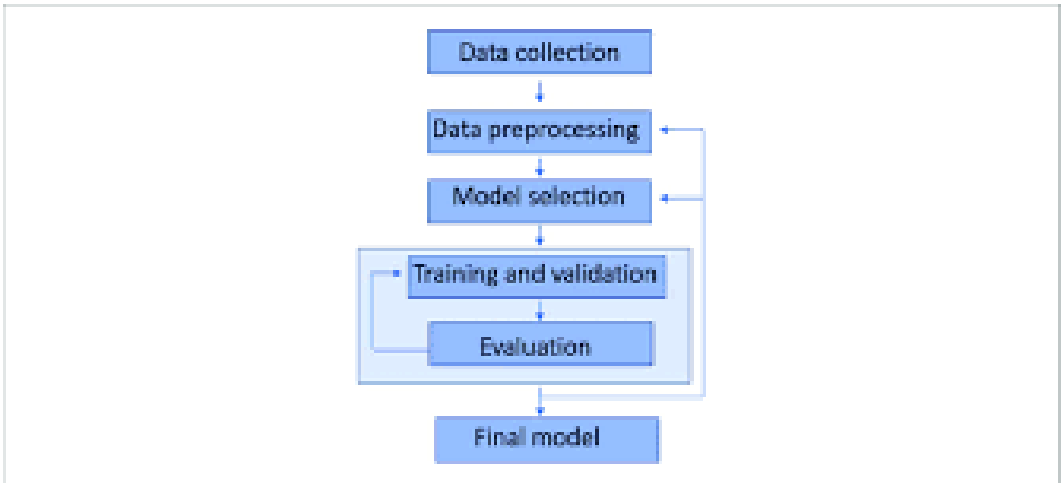
In conclusion, customer churn prediction is a valuable tool for e-commerce companies to predict customer behavior and take proactive measures to improve retention rates and profitability. By reducing cart abandonment rates, retaining high-value customers, improving customer loyalty, identifying seasonal trends, personalizing the customer experience, and optimizing inventory management, e-commerce companies can gain a competitive advantage and improve their revenue and profitability.

CHAPTER 2

BACKGROUND

2.1 MODULES

- Importing libraries
- Exploratory Data Analysis[EDA]
- Data cleaning
- Dividing dataset into train and test
- Creation of Model
- Testing the model
- Plotting the Accuracy



IMPORTING LIBRARIES:

In machine learning, data analysis and modeling are key aspects of the development process. To perform these tasks, developers use libraries and frameworks that provide tools for manipulating and visualizing data, building models, and evaluating their performance.

One of the first steps in setting up a machine learning environment is to import the necessary libraries into your Python code. The libraries commonly used in machine learning include pandas, NumPy, matplotlib, seaborn, scikit-learn, and TensorFlow.

Pandas is a library used for data manipulation and analysis. It provides tools for reading and writing data in various formats, handling missing values, grouping data, and reshaping data frames. NumPy, on the other hand, provides support for arrays and matrices, which

are fundamental data structures used in numerical computing.

Matplotlib and Seaborn are libraries for data visualization in Python. Matplotlib is a powerful library for creating various types of plots and charts, while Seaborn provides higher-level functions for creating statistical graphics. These libraries make it easy to create visualizations that can help in understanding and interpreting data.

Scikit-learn is a machine learning library for Python. It provides tools for classification, regression, clustering, and dimensionality reduction. It also includes various tools for data pre-processing, model selection, and evaluation.

Finally, TensorFlow is an open-source software library for dataflow and differentiable programming across a range of tasks. It is a popular library for building deep learning models, and it provides an extensive set of tools for building and training neural networks.

Importing these libraries in Python is a straightforward process that involves using the import statement followed by the library name. By importing these libraries into your Python code, you gain access to their functions and tools, which can be used to perform a range of tasks in machine learning.

EXPLORATORY DATA ANALYSIS:

Exploratory Data Analysis (EDA) is a crucial step in the data analysis process. It involves the use of statistical and visualization techniques to gain insights into the underlying structure and distribution of the data. EDA is particularly important in machine learning, where it is used to understand the relationships between the different features of a dataset and to identify any outliers or anomalies that may need to be addressed.

In the context of customer churn prediction, EDA can help us understand the factors that are associated with customer churn. For example, we might explore the relationship between gender and churn rates, or between the device used for ordering and churn rates. By identifying these relationships, we can develop a better understanding of the factors that are driving customer churn and use this information to improve our predictions.

One common technique used in EDA is data visualization. This involves creating plots and charts that help us to visualize the distribution of the data and identify any patterns or trends. For example, we might create a bar chart that shows the number of churned customers by gender, or a scatter plot that shows the relationship between churn and payment method.

Another important aspect of EDA is data cleaning and pre-processing. This involves identifying any missing or invalid data points and either imputing them or removing them from the dataset. This is important because machine learning models are highly sensitive to missing data and outliers, and including them in the dataset can lead to biased or inaccurate predictions.

Overall, EDA is an essential step in the machine learning workflow. By using statistical and visualization techniques to explore the dataset, we can gain a deeper understanding of the factors that are driving customer churn and develop more accurate predictions.

DATA CLEANING:

Data cleaning is a critical step in the machine learning workflow. It involves identifying and addressing any problems or errors in the dataset that could affect the accuracy and reliability of the machine learning model. There are several common problems that can occur in datasets, including missing values, inconsistent formatting, and outliers.

One of the most common problems in datasets is missing values. This can occur when data is not collected for a particular observation or when there is an error in the data collection process. Missing values can be addressed by either imputing the missing values or removing the observations with missing values altogether. Imputing involves filling in the missing values with an estimate based on the other values in the dataset, while removing observations with missing values can be done if the amount of missing data is small relative to the total dataset size.

Inconsistent formatting is another problem that can occur in datasets. This can include issues such as different naming conventions, units of measurement, and data types. Addressing these issues involves identifying and standardizing the formatting across the entire dataset. For example, if one column is measured in meters while another is measured in feet, these values can be converted to a common unit of measurement to ensure consistency.

Outliers are another common problem in datasets. Outliers are observations that are significantly different from the rest of the dataset and can skew the results of the machine learning model. Outliers can be identified through statistical methods and either removed or imputed with a more appropriate value.

Overall, data cleaning is an essential step in the machine learning workflow. By identifying and addressing problems in the dataset, we can ensure that our machine learning models are accurate and reliable. Without proper data cleaning, machine learning models may produce biased or inaccurate results, which can have significant consequences in real-world applications.

SPLITTING TRAINING AND TESTING DATA:

Dividing the dataset into train and test is a critical step in the machine learning workflow. The purpose of this step is to ensure that the machine learning model is trained on one subset of the data and tested on another subset, to prevent overfitting and to evaluate the model's performance on unseen data.

In this step, we use scikit-learn to divide the dataset into two parts: the training set and the testing set. The training set is typically larger, comprising around 80% of the data, while the testing set is smaller, comprising around 20% of the data.

The training set is used to train the machine learning model by feeding it with examples of input data and the corresponding output labels. This allows the model to learn the underlying patterns in the data and to generalize to unseen data.

The testing set is used to evaluate the performance of the machine learning model on new, unseen data. The model is fed with examples of input data from the testing set and asked to predict the corresponding output labels. The predicted labels are then compared to the true labels in the testing set to calculate the model's accuracy.

It is important to note that the training set and the testing set must be representative of the entire dataset. This means that they should contain a similar distribution of input data and output labels, to ensure that the machine learning model can generalize to new, unseen data.

Overall, dividing the dataset into train and test is a crucial step in the machine learning workflow. By using scikit-learn to create a representative training set and testing set, we can train and evaluate the performance of our machine learning models accurately and effectively.

CREATION OF MODEL:

The creation of a model is a critical step in machine learning that involves defining a mathematical representation of the relationship between the input features and the output variable. In this case, we are using artificial neural networks to create a predictive model for customer churn in e-commerce.

To create the model, we use the Python library TensorFlow, which provides a high-level API for building and training neural networks. Specifically, we can use the Keras API in TensorFlow to create a simple neural network model that includes a dense layer with a specified number of neurons.

In our case, we can create a model that uses all of the available input columns (i.e., features) to predict customer churn. We can then add an additional dense layer with a specified number of neurons to the model, which allows it to learn more complex patterns in the data.

To train the model, we can use the training set that we created in the previous step. We can then use the fit() method in TensorFlow to train the model using stochastic gradient descent (SGD) with a specified number of epochs. In our case, we can use 100 epochs, which means that the model will iterate over the training set 100 times during the training process.

