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**Faculty of new Technologies of Information and Communication**  
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**Dissertation**

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**In Computer Science**

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**Topic:**

**Analysing Product Reviews Using Artificial  
Neural Network (ANN)**

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**Academic year: 2022/2023**

# Dedication

We dedicate this humble act to our dear parents for their constant

encouragement,

To our dear brothers,

Our dear sisters,

For our entire family,

To all our friends,

Thank you.

# Acknowledgments

We thank Almighty God for granting us the courage, strength, and determination to accomplish this humble work. Our sincere gratitude goes to our supervisor, Dr. Mazouz Mihoub from Kasdi Merbah Ouargla University, for his patience, support, and continuous encouragement that contributed to the completion of these efforts despite the difficulties we faced in this work. We would also like to thank everyone who has provided us with direct or indirect assistance and contributed to the development of our project.

## Abstract

This study focuses on the development of an AI model to analyze client reviews of a specific product and determine their sentiment towards the product. The primary objective is to assess whether clients liked or disliked the product based on their feedback. The study presents a program utilizing an Artificial Neural Network architecture for opinion analysis.

**Keywords:** Machine Learning, Sentiment analysis, Artificial Neural Network (ANN).

## Résumé

Cette étude se concentre sur le développement d'un modèle d'intelligence artificielle (IA) pour analyser les avis des clients sur un produit spécifique et déterminer leur sentiment à l'égard du produit. L'objectif principal est d'évaluer si les clients ont aimé ou n'ont pas aimé le produit en fonction de leurs commentaires. L'étude présente un programme utilisant une architecture de réseau neuronal artificiel pour l'analyse des opinions.

**Mots-clés :** Apprentissage Automatique, analyse des sentiments, réseau neuronal artificiel.

## المخلص:

تركز هذه الدراسة على تطوير نموذج ذكاء اصطناعي لتحليل آراء العملاء حول منتج محدد وتحديد مشاعرهم تجاه المنتج. الهدف الرئيسي هو تقييم ما إذا كان العملاء يحبون أم لا يحبون المنتج استنادًا إلى تعليقاتهم. تقدم الدراسة برنامجًا يستخدم هندسة شبكة عصبية اصطناعية لتحليل الآراء.

**الكلمات المفتاحية:** تعلم الآلة، تحليل المشاعر، شبكة عصبية اصطناعية.

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# **GENERAL INTRODUCTION**

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## **General Introduction**

The impact of product reviews on consumer behavior has grown significantly in the digital era. A product's marketability can be determined by the comments and experiences that users post on online forums. For firms looking to gain a competitive edge, the capacity to capture and evaluate the quantity of information present in these reviews is of utmost importance. In order to understand the underlying sentiments in product reviews, this manuscript digs into the fascinating world of semantic analysis. It examines the revolutionary power of machine learning, artificial neural networks, and coding and implementation methodologies.

### **Chapter 1: Machine Learning**

We start our trip into the fundamentals of machine learning as it relates to semantic analysis in the first chapter. With a focus on sentiment analysis, we examine the ideas of supervised, unsupervised, and reinforcement learning. We examine the preprocessing stages, feature extraction methods, and selection strategies required for developing machine learning models. Furthermore, we address the advantages and disadvantages of well-known algorithms like Naive Bayes, Support Vector Machines, and Random Forests in the context of semantic analysis.

### **Chapter 2: Artificial Neural Networks**

The second chapter delves into the captivating world of artificial neural networks, a paradigm inspired by the intricacies of the human brain. We explore the architecture and workings of feedforward neural networks, recurrent neural networks, and convolutional neural networks. The manuscript investigates the role of neural networks in sentiment analysis, showcasing how they excel at capturing complex patterns and semantic nuances within product reviews. We also discuss optimization algorithms, regularization techniques, and approaches to handling imbalanced datasets, all essential components for building robust and accurate models.

### **Chapter 3: Developed Model**

Our attention shifts to the practical facets of coding and implementation in the last chapter. Here, we look at the frameworks and technologies that make it easier to create sentiment analysis systems. We go into well-known programming languages like Python and R, revealing packages like TensorFlow and Scikit-learn that offer a rich ecosystem for the creation of neural networks and machine learning. We also cover best practices for deploying and integrating sentiment

analysis systems into practical applications, model evaluation metrics, and data pretreatment methods.