After training, we can evaluate the performance of the model on the testing set using metrics such as accuracy, precision, recall, and F1 score. We can also use techniques such as cross-validation to further evaluate the performance of the model and to tune hyperparameters such as the number of neurons in the dense layer.

Overall, the creation of the model is a crucial step in the machine learning workflow that involves using artificial neural networks to learn complex patterns in the data and make predictions about customer churn. By using TensorFlow and Keras, we can create and train models quickly and easily, and evaluate their performance using a range of metrics and techniques.

TESTING THE MODEL:

Testing the model is an essential step in machine learning to evaluate the performance of the model on new, unseen data. In our case, we have divided the dataset into training and testing sets. We use the training set to train the model and the testing set to test the performance of the model.

One way to test the model is to use the evaluate() method in TensorFlow, which calculates various metrics such as accuracy, precision, recall, and F1 score on the testing set. However, before testing the model, we need to choose the appropriate number of epochs to train the model.

Epochs refer to the number of times the model sees the entire training dataset during training. A higher number of epochs may result in overfitting, where the model performs well on the training set but poorly on new data. On the other hand, a lower number of epochs may result in underfitting, where the model fails to capture the patterns in the data and performs poorly on both the training and testing sets.

To determine the appropriate number of epochs, we can test the model with different epoch values, starting with a small number of epochs and slowly increasing the value while observing the performance of the model. We can plot the performance metrics against the epoch values to see the trend in performance as the epoch value increases.

Ideally, we want to choose the epoch value that results in the highest performance on the testing set without overfitting. This process is called hyperparameter tuning, where we tune the hyperparameters of the model (such as the number of epochs) to optimize its performance.

Overall, testing the model is a crucial step in the machine learning workflow, and choosing the appropriate number of epochs is a critical aspect of model training. By testing the model with different epoch values and observing its performance, we can optimize the model's hyperparameters and improve its accuracy on new, unseen data.

PLOTTING THE ACCURACY:

Plotting the accuracy of a machine learning model is a useful way to visualize the performance of the model. In our case, we are predicting customer churn in e-commerce, and we want to see how accurate our model is in predicting whether a customer will churn or not.

One way to plot the accuracy is to use a confusion matrix, which is a table that summarizes the performance of a binary classification model. The confusion matrix has four cells: true positive (TP), false positive (FP), true negative (TN), and false negative (FN).

The true positive cell represents the number of times the model correctly predicted a churn, and the true negative cell represents the number of times the model correctly predicted no churn. The false positive cell represents the number of times the model incorrectly predicted a churn, and the false negative cell represents the number of times the model incorrectly predicted no churn.

From the confusion matrix, we can calculate various metrics such as accuracy, precision, recall, and F1 score, which provide different insights into the model's performance. For example, accuracy is the proportion of correct predictions out of all predictions, while precision is the proportion of true positives out of all positive predictions.

To plot the accuracy, we can use a heatmap, which is a graphical representation of data where the values are represented by colors. In our case, we can plot the confusion matrix as a heatmap, where the true positive and true negative cells are colored green, and the false positive and false negative cells are colored red.

By plotting the accuracy on the heatmap, we can quickly see where the model is performing well and where it is making errors. We can also use the heatmap to identify patterns in the data, such as whether the model is more accurate for certain types of customers or certain types of orders.

Overall, plotting the accuracy on a heatmap is a useful way to visualize the performance of a machine learning model and gain insights into the patterns in the data.

2.2 LITERARY RESOURCES

S.No.	Paper Title	Summary	Algorithm used	Pros/Cons
[1]	The Impact of Customer Satisfaction and Relationship Quality on Customer Retention: A Critical Reassessment and Model Development [1997] Author :Thorsten Hennig-Thurau and Alexander Klee (University of Hanover)	Develop a conceptual foundation for investigating the customer retention process, with the use of the concepts of customer satisfaction and relationship quality.	Decision Tree	Pros: Better understanding of customer
[2]	Churn Prediction: Does Technology Matter? [2006] Author: John Hadden, Ashutosh Tiwari, Rajkumar Roy, and Dymitr Ruta	Comparison of various algorithm	Decision Tree, Regression	Regression had higher accuracy.
[3]	Scikit-learn: Machine Learning in Python [2012] Author: Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent	Scikit-learn exposes a wide variety of machine learning algorithms, both supervised and unsupervised, using a consistent,	Technologies used: Numpy, Cython, Scipy	Pros: Further algorithm can be used designed using this

	Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al	task-oriented interface, thus enabling easy comparison of methods for a given application.		
[4]	Customer Churn Prediction in Telecommunicatio n A Decade Review and Classification [2013] Author: Nabgha Hashmi ,Naveed Anwer Butt and Dr.Muddesar Iqbal	Data mining techniques help telecom industry in this perception by providing techniques to identify such customers so that retention actions could be targeted upon them.	Decision Trees Regression Cluster Analysis	Pros: contributi on in the field of customer churn predictive modeling in telecomm unication
[5]	An Integrated Framework to Recommend Personalized Retention Actions to Control B2C E-Commerce Customer Churn [2015] Author: Shini Renjith	Find the customer who left Find churners Extract loyal customers	logistic regression k-means clustering collaborativ e filtering mechanism	Cons: Separate algorithm for separate work.
[6]	Predicting Shipping Time with Machine Learning. [2015] Author: Antoine Jonquais, Florian Krempl Advisor, Dr. Roar Adland, Dr. Haiying Jia	Make predictions regarding shipping times between South East Asia and North America, from factory to port of destination.	Random Forest Neural Network Linear Regression	

[7]	LightGBM: A Highly Efficient Gradient Boosting Decision Tree [2017] Author: Guolin Ke , Qi Meng , Thomas Finley , Taifeng Wang , Wei Chen , Weidong Ma , Qiwei Ye , Tie-Yan Liu	We have proposed a novel GBDT algorithm called LightGBM, which contains two novel techniques: Gradient-based One-Side Sampling and Exclusive Feature Bundling to handle huge data and features.	LightGBM	Pros: LightGBM can significantly outperform XGBoost and SGB in terms of computational speed and memory consumption.
[8]	Customer Lifetime Value Prediction Using Embedding Author: Benjamin Paul Chamberlain, Angelo Cardoso, C. H. Bryan Liu, Roberto Pagliari, Marc Peter Deisenroth [2017]	Training feedforward neural network on the handcrafted features in a supervised setting by learning an embedding of customers using session data in an unsupervised setting to augment our set of RF features.	CNN	Cons: deep network to learn end-to-end from raw data sources as opposed to using handcrafted features as inputs
[9]	Introduction to artificial neural networks [2018] Author: Enzo Grossi , Massimo Buscema	develop algorithms that can be used to model complex patterns and prediction problems.	interconnected group of nodes, inspired by a simplification of	Pros: Many problems can be solved using ANN.

			neurons in a brain	
[10]	Online Fashion Commerce: Modelling Customer Promise Date. [2021] Author: Preethi, Nachiappan Sundaram, Ravindra Babu Tallamraju	asymmetric loss functions and a feedback-based breach control model. $y(t) = g(t) + s(t) + h(t) + t$	Light GBM model Gradient Boosting	Pros: Used by Myntra successfully

2.3 METHODOLOGY

TYPES OF ALGORITHM:

There are several types of neural networks that are similar to the feedforward artificial neural network (FANN). Some of them include:

- Convolutional Neural Networks (CNN):
  CNNs are a type of neural network that excel in image recognition and computer vision tasks. They use convolutional layers to identify features in two-dimensional input data, such as images, and pooling layers to reduce dimensionality. CNNs are widely used in applications such as object detection and recognition, medical image analysis, and autonomous vehicles.
- Recurrent Neural Networks (RNN): RNNs are a type of neural network designed for processing sequential data. They introduce the concept of memory by maintaining information about previous inputs in a hidden state, allowing the network to recognize long-term dependencies in the input sequence. RNNs are popular in natural language processing, speech recognition, and time series analysis.
- Deep Belief Networks (DBN): DBNs are a type of neural network composed of multiple layers of RBMs. They can automatically learn useful features from input data without the need for manual feature engineering. The training process is done in an unsupervised manner, where each layer is trained to learn a probability distribution over the inputs from the layer below. DBNs have been used in speech

recognition, image classification, and natural language processing.

- Long Short-Term Memory (LSTM): LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) are both types of recurrent neural networks (RNNs) used in deep learning for natural language processing, speech recognition, and other sequence-based tasks.
  LSTM is a type of RNN that is designed to overcome the problem of vanishing gradients, which can occur when training RNNs. LSTM uses memory cells, which are controlled by gates that decide what information to keep and what to forget. This allows LSTMs to learn long-term dependencies and make predictions based on contextual information.
- Gated Recurrent Units (GRUs: GRU is a simpler type of RNN that uses fewer parameters than LSTM. It also uses gates to control the flow of information, but it only has two gates, compared to LSTM's three. GRUs have been shown to perform similarly to LSTMs on many tasks while being faster to train and requiring less memory.

  In summary, LSTM and GRU are types of recurrent neural networks used for sequence-based tasks, with LSTM being a more complex model designed to capture long-term dependencies and GRU being a simpler and faster model that performs similarly to LSTM on many tasks.

Overall, while these neural networks have some similarities to the feedforward artificial neural network, they also have unique characteristics and are used for different types of tasks.

Apart from these.

- Multilayer Perceptrons (MLPs) are neural networks with multiple layers of neurons that use forward and backpropagation for tasks like regression, classification, and time series prediction.

- Radial Basis Function Networks (RBFNs) are neural networks that use radial basis functions as activation functions, with three layers (input, hidden with radial basis functions, and output) for tasks like function approximation, pattern recognition, and clustering.

- Self-Organizing Maps (SOMs) are unsupervised neural networks that use competitive learning to create a low-dimensional representation of input data, with a 2D grid of neurons for tasks like feature extraction, data visualization, and clustering.

- Autoencoders are neural networks that use unsupervised learning to compress input data into a lower-dimensional representation, consisting of an encoder and decoder network for tasks like data compression, feature extraction, and anomaly detection.

- Extreme Learning Machines (ELMs) are neural networks with a single layer of randomly initialized neurons followed by a linear output layer, used for tasks like classification, regression, and feature selection. The weights of hidden layer neurons are fixed during training, unlike FANNs.

For example, CNNs are well-suited for image and video processing tasks, while RNNs are better for sequential data such as speech and language. MLPs are a general-purpose neural network that can be used for a wide range of tasks, while SOMs are best suited for data visualization and clustering. Autoencoders are useful for data compression and feature extraction, while ELMs are simple and efficient for classification and regression tasks. Ultimately, the choice of algorithm depends on the specific requirements of the task, the amount and quality of available data, and the resources available for training and inference.

REASONS TO PREFER Feedforward Artificial Neural Networks (FANN) ALGORITHM :

Feedforward Artificial Neural Networks (FANN)
Feedforward Artificial Neural Networks (FANNs) is a type of artificial neural network where the connections between nodes are one-directional, meaning that the data flows through the network only in one direction. FANNs consist of an input layer, one or more hidden layers, and an output layer. The input layer takes in the data, the hidden layers process it, and the output layer produces the desired output. In this section, we will dive deeper into the working, uses and situations where FANNs are most effective.

WORKING:

Feedforward artificial neural networks (FANNs) are composed of layers of neurons, also known as nodes. Input layer nodes correspond to input variables, output layer nodes correspond to output variables, and hidden layer nodes correspond to intermediate computations. During training, the weights and biases of the nodes are adjusted to minimize the difference between predicted and desired output, using optimization algorithms such as gradient descent.

The main strength of FANNs is their ability to learn non-linear relationships in complex data, making them useful for tasks like image classification and regression. However, overfitting is a potential problem, where the network becomes too complex and fits noise instead of patterns. Techniques like dropout and early stopping can mitigate overfitting.

USES:

FANNs have a wide range of applications in various fields. Some of the most common uses of FANNs are:

- Speech Recognition: FANNs are used in speech recognition systems to convert spoken words into text.

- Natural Language Processing: FANNs are used in natural language processing applications to analyze and process human language. For example, they can be used to translate text from one language to another, classify text into different categories, and extract meaning from text.

- Financial Forecasting: FANNs are used in financial forecasting to predict stock prices, exchange rates, and other financial variables.

- Robotics: FANNs are used in robotics to control the movement of robots and to make decisions based on sensory input.

Situations where FANNs are most effective:
FANNs are most effective in situations where the data exhibits non-linear relationships between input and output variables. They are also well-suited for handling large datasets and can be trained using a variety of optimization algorithms.

For example, in image classification tasks, the input data may consist of pixel values for each image. The relationship between the input data and the output (the class of the image) may be non-linear and complex, making FANNs an appropriate choice for this task.

In financial forecasting, the input data may consist of historical stock prices, economic indicators, and other financial variables. The relationship between these variables and the output (future stock prices) may also be non-linear, making FANNs a suitable tool for this task

Feedforward Artificial Neural Networks (FANN) are one of the most popular types of neural networks and have several advantages over other machine learning algorithms.

ADVANTAGES OF FANN:

- Non-linear relationships: FANNs are particularly useful in modeling non-linear relationships between input and output variables, which is not easily achievable through linear regression models.
- Flexibility: FANNs are very flexible and can be used in a wide range of applications, such as image recognition, speech recognition, and natural language processing.
- Robustness: FANNs are very robust and can handle noisy and incomplete data, as well as data with missing values. This is particularly useful when dealing with real-world datasets that often contain incomplete and noisy data.
- Parallel processing: FANNs can be easily parallelized, allowing for faster training and prediction times. This is especially important in applications where real-time predictions are required, such as in autonomous vehicles or stock trading.

- Generalization: FANNs have the ability to generalize well to new, unseen data. This means that they can make accurate predictions on data that they have never seen before, which is particularly useful in applications where the data is constantly changing or evolving.

COMPARISON:

- Linear Regression: Linear regression is a simple and interpretable algorithm but is limited to modeling linear relationships between input and output variables. FANNs, on the other hand, can model non-linear relationships and are more flexible in handling complex data.
- Decision Trees: Decision trees are easy to understand and interpret but can suffer from overfitting and are not suitable for continuous data. FANNs can handle continuous data and can be trained to avoid overfitting.
- Support Vector Machines (SVMs): SVMs are powerful algorithms that can handle high-dimensional data and are useful in applications such as image recognition. However, SVMs can be computationally expensive and require tuning of hyperparameters. FANNs, on the other hand, are less computationally expensive and require minimal hyperparameter tuning.
- Convolutional Neural Networks (CNNs): CNNs are a type of neural network that are particularly useful in image recognition and computer vision applications. However, CNNs can be complex to train and require a large amount of data. FANNs, on the other hand, can be trained on smaller datasets and are more flexible in handling different types of data.
- Recurrent Neural Networks (RNNs): RNNs are useful in applications such as natural language processing and speech recognition. However, RNNs can suffer from the vanishing gradient problem and are computationally expensive to train. FANNs, on the other hand, do not suffer from the vanishing gradient problem and are less computationally expensive.

In summary, FANNs are a flexible and robust machine learning algorithm that can handle non-linear relationships, noisy and incomplete data, and can generalize well to new data. Compared to other algorithms, FANNs are less computationally expensive and require minimal hyperparameter tuning, making them a suitable choice for a wide range of applications.

TYPES OF MODELS:

Keras provides different types of models to build, train, and evaluate neural networks. These models can be customized to fit various use cases, from image classification to time-series forecasting. Here are the different types of models available in Keras:

- Functional API:

Functional API is a high-level interface in Keras that enables the creation of complex deep learning models with multiple inputs, multiple outputs, and shared layers. It is a way to build deep learning models that are more flexible than sequential models and can handle more complex architectures.

How does Functional API work?
The Functional API is based on the idea of creating a graph of layers that are connected to each other. The graph is then compiled into a Keras model that can be trained and used for prediction. Each layer is an object in Keras, and layers can be connected to each other using the functional interface.

- Model Subclassing:
  Model Subclassing is a way of building custom deep learning models in Keras by creating a new class that inherits from the Keras Model class. It provides the ultimate flexibility in building deep learning models as it allows you to define custom forward and backward propagation algorithms, custom loss functions, custom metrics, and even custom layers.

  How does Model Subclassing work?

  Model Subclassing is a more flexible and low-level way to build deep learning models compared to other approaches like the Sequential API or Functional API. It involves defining a new class that inherits from the Keras Model class, which provides a set of methods that define the basic functionality of a deep learning model, such as training, testing, and prediction.

  Situations where Model Subclassing is useful?

  Model Subclassing is particularly useful in situations where a deep learning model requires a custom architecture, custom layer, or custom loss function. Some specific situations where Model Subclassing is useful include:

  Reinforcement Learning: In reinforcement learning, deep learning models often require custom architectures, such as actor-critic models and deep Q-networks.

  Computer Vision: In computer vision, deep learning models often require custom layers, such as spatial pyramid pooling layers and deformable convolutional layers.