This manuscript provides a thorough overview of the fascinating topic of semantic analysis of product reviews by fusing theoretical insights with real-world experiences. By the end, readers will have a deeper understanding of how sentiments are decoded using machine learning, artificial neural networks, coding, and implementation techniques, empowering businesses to make data-driven decisions and create lasting relationships with their clients in an increasingly digital world.

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## **CHAPITRE I: Machine Learning**

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## 1-Introduction

Machine learning is a subset of artificial intelligence that involves using algorithms and statistical models to enable computers to learn and improve from experience without being explicitly programmed. It is a method of teaching computers to recognize patterns in data, make predictions, and automate tasks based on that data. Machine learning algorithms use large sets of data to learn and improve their performance over time, making them increasingly accurate and efficient in their predictions and decision-making. Machine learning has become increasingly important in many areas of business, science, and technology, including image and speech recognition, natural language processing, predictive analytics, and robotics.

## 2-Machine Learning Definition

Developing algorithms and statistical models that allow computers to learn from data, recognize patterns, and make predictions or judgments without being explicitly programmed is known as machine learning, and it is one of the subfields of artificial intelligence (AI). Instead of manually programming computers, it entails teaching them to see patterns and make judgments by training them on massive datasets.[1][2][3]

Computer vision, natural language processing, speech recognition, recommendation systems, and predictive modelling are just a few of the fields that use machine learning.

Popular machine learning methods include neural networks, support vector machines, decision trees, random forests, logistic regression, linear regression, and k-nearest neighbours.

Artificial intelligence pioneer **Arthur Samuel** provided the following definition of machine learning: “Machine learning is the field of study that gives computers the ability to learn without being explicitly programmed.” [4]

This definition emphasizes the notion that artificial intelligence's area of machine learning is teaching a computer system to learn from data, spot patterns, and make judgment calls. The meaning Samuel gave still holds true today.

Computer scientist and machine learning specialist **Tom Mitchell** provided the following definition of machine learning: “A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance on tasks in T, as measured by P, improves with experience E.”[5]

Mitchell's formulation highlights the three crucial elements task, performance measure, and experience or data and underlines the significance of experience or data in machine learning.

### 3-Application of Machine Learning

Several industries, including healthcare, banking, retail, speech recognition, email spam detection, manufacturing, image recognition, transportation, and many more use machine learning techniques. Here is a detailed explanation of a few of them:

**Healthcare:** Machine learning is utilized in the industry for a variety of tasks, including diagnosing illnesses and recommending treatments. Deep learning, for instance, was employed in a study by Esteva et al. (2017) to classify skin cancer with accuracy that was on par with or better than that of dermatologists.[6]

**Finance:** To identify fraud, forecast market trends, and make investment decisions, machine learning algorithms are used. For instance, Nair et al (2018). 's work employed machine learning to forecast stock values based on the tone of market news.[7]

**Retail:** Based on a customer's browsing and purchasing history, machine learning algorithms are used to offer things to them. For instance, Amazon makes product recommendations to its consumers based on their past purchases and search history using machine learning.

**Speech recognition:** When using Google, we have the option to "Search by voice," which falls under speech recognition and is a well-known machine learning application.

Voice recognition, often known as "Speech to text" or "Computer speech recognition," is the process of turning spoken commands into text. Speech recognition applications currently use machine learning algorithms extensively. Speech recognition technology is used by Alexa, Google Assistant, Siri, Cortana, and Microsoft Cortana to carry out voice commands.

**Manufacturing:** Machine learning is used to enhance quality assurance, predict equipment breakdowns, and optimize manufacturing processes. For instance, Zhou et al (2018) .'s work employed machine learning to forecast how long cutting tools will be helpful in a manufacturing process.

**Image recognition:** One of the most popular uses of machine learning is image identification. It is used to identify things like digital photos, people, places, and items. Automated friend tagging recommendation is a common use of picture recognition and facial identification.