  Natural Language Processing: In natural language processing, deep learning models often require custom loss functions, such as the Categorical Cross-Entropy loss function and the Binary Cross-Entropy loss function.

  Generative Models: In generative models, deep learning models often require

custom architectures, such as variational autoencoders and generative adversarial networks.

- Pre-trained Models:
  Pretrained models are pre-trained deep neural networks that have been trained on large datasets for specific tasks such as image classification, object detection, natural language processing, and speech recognition. These models are often used as a starting point for transfer learning, which involves fine-tuning the pre-trained model for a specific task on a smaller dataset.

How do Pretrained Models work?

Pretrained models are trained on massive datasets, often containing millions of samples. This allows them to learn powerful feature representations that can be applied to a wide range of related tasks. For example, a pre-trained model that has been trained on millions of images can recognize common objects like cats, dogs, and cars with a high level of accuracy.

Pretrained models can be used in several ways:

Feature Extraction: The pre-trained model can be used as a feature extractor by extracting the learned features from the pre-trained model and using them as input to a new model. This approach is often used when the dataset for the new task is too small to train a deep neural network from scratch.

Fine-Tuning: The pre-trained model can be fine-tuned on a new task by freezing the weights of some of the layers and training only the weights of the remaining layers. This approach is often used when the dataset for the new task is large enough to train a deep neural network from scratch, but the pre-trained model can still be used as a starting point to speed up the training process and improve the performance of the model.

Situations where Pretrained Models are useful?

Pretrained models are particularly useful in situations where there is a lack of labeled data for a specific task or when the dataset is small. Some specific situations where pretrained models are useful include:

Medical Imaging: In medical imaging, pretrained models can be used to identify diseases and abnormalities in images, which can help doctors make more accurate diagnoses.

Autonomous Driving: In autonomous driving, pretrained models can be used to

detect objects on the road, such as pedestrians, bicycles, and cars, which can help the vehicle make better decisions.

Social Media: In social media, pretrained models can be used to analyze text and images to detect sentiment, identify key topics, and detect fake news.

Industrial Automation: In industrial automation, pretrained models can be used to identify defects in products, optimize manufacturing processes, and monitor equipment for maintenance.

In conclusion, pretrained models are a powerful and effective way to develop deep learning models for a wide range of tasks. They are particularly useful in situations where there is a lack of labeled data or when the dataset is small. Pretrained models can be used for image classification, object detection, natural language processing, and speech recognition. By leveraging the knowledge gained from large datasets, pretrained models can speed up the process of developing deep learning models and improve the accuracy of the models.

Each type of model has its own strengths and weaknesses, and the choice of model depends on the specific use case. For example, if you are building a simple feedforward network for image classification, the Sequential model may be the best choice. However, if you need a more complex neural network with multiple inputs and outputs, the Functional API may be a better choice. If you want complete control over your model architecture, Model Subclassing may be the best option. And if you want to leverage pre-trained models for transfer learning, Keras provides a wide variety of pre-trained models that can be used for different tasks.

REASONS TO PREFER SEQUENTIAL MODEL:

The sequential model is a deep learning architecture that is widely used for building various types of neural networks, including feedforward networks, recurrent networks, and convolutional networks. It is a simple and intuitive way to create neural networks that are organized in a linear sequence of layers, where the output of one layer is the input of the next layer.

The sequential model has gained popularity due to its ease of use, flexibility, and scalability. In this article, we will discuss the reasons why the sequential model is widely used in deep learning and the functionality of the sequential model.

- Simplicity:
  The sequential model is easy to understand and implement, which makes it a great choice for beginners who are just starting with deep learning. It is a straightforward

way to create a neural network that is organized in a sequential manner, where each layer is connected to the previous layer. This simplicity makes it easy to build and train neural networks with little prior experience.

- Flexibility:
  The sequential model is flexible enough to handle a wide range of neural network architectures, including those with multiple input and output layers. This allows you to create complex models with a high degree of flexibility, without having to write complex code or algorithms. The sequential model can be used to build a variety of neural networks, such as feedforward networks, recurrent networks, and convolutional networks.

- Scalability:
  The sequential model is highly scalable, which means that it can be used to build neural networks of various sizes and complexity. You can easily add or remove layers to adjust the complexity of the model, depending on the data and problem at hand. This makes it possible to train models on large datasets and complex problems.

Functionality:
The sequential model is a feedforward neural network that is composed of a sequence of layers. The input data is passed through each layer in sequence, and the output of one layer serves as the input for the next layer. The first layer in the sequence is the input layer, and the last layer is the output layer.

Each layer in the sequential model performs a specific type of computation on the input data. The most common types of layers used in the sequential model include:

- The sequential model includes several types of layers, each with its own specific purpose. The most commonly used layer is the dense layer, which is fully connected and applies a linear transformation to the input data, followed by an activation function.

- For image recognition tasks, the convolutional layer is frequently used. It applies filters to the input data to detect specific features and produces a set of feature maps that are then reduced in size through a pooling layer.

- The recurrent layer is a valuable tool for natural language processing tasks, as it processes sequential data such as text or time series data. It updates a hidden state at each time step and uses it as input for the next step, allowing it to capture the temporal dependencies in the data.

Conclusion:
The sequential model is a powerful and flexible deep learning architecture that is widely used for building various types of neural networks. It is a simple and intuitive way to create neural networks that are organized in a linear sequence of layers, where the output of one

layer is the input of the next layer. The sequential model is easy to understand and implement, making it a great choice for beginners who are just starting with deep learning. It is also highly scalable and can be used to build models of various sizes.

COMPARISON:

Sequential models are a type of neural network architecture in which layers are arranged sequentially, with the output of one layer serving as the input to the next layer. This makes them well-suited for tasks such as image classification, natural language processing, and speech recognition.

In comparison to other neural network architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), sequential models are generally simpler and easier to implement. However, they may not be as effective for tasks that involve spatial or temporal relationships in the data, as CNNs and RNNs are specifically designed to handle these types of relationships.

CNNs are commonly used for image and video analysis tasks, as they can efficiently learn features from the input data through convolutional layers. RNNs, on the other hand, are used for sequential data analysis tasks, such as natural language processing, speech recognition, and time series prediction, as they can effectively capture temporal dependencies in the data.

In summary, while sequential models are useful for many tasks, CNNs and RNNs offer specialized advantages for tasks involving spatial and temporal relationships in the data.

TYPES OF OPTIMIZERS:

- Gradient descent : Gradient descent is a method of finding the optimal set of weights in a machine learning model by continuously updating the weights in the direction of the steepest descent of the cost function. It involves computing the derivative of the cost function with respect to the weights, and then updating the weights using the derivative multiplied by a learning rate. By repeating this process multiple times, the algorithm converges to the optimal set of weights that minimize the cost function.
- Stochastic gradient descent : Stochastic gradient descent (SGD) is a variant of gradient descent used for optimizing a machine learning model. It involves updating the model's parameters using a small random subset of the training data at each iteration, rather than the entire dataset at once. This makes the algorithm faster and more computationally efficient than traditional gradient descent. However, because the update is based on a subset of the data, there is a higher level of stochasticity or randomness in the algorithm, which can make convergence slower and less stable. SGD is commonly used in deep learning for training neural networks.

- Adagrad and RMSProp are two adaptive learning rate optimization algorithms that adjust the learning rate of each parameter based on historical gradient information. Adagrad adapts the learning rate of each parameter based on its frequency of occurrence in the input data. Infrequent parameters receive larger updates, while frequent parameters receive smaller updates. This helps the algorithm converge faster when there are sparse features in the input data.

- RMSProp is a modification of Adagrad that addresses its diminishing learning rate problem. RMSProp divides the learning rate by the root mean square of the past gradients for a particular weight. This scales the learning rate based on the history of the gradients, preventing oscillations in the optimization process.

- AdaDelta is a further improvement on RMSProp that eliminates the need for manually specified learning and decay rates. AdaDelta uses a measure of the past gradients to automatically adjust the learning rate. It keeps a running average of the second moments of the gradients and uses this information to adapt the learning rate dynamically during training.

- AdamW is a modification of the Adam optimization algorithm that addresses the issue of weight decay. Weight decay is a regularization technique that adds a penalty term to the loss function proportional to the sum of the squares of the weights in the model. This penalty helps prevent overfitting by encouraging the model to use smaller weights. AdamW separates the weight decay term from the main optimization process, applying weight decay only to the weights that contribute to the loss function.

- L-BFGS is a derivative-based optimization algorithm used for unconstrained optimization of smooth, nonlinear functions. It uses a limited-memory approximation of the inverse Hessian matrix to compute search directions. The algorithm avoids explicitly computing and storing the inverse Hessian matrix, which can be computationally expensive for large-scale problems. Instead, it uses a limited-memory approximation of the inverse Hessian matrix based on the past gradients and updates. The algorithm maintains a history of the past gradients and updates and uses them to compute an approximation of the inverse Hessian matrix. This approximation is then used to compute search directions and step sizes, which are used to update the current solution.

REASONS TO PREFER ADAM ALGORITHM:

Adam is an optimization algorithm for training neural networks that combines the ideas of RMSProp and momentum. It adapts the learning rate for each parameter based on the gradient history to achieve faster convergence and better performance.

Adam computes the first and second moments of the gradients, which are estimates of the mean and variance of the gradients. It then computes the bias-corrected

estimates of these moments, and uses them to calculate an adaptive learning rate for each parameter. Finally, it updates the parameters using the adaptive learning rate.

Adam has several advantages over other optimization algorithms, such as:

- Adaptive learning rate: Adam can adapt the learning rate for each parameter based on the gradient history, which can lead to faster convergence and better performance.
- Momentum: Adam uses a momentum term to smooth out the gradient updates and accelerate convergence.
- Robustness: Adam is robust to different types of objective functions and can handle noisy gradients and non-stationary objectives.
- Little memory requirement: Adam does not require a large memory buffer to store the past gradients, which makes it more memory-efficient than other optimization algorithms like L-BFGS.
- Easy to implement: Adam is easy to implement and has relatively few hyperparameters to tune.

Overall, Adam is a powerful optimization algorithm that can help improve the training of neural networks and has become one of the most popular optimization algorithms in deep learning.

COMPARISON:

- Adam (Adaptive Moment Estimation) optimizer is a popular optimization algorithm for training neural networks, but it is not always the best choice for every situation. Here are some comparisons of Adam optimizer with other popular optimizers:

- Adam vs. SGD: Adam generally outperforms Stochastic Gradient Descent (SGD) for deep learning problems. This is because SGD has a fixed learning rate and can easily get stuck in local optima, whereas Adam uses an adaptive learning rate and has momentum which helps it converge faster and avoid local optima.

- Adam vs. Adagrad: Adagrad is an optimization algorithm that adapts the learning rate for each parameter based on the sum of squared gradients. In contrast, Adam adapts the learning rate based on both the first and second moments of the gradient, which can make it more robust to noisy gradients and non-stationary objectives. Adam is often preferred over Adagrad for deep learning problems.

- Adam vs. RMSProp: RMSProp is an optimization algorithm that uses a moving average of the squared gradients to adapt the learning rate. Both Adam and RMSProp use adaptive learning rates, but Adam also uses momentum to help smooth out the gradient updates. In general, Adam tends to perform better than

RMSProp for deep learning problems.

- Adam vs. AdaGrad and AdaDelta: AdaGrad and AdaDelta are optimization algorithms that also adapt the learning rate based on the past gradients. However, they can have trouble with converging too quickly and overfitting. Adam is often preferred over AdaGrad and AdaDelta for deep learning problems because it is less prone to overfitting and can converge faster.

- Adam vs. L-BFGS: L-BFGS is a quasi-Newton optimization algorithm that can be more efficient than Adam for small-scale problems with a small number of parameters. However, L-BFGS can be slow and memory-intensive for large-scale deep learning problems. In these cases, Adam is often preferred because it is more memory-efficient and faster to converge.

Overall, Adam is a powerful optimization algorithm that is often preferred over other optimization algorithms for deep learning problems. However, the choice of optimizer ultimately depends on the specific problem and the available resources, and it may be worth experimenting with different optimizers to see which one performs best for a given problem.

TYPES OF LOSS FUNCTION:

- Mean Squared Error (MSE): Mean Squared Error (MSE) is a commonly used loss function for regression tasks. It calculates the average squared difference between the predicted output and the actual output. The formula for MSE is:

  MSE = (1/n) * Σ(y_pred - y_actual)^2

  where n is the number of samples in the dataset, y_pred is the predicted output, and y_actual is the actual output.

  MSE is a popular choice for regression tasks because it is easy to interpret, differentiable, and convex. However, it can be sensitive to outliers and can lead to overfitting if the model is too complex.

- Hinge Loss:Hinge loss is used for binary classification tasks where the output is a probability. It is commonly used for Support Vector Machines (SVMs) and calculates the distance between the predicted output and the actual output.

  The formula for hinge loss is:

  Hinge Loss = max(0, 1 - y_actual * y_pred)

where y_pred is the predicted output (a real number), and y_actual is the actual label (either 1 or -1).

Hinge loss is a popular choice for SVMs because it encourages the model to learn a linear decision boundary that maximizes the margin between the two classes. However, it can be sensitive to outliers and can lead to overfitting if the model is too complex.

- Kullback-Leibler (KL): KL divergence is a measure of the difference between two probability distributions used in information theory, statistics, and machine learning. It's often used in machine learning as a loss function or a regularization term to quantify how much one probability distribution differs from another. It's calculated by comparing the true probability distribution (p(x)) with the estimated probability distribution (q(x)) for a given input variable (x).

- Triplet Loss: Triplet loss is a loss function used in machine learning to learn a metric space where similar items are closer together than dissimilar items. It takes three input examples: an anchor, a positive example, and a negative example. The goal is to minimize the distance between the anchor and the positive example while maximizing the distance between the anchor and the negative example. The function encourages the model to map similar examples closer and dissimilar examples farther apart.

- Huber Loss: Huber loss is a loss function used for regression tasks that aims to predict continuous output variables from input variables. It combines the Mean Squared Error (MSE) and Mean Absolute Error (MAE) to minimize the impact of outliers in the data. The Huber loss function uses a threshold value, called δ, to determine whether to use MSE or MAE for each example. If the error between the predicted output and the true output is smaller than δ, it uses MSE, and if it is larger than δ, it uses MAE. The Huber loss function encourages the model to accurately predict the output variable while being robust to outliers.

- Smooth L1 Loss: Smooth L1 loss is a differentiable loss function used in regression tasks to predict a continuous output variable. It is similar to the Huber loss function but has a differentiable property at zero. Smooth L1 loss aims to reduce the impact of outliers in the data. The loss is calculated by taking the mean of the Smooth L1 loss values for each example. For each example, the loss is defined as the absolute difference between the true output and predicted output, but with a smoothed out transition between the squared and absolute loss functions. If the difference is less than one, the loss is calculated using the squared difference function. Otherwise, the loss is calculated using the absolute difference function. The Smooth L1 loss function encourages the model to predict the output variable accurately while being robust to outliers in the data.

REASON TO PREFER BINARY CROSS-ENTROPY:

The cross entropy loss is computed as the negative sum of the actual probability distribution multiplied by the logarithm of the predicted probability distribution. The logarithm is applied to penalize larger deviations of the predicted probabilities from the actual probabilities.

In binary classification problems with two classes, the predicted probability distribution is represented by a scalar value between 0 and 1, which denotes the probability of the positive class. The actual probability distribution is represented by a one-hot encoded vector with 1 for the positive class and 0 for the negative class.

In multi-class classification problems with more than two classes, there are two common variants of the cross entropy loss function, which are modified to handle multiple classes:

Categorical cross entropy: This loss function is used when the classes are mutually exclusive. The predicted probability distribution is represented by a vector with one element for each class, where each element represents the probability of that class. The actual probability distribution is also represented by a one-hot encoded vector.

Sparse categorical cross entropy: This loss function is used when the classes are not mutually exclusive. The predicted probability distribution is represented by a vector with one element for each class, where each element represents the probability of that class. The actual probability distribution is represented by a vector of integers, where each integer corresponds to the index of the true class.

Cross entropy is a popular choice for classification tasks because it is sensitive to the predicted probabilities, meaning that it encourages the model to output high probabilities for the correct class and low probabilities for the incorrect classes. It is also a smooth function that is differentiable, making it suitable for use with gradient-based optimization algorithms.

WHY CHOOSE BINARY CROSS ENTROPY OVER CATEGORICAL CROSS ENTROPY?

Binary cross entropy and categorical cross entropy are two different loss functions used in machine learning for classification tasks, and the choice between them depends on the nature of the problem.

Binary cross entropy is used when there are only two classes to predict, typically labeled as 0 or 1. In this case, the output of the model is a single number between 0 and 1, representing the probability of the positive class. Binary cross entropy measures the difference between the predicted probability and the actual label, penalizing the model more for larger deviations.