Facebook offers us an automatic buddy tagging recommendation option. The face identification and recognition technique used in machine learning is what gives us an automatic tagging recommendation with names whenever we submit a photo of one of our Facebook friends.

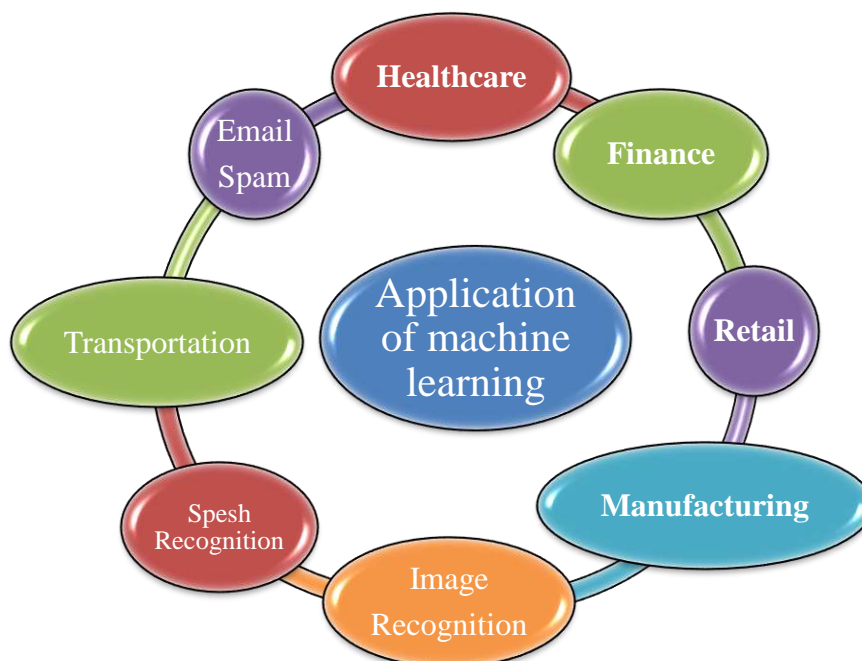
It is based on the "Deep Face" technology from Facebook, which handles facial recognition and human identification in photos.

**Email Spam:** Every new email that we get is immediately classified as essential, common, or spam. Machine learning is the technology that enables us to consistently receive essential emails marked with the important sign in our inbox and spam emails in our spam box. Here are a few spam filters that Gmail employs:

- ✓ Filtering Content.
- ✓ headline filter.
- ✓ filters for general blacklists.
- ✓ filters with rules.
- ✓ Allowance filters.

For email spam filtering and virus identification, some machine learning methods are utilized, including Multi-Layer Perceptron, Decision tree, and Nave Bayes classifier.

**Transportation:** Machine learning techniques are utilized to enhance navigational systems, forecast vehicle repair requirements, and manage traffic flow. For instance, Zhang et al studies from 2021 employed machine learning to forecast traffic jams and suggest the best paths for moving vehicles.



*Figure 1- Some application of machine learning*

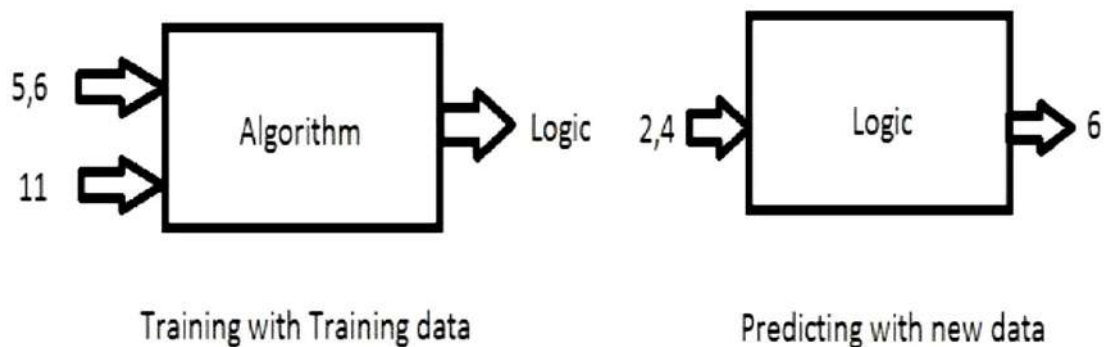
## 4-Types of Machine Learning

Supervised learning, unsupervised learning, and reinforcement learning are the three main categories of machine learning.