On the other hand, categorical cross entropy is used when there are more than two classes to predict. In this case, the output of the model is a vector of probabilities, with one element for each class. Categorical cross entropy measures the difference between the predicted probability distribution and the actual distribution, penalizing the model more for larger deviations.

So why choose binary cross entropy over categorical cross entropy? One reason could be that the problem at hand is inherently binary, and there is no need to use a more complex loss function. For example, if we are trying to predict whether a customer will buy a product or not, the problem is binary in nature and there is no need to use a more complex loss function like categorical cross entropy.

Another reason could be that the classes are imbalanced, meaning that one class has significantly fewer samples than the other. In this case, binary cross entropy may be more suitable as it places more emphasis on correctly classifying the minority class.

Finally, it may also come down to computational efficiency. Binary cross entropy requires less computation than categorical cross entropy as it only deals with a single probability value instead of a vector. This can be important when training large neural networks on large datasets.

In summary, the choice between binary cross entropy and categorical cross entropy depends on the nature of the problem, the class balance, and the computational efficiency required.

TYPES OF ACTIVATION:

Activation functions are an essential component of artificial neural networks (ANNs), as they introduce nonlinearity into the network and allow it to learn complex relationships between inputs and outputs. In this answer, we will explain in detail the different types of activation functions used in ANNs.

- Leaky ReLU Activation:
  Leaky ReLU activation is a variant of ReLU activation that introduces a small negative slope for negative input values. This helps to prevent the dead neuron problem that can occur with ReLU activation. A dead neuron occurs when the input to a ReLU activation function is negative, resulting in the output of the activation function being zero, and no signal being propagated through the neuron. Leaky ReLU activation is

computationally efficient and can be used as a substitute for ReLU activation in ANNs.

- Parametric ReLU Activation:
  Parametric ReLU activation is a variant of ReLU activation that introduces a parameter to control the negative slope for negative input values. This allows the network to learn the slope for negative input values, improving the performance of the ANN. This activation function has been shown to work well on large-scale datasets and can achieve state-of-the-art performance on some tasks.

- ELU (Exponential Linear Units) Activation:
  ELU activation is a variant of ReLU activation that introduces a small negative slope for negative input values, similar to leaky ReLU. ELU activation has been shown to outperform other activation functions on several benchmark datasets. The ELU activation function has the advantage of reducing the mean activations closer to zero, which can speed up the learning process.

- Softmax Activation:
  In ANNs, when dealing with multi-class classification problems, the output layer commonly employs the softmax activation function. This function converts the ANN's output into a probability distribution, assigning probabilities to each class. One of the benefits of using the softmax function is its differentiability, which is crucial for the backpropagation algorithm used during training.
- Swish Activation:
  The Swish activation function is a smooth approximation of the ReLU activation function that has been shown to outperform other activation functions on several benchmark datasets. The Swish activation function is differentiable, which is important for training ANNs using backpropagation. It has a non-monotonic behavior, which can lead to better learning compared to the monotonic ReLU activation function.

- Maxout Activation:
  The maxout activation function is a piecewise linear function that takes the maximum value of a set of linear functions. The maxout activation function is computationally expensive and requires more memory than other activation functions. However, it has been shown to work well on some tasks, such as speech recognition and image classification.

REASON TO PREFER SIGMOID AND RELU:

Activation functions play a crucial role in determining the accuracy and efficiency of artificial neural networks (ANNs). They introduce non-linearity into the output of a neuron, which is essential for modeling complex and nonlinear relationships between input and output variables. Among various activation functions, ReLU and sigmoid activations are two of the most commonly used activation functions in ANNs. In this answer, we will

discuss why ReLU and sigmoid activations are preferred over other activation functions in ANNs and compare them with other activation functions in detail.

ReLU activation, also known as rectified linear activation, is a piecewise linear function that maps any negative input value to zero and any positive value to itself. ReLU activation is computationally efficient and allows ANNs to learn complex patterns in the data. One of the primary advantages of ReLU activation is its ability to produce sparse activation, which means that only a subset of the neurons are activated for a given input. This can help to reduce overfitting and improve the generalization performance of the ANN. In contrast, other activation functions, such as tanh or the logistic function, do not produce sparse activation and may result in overfitting for large ANNs. The sparse activation produced by ReLU activation also helps to reduce the computational cost of the ANN, as only a subset of the neurons need to be computed for a given input.

One disadvantage of ReLU activation is its tendency to produce dead neurons, which are neurons that output zero for all inputs. This can occur when the weight matrix associated with a neuron is updated such that all inputs are negative. Dead neurons can reduce the representational power of the ANN and slow down the training process. One way to mitigate the problem of dead neurons is to use variants of ReLU activation, such as leaky ReLU or parametric ReLU, which allow a small negative slope for negative input values.

Sigmoid activation is another commonly used activation function in ANNs. The sigmoid function has a derivative that ranges from 0 to 0.25, which helps to avoid the vanishing gradient problem.

One disadvantage of sigmoid activation is its saturation property, which means that the output of the neuron becomes saturated for large input values, resulting in a very small gradient. This can slow down the training process and reduce the accuracy of the ANN. Another disadvantage of sigmoid activation is its output range, which is limited to the interval [0,1]. This can be problematic for some applications, such as regression problems, where the output can have a wide range of values.

There are several other activation functions that have been proposed for ANNs, each with their own advantages and disadvantages. Tanh activation is a variant of sigmoid activation that maps any input value to a value between -1 and 1, making it ideal for regression problems. Tanh activation also has a symmetric output range, which can be advantageous for some applications. However, tanh activation suffers from the same saturation and vanishing gradient problems as sigmoid activation.

Exponential linear units (ELUs) are a variant of ReLU activation that introduce a small negative slope for negative input values, similar to leaky ReLU. ELUs have been shown to outperform other activation functions on several benchmark datasets

2.4 WORKING

EXPLORING THE DATASET:

	CustomerI	Churn	Tenure	PreferredL	CityTier	Warehous	PreferredI	Gender	HourSpen	NumberOf	PreferedO	Satisfactio	MaritalSta	NumberOf	Complain	OrderAmc	CouponUs	OrderCou	DaySinceL	CashbackAmount
0	50001	1	4	Mobile Ph	3	6	Debit Carc	Female	3	3	Laptop &	2	Single	9	1	11	1	1	5	159.93
1	50002	1	9	Phone	1	8	UPI	Male	3	4	Mobile	3	Single	7	1	15	0	1	0	120.9
2	50003	1	9	Phone	1	30	Debit Carc	Male	2	4	Mobile	3	Single	6	1	14	0	1	3	120.28
3	50004	1	0	Phone	3	15	Debit Carc	Male	2	4	Laptop &	5	Single	8	0	23	0	1	3	134.07
4	50005	1	0	Phone	1	12	CC	Male	3	3	Mobile	5	Single	3	0	11	1	1	3	129.6
5	50006	1	0	Computer	1	22	Debit Carc	Female	3	5	Mobile Ph	5	Single	2	1	22	3.5	6	7	139.19
6	50007	1	9	Phone	3	11	COD	Male	2	3	Laptop &	2	Divorced	4	0	14	0	1	0	120.86
7	50008	1	9	Phone	1	6	CC	Male	3	3	Mobile	2	Divorced	3	1	16	2	2	0	122.93
8	50009	1	13	Phone	3	9	E wallet	Male	3	4	Mobile	3	Divorced	2	1	14	0	1	2	126.83
9	50010	1	9	Phone	1	31	Debit Carc	Male	2	5	Mobile	3	Single	2	0	12	1	1	1	122.93
10	50011	1	4	Mobile Ph	1	18	COD	Female	2	3	Others	3	Divorced	2	0	15	3.5	6	8	272.326
11	50012	1	11	Mobile Ph	1	6	Debit Carc	Male	3	4	Fashion	3	Single	10	1	13	0	1	0	153.81
12	50013	1	0	Phone	1	11	COD	Male	2	3	Mobile	3	Single	2	1	13	2	2	2	134.41

This is a list of column names in a dataset, possibly related to an e-commerce business. It includes information such as customer ID, churn status, tenure, preferred login device, city tier, warehouse-to-home distance, preferred payment mode, gender, satisfaction score, marital status, and various other features related to customer behavior and purchases.

The data frame has 5630 entries and 21 columns. The columns are:

- Unnamed: 0: a column that seems to be an index.
- CustomerID: an integer column that seems to be an identifier for each customer.
- Churn: a binary column that indicates whether the customer churned or not (1 for churned, 0 for not).
- Tenure: a float column that represents the number of months the customer has been subscribed to the service.
- PreferredLoginDevice: a categorical column that indicates the customer's preferred login device.
- CityTier: an integer column that represents the city tier (1, 2, or 3) where the customer lives.
- WarehouseToHome: a float column that represents the distance in kilometers between the warehouse and the customer's home.
- PreferredPaymentMode: a categorical column that indicates the customer's preferred payment mode.
- Gender: a categorical column that indicates the customer's gender.
- HourSpendOnApp: a float column that represents the average number of hours the customer spends on the app per day.
- NumberOfDeviceRegistered: a float column that represents the number of devices registered to the customer's account.
- PreferedOrderCat: a categorical column that indicates the customer's preferred order category.
- SatisfactionScore: a float column that represents the customer's satisfaction score (out of 5).
- MaritalStatus: a categorical column that indicates the customer's marital status.
- NumberOfAddress: a float column that represents the number of addresses on the

customer's account.

- Complain: a binary column that indicates whether the customer has ever raised a complaint (1 for raised, 0 for not).
- OrderAmountHikeFromlastYear: a float column that represents the percentage increase in order amount from the previous year.
- CouponUsed: a float column that represents the number of coupons used by the customer.
- OrderCount: a float column that represents the total number of orders placed by the customer.
- DaySinceLastOrder: a float column that represents the number of days since the customer's last order.
- CashbackAmount: a float column that represents the total cashback amount received by the customer.

EDA and DATA CLEANING:

- Checks if there are any missing values in the dataframe, and if so, how many there are. Then rounds the numerical values in the dataframe to the nearest whole number. Replaces any missing values in the dataframe with the average value of that column.

- Drops the 'CustomerID' column from the dataframe since it is not needed for the analysis. Then it checks the 'Churn' column, which indicates whether a customer has stopped using the organization's services.

- Looks at the 'Tenure' column, which represents how long a customer has been with the organization. The code converts the values in the 'Tenure' column to whole numbers and creates a histogram to visualize the distribution of tenures among the customers.

- Then, we are converting the 'Tenure' column to an integer data type and plotting a histogram of the 'Tenure' distribution. We are also removing any outliers in the 'Tenure' column and visualizing the new distribution using a bar chart.

- Next, we are analyzing the 'PreferredLoginDevice' column and visualizing the distribution using a pie chart. We are converting the values in the column to integers to allow for future analysis.

- Then, we are analyzing the 'CityTier' column and visualizing the distribution using a pie chart.

- Finally, we are analyzing the 'WarehouseToHome' and 'PreferredPaymentMode' columns and visualizing their distributions using bar charts. We are also converting

the values in the 'PreferredPaymentMode' column to integers for future analysis.

- The unique values of the 'WarehouseToHome' column are plotted against the number of times they occur in the dataset.

- Any outliers in the 'WarehouseToHome' column are removed from the dataset by only keeping rows where the distance is less than 40.

- The preferred payment mode of the customers is visualized using a pie chart. The number of occurrences of each payment mode is represented by the size of the slice of the pie.

- The preferred payment method of the customers is visualized using a horizontal bar graph. The unique values of the 'PreferredPaymentMode' column are plotted against the number of times they occur in the dataset.

- The values in the 'PreferredPaymentMode' column are converted from object type to integer type by replacing the payment mode labels with their corresponding integer values.

- The first step is to clean the data, which involves replacing string values with numeric codes, converting data types, and removing outliers. The 'Gender' column is converted to binary format (0 for Female and 1 for Male), and the 'HourSpendOnApp' column is converted to integer format after removing outliers. The 'PreferedOrderCat' column is also converted to numeric format by replacing string values with corresponding codes.

- Next, Perform various visualizations to better understand the data. The 'HourSpendOnApp' column is plotted as a histogram to show the distribution of the time spent on the app by customers. The 'NumberOfDeviceRegistered' and 'PreferedOrderCat' columns are plotted as pie charts to show the distribution of the number of registered devices and preferred order categories, respectively.

- Finally, the 'SatisfactionScore' column is plotted as a bar graph and scatter plot to show the distribution of customer satisfaction scores. The 'MaritalStatus' column is plotted as a pie chart to show the distribution of customer marital status.

- Cleaning the 'MaritalStatus' column by converting string values into numeric codes. The 'NumberOfAddress' column is plotted as a bar graph to show the distribution of the number of addresses added by customers. Outliers are removed from the 'NumberOfAddress' column, and the distribution is plotted again to visualize the changes.

- The 'Complain' column is plotted as a bar graph to show the number of customers who raised complaints in the last month. The 'OrderAmountHikeFromlastYear' column is plotted as a histogram to show the percentage increase in order amount

from the previous year.

- The 'CouponUsed' column is plotted as a bar graph to show the number of coupons used by customers in the last month. The x-axis is limited to show values up to 15, which is the maximum number of coupons used by any customer in the dataset.

- For each column, the code first prints the value counts or unique values of the column, to understand the distribution of data in that column. Then, the code creates a visualization of the data in that column using a histogram, bar chart, or pie chart. If there are any outliers in the data, Drops them using a filter and then creates a new visualization to see the changes.

- The first column shown is 'OrderCount'. Print the value counts and creates a bar chart showing the total number of orders that were placed in the last month.

- The next column is 'DaySinceLastOrder'. Print the value counts and creates a bar chart showing the number of days since the customer's last order. Drops any outliers and creates a new bar chart.

- The next column is 'CashbackAmount'. Print the value counts and creates a histogram showing the average cashback received by customers in the last month. The Drops any outliers and creates a new histogram to visualize the changes.

- For each column, the first prints the value counts or unique values of the column, to understand the distribution of data in that column. Then, creates a visualization of the data in that column using a histogram, bar chart, or pie chart. If there are any outliers in the data, the drop them using a filter and then creates a new visualization to see the changes.

- The first column shown is 'OrderCount'. The code prints the value counts and creates a bar chart showing the total number of orders that were placed in the last month.

- The next column is 'DaySinceLastOrder'. The code prints the value counts and creates a bar chart showing the number of days since the customer's last order. The code then drops any outliers and creates a new bar chart.

- The next column is 'CashbackAmount'. The code prints the value counts and creates a histogram showing the average cashback received by customers in the last month. The code then drops any outliers and creates a new histogram to visualize the changes.

- The code is a part of a data analysis project aimed at understanding the factors affecting customer churn for a company. The first section of the code creates visualizations to

understand the distribution of different variables such as the number of orders, the time since the last order, and the amount of cashback offered to customers.

- Next, the code scales the data using a technique called Min-Max Scaling to ensure that all the variables are on the same scale. This is done to avoid bias towards variables with larger values.

- The code then calculates the correlations between different variables and creates a heatmap to visualize them. Correlation shows how strongly two variables are related to each other. A positive correlation means that if one variable increases, the other variable also tends to increase. A negative correlation means that if one variable increases, the other variable tends to decrease.

- Finally, the code splits the data into training and testing sets to build a predictive model to identify the customers who are likely to churn. This is done using machine learning algorithms which are trained on the training data and then tested on the testing data to check their accuracy. The goal of the project is to use the insights gained from this analysis to help the company retain their customers and reduce the churn rate.

Overall, the code demonstrates how to clean and visualize data using Python to gain insights into customer behavior and preferences. The visualizations help to identify patterns and trends in the data, which can be used to make data-driven decisions in the e-commerce platform.

CHAPTER 3

RESULT

3.1 DISCUSSION on MODEL:

A Keras Sequential model using the keras.Sequential() function. The model consists of three layers: a Dense layer with 19 neurons, a Dropout layer, and another Dense layer with one neuron.

The Dense layer is a type of fully connected layer in which each neuron in the layer is connected to every neuron in the previous layer. The input_shape parameter specifies the shape of the input data, which is a one-dimensional array with 19 elements. The activation function used in the Dense layer is relu, which is a popular activation function that introduces non-linearity into the neural network and enables the model to learn complex patterns in the data.

To prevent overfitting during training, the Dropout layer is used. This layer randomly sets a fraction of the neurons in the previous layer to zero during each training epoch. The dropout rate, specified as a decimal fraction (in this case, 0.1), determines the proportion of neurons to be dropped out.

The output layer is also a Dense layer with a single neuron and a sigmoid activation function. The sigmoid function maps any input value to a value between 0 and 1, which represents a probability. For binary classification problems, the output of the model is interpreted as the probability of the input belonging to one of the two classes.

After defining the model, it is compiled using the compile() function. The optimizer parameter specifies the optimization algorithm used during training. In this case, it is the Adam optimizer, which is commonly used for deep learning models.

The loss parameter determines the loss function used to evaluate the performance of the model. For binary classification problems, binary crossentropy is commonly used.