**Supervised Learning:** In supervised learning, a labeled dataset with known accurate outputs is used to train the computer. The system must learn to predict the right result from novel, unknown inputs. Speech recognition, fraud detection, and image categorization are a few applications of supervised learning.[7]

There are many algorithms used in supervised learning, each with its own strengths and weaknesses. Here are some common types of supervised learning algorithms:

- Artificial Neural Network (ANN): Look at CHAPTER II.
- k-Nearest Neighbors (k-NN).
- Support Vector Machines (SVM).

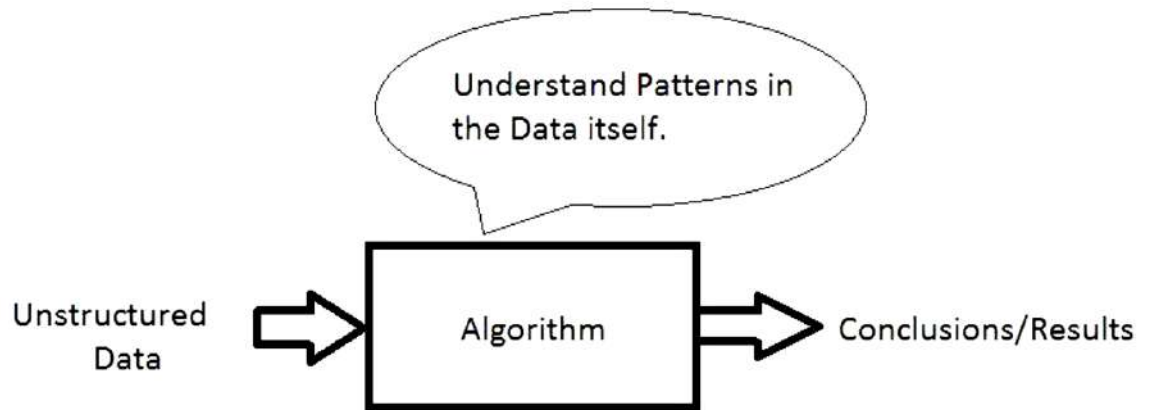


*Figure 2- Supervised Learning Model [9]*

**Unsupervised learning:** In unsupervised learning, a machine is tasked with identifying patterns or other structures in a dataset that has not been labelled. There is no accurate output for the system to learn from, unlike supervised learning. Instead, it is up to the machine to determine how the data is actually structured. Anomaly detection, dimensionality reduction, and grouping are a few examples of unsupervised learning.[10]

There are many algorithms used in unsupervised learning, each with its own strengths and weaknesses. Here are some common types of unsupervised learning algorithms:

- Singular Value Decomposition (SVD).
- Principal Component Analysis (PCA).