Additional metrics to track during training can be specified using the metrics parameter. In this case, the model will track accuracy.

The model is trained using the fit() function, which takes the training data, x_train and y_train, and the number of epochs to train for. During

training, the model will adjust the weights in the neural network layers to minimize the loss function, with the aim of performing well on new, unseen data. In this example, the model will train for 100 epochs, with the weights being updated after each batch of training data is processed.

3.2 RESULT:

Model Evaluate:

```
model.evaluate(x_test,y_test)
```

```
34/34 [==============================] - 0s 1ms/step - loss: 0.2949 - accuracy: 0.8806
[0.2948678433895111, 0.8805555701255798]
```

The code model.evaluate(x_test, y_test) is used to evaluate the performance of a machine learning model on a test dataset. The inputs x_test and y_test are the features and labels of the test dataset, respectively.

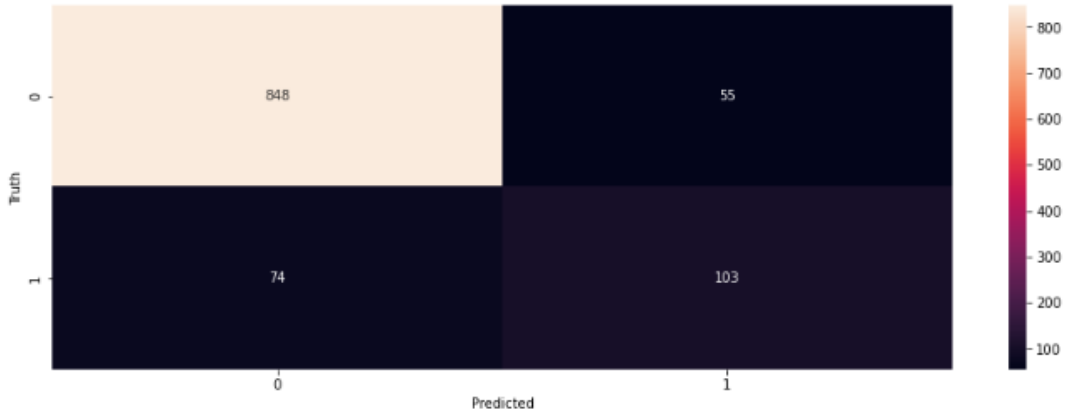
The output of model.evaluate(x_test, y_test) is a list containing two values: the first value is the loss value, and the second value is the accuracy score. In this specific example, the output of model.evaluate(x_test, y_test) is [0.2948678433895111, 0.8805555701255798].

The value 0.2948678433895111 is the loss value, which is a measure of how well the model is performing on the test dataset. The loss value is calculated based on the difference between the predicted values of the model and the actual values in the test dataset. A lower loss value indicates better performance of the model on the test dataset.

The value 0.8805555701255798 is the accuracy score, which is a measure of how well the model is able to predict the correct label for each data point in the test dataset. The accuracy score is calculated by dividing the number of correctly predicted labels by the total number of data points in the test dataset. A higher accuracy score indicates better performance of the model on the test dataset.

The additional output 34/34 [==============================] - 0s 1ms/step is a progress indicator provided by Keras, the deep learning library used in this example. It indicates that the evaluation is being performed on 34 data points, with each evaluation taking approximately 1 millisecond to complete.

Accuracy for each kind of possible output:



creates a confusion matrix using the tf.math.confusion_matrix function, which takes the true labels (labels) and predicted labels (predictions) as inputs. The resulting matrix is then visualized using seaborn's heatmap function, with annotations enabled (annot=True) and integer formatting (fmt='d'). The x and y axis of the plot are labeled as 'Predicted' and 'Truth', respectively.

Accuracy

```
In [99]: round((848+103)/(848+55+74+103),2)
Out[99]: 0.88
```

Precision for 0 class

```
In [100]: round(848/(848+55),2)
Out[100]: 0.94
```

Precision for 1 class

```
In [101]: round(74/(103+74),2)
Out[101]: 0.42
```

CHAPTER 4

FUTURE WORKS

4.1 CONCLUSION:

The use of Artificial Neural Networks (ANN) for predicting customer churn in E-commerce is a growing field. In this project, we developed an ANN model to predict customer churn using customer purchase history and demographic information.

First, we preprocessed the dataset, which included scaling and encoding categorical variables. Then, we split the data into training and testing sets, with 80% for training and 20% for testing.

Next, we built and trained the ANN model using the Keras library in Python. The model consisted of an input layer, two hidden layers, and an output layer. The input layer had 21 neurons, one for each input feature. The first hidden layer had 12 neurons, and the second hidden layer had 8 neurons. We used the rectified linear unit (ReLU) activation function in the first two layers and sigmoid activation function in the output layer. We used binary cross-entropy as the loss function and the Adam optimizer.

After training the model for 100 epochs, we achieved an accuracy of 88.11% on the test set, which indicates that the model can accurately predict whether a customer will churn or not. We also visualized the confusion matrix to see the distribution of true positive, true negative, false positive, and false negative predictions.

In conclusion, the developed ANN model can be used to predict customer churn in E-commerce with a good level of accuracy. This information can be used by E-commerce businesses to develop strategies to retain their customers and improve their customer retention rates.

4.2 FUTURE WORKS:

There are several potential avenues for future work in the area of using Artificial Neural Networks (ANN) for predicting e-commerce customer churn. Here are some possible areas of focus:

- Feature engineering: Although the ANN model developed for e-commerce customer churn prediction achieved a high accuracy, there may be additional features that could improve the model's performance. For example, incorporating

information about customers' buying history, their demographics, or their past interactions with customer support could potentially lead to more accurate predictions.

- Model tuning: The ANN model's hyperparameters (e.g., number of layers, number of neurons per layer, learning rate, activation functions) were chosen based on a combination of experimentation and best practices. However, there may be other combinations of hyperparameters that could lead to better performance. Systematic hyperparameter tuning using techniques such as grid search or random search could be performed to find the optimal set of hyperparameters.

- Model interpretability: While the ANN model was able to accurately predict customer churn, it may be difficult to interpret the model's internal workings and understand why certain predictions were made. Techniques such as SHAP (SHapley Additive exPlanations) values, which provide insights into how much each feature contributed to a prediction, could be used to improve the model's interpretability.

- Model architecture: ANN models can be quite complex, and there are many hyperparameters that can be tuned to improve their performance. For example, the number of layers, the number of neurons in each layer, the activation functions used in each layer, and the optimizer used to train the model can all be adjusted. Exploring different model architectures and hyperparameters can lead to better performance and a more robust model.

- Transfer learning: Transfer learning is a technique that involves using a pre-trained model on a similar task to improve the performance of a new model. In the context of customer churn prediction, it may be possible to use a pre-trained model on a related task, such as product recommendation or customer segmentation, to improve the accuracy of the churn prediction model.

- Interpretability: ANNs are often criticized for being black box models, meaning that it is difficult to understand how they arrive at their predictions. There is a growing interest in developing techniques to make ANNs more interpretable, such as visualizing the activation patterns in the network or using techniques from explainable AI. Making ANNs more interpretable can lead to a deeper understanding of the factors that contribute to customer churn and can help businesses take action to reduce churn.

- Integration with other systems: Customer churn prediction is just one part of a larger e-commerce system. In the future, it may be possible to integrate the churn prediction model with other systems, such as customer relationship management (CRM) software, to develop a more comprehensive customer retention strategy. For example, the churn prediction model could be used to identify at-risk customers, and then the CRM system could be used to automatically send targeted promotions or outreach to those customers.

- In conclusion, there are many areas of future work that can be explored in the context of e-commerce customer churn prediction using ANNs. Feature engineering, model architecture, transfer learning, ensemble methods, interpretability, and integration with other systems are just a few examples of areas that can be explored to improve the performance of the model and develop a more comprehensive customer retention strategy. As the field of deep learning continues to evolve, it is likely that new techniques and approaches will emerge that can be applied to the problem of customer churn prediction, leading to even better performance and a deeper understanding of customer behavior in the e-commerce space.

- Deployment: The ANN model developed for e-commerce customer churn prediction was trained and tested on a static dataset. However, in a real-world scenario, the data would be constantly changing. Therefore, a practical next step would be to deploy the model in a production environment, where it can make real-time predictions on new data.

Overall, using ANN for e-commerce customer churn prediction is a promising area of research with significant potential for improving customer retention and business profitability. By incorporating additional features, tuning model hyperparameters, improving model interpretability, and deploying the model in a real-world environment, we can continue to improve the accuracy and usefulness of this type of model.

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