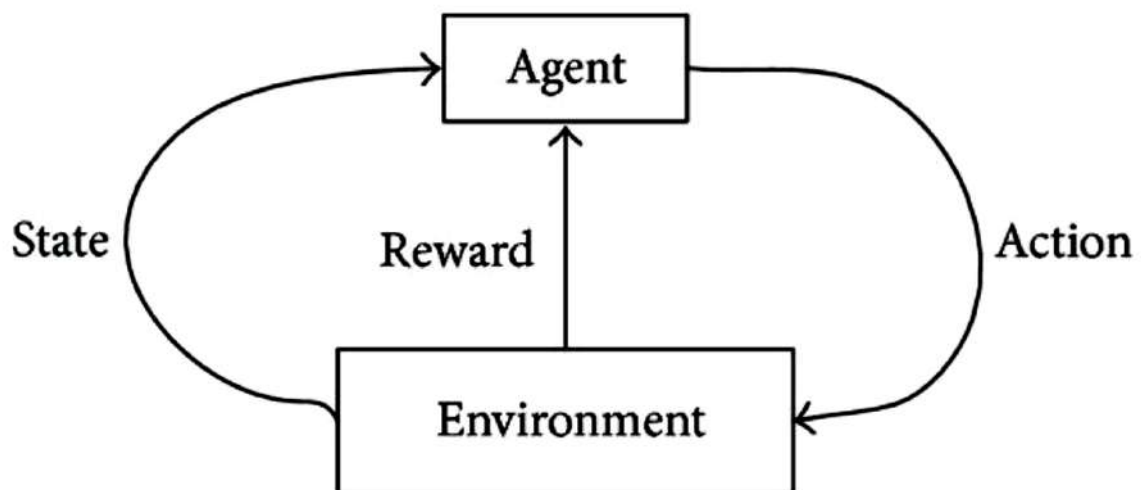


*Figure 3- Unsupervised Learning Model*

**Reinforcement learning:** In reinforcement learning, the computer learns by making mistakes and receiving feedback in the form of incentives or punishments. The machine should learn to behave in a way that maximizes the cumulative reward over time. Gaming, robots, and autonomous driving are a few instances of reinforcement learning.[11][12]

Here are some common algorithms used in reinforcement learning:

- Deep Q-Networks (DQN).
- Actor-Critic Methods (ACM).



*Figure 4- Reinforcement Learning Model [13]*

<b>Machine Learning Types</b>	<b><i>Used Algorithms</i></b>
<b><i>Supervised Learning</i></b>	Artificial Neural Network (ANN), k-Nearest Neighbors (k-NN), Support Vector Machines (SVM)
<b><i>Unsupervised learning</i></b>	Singular Value Decomposition (SVD), Principal Component Analysis (PCA)
<b><i>Reinforcement learning</i></b>	Deep Q-Networks (DQN), Actor-Critic Methods (ACM)

*Table 1- Types of machine learning*

## **5-Conclusion**

Machine learning has become a powerful tool for enabling computers to learn and make predictions based on data. It has applications in a wide range of fields, including business, science, and technology, and is playing an increasingly important role in many industries. As machine learning algorithms continue to improve and become more sophisticated, their potential for enabling new insights and innovations is only growing. However, it is important to remember that machine learning is not a silver bullet solution and must be used responsibly and ethically, taking into account issues such as bias, privacy and transparency.

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## **CHAPITRE II : Artificiel Neural Network Algorithm**

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## 1-Introduction

Artificial Neural Networks (ANN) are algorithms that simulate brain activity and are used to model complex patterns and make predictions about future events. The idea of biological neural networks in the human brain gave rise to the Artificial Neural Network (ANN), a deep learning technique. An effort to simulate how the human brain functions led to the creation of ANN. Although they are not exactly the same, the operations of ANN and biological neural networks are very similar. Only structured and numeric data are accepted by the ANN algorithm.

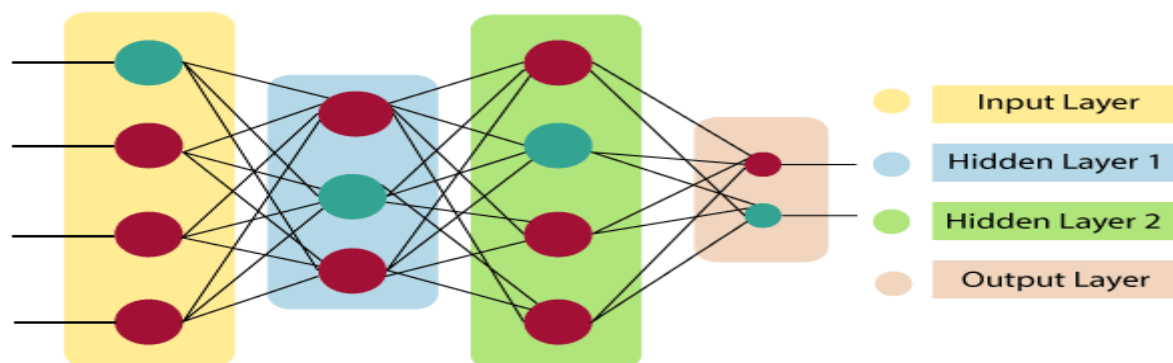
## 2-Artificial Neural Network

### 2-1- Definition

An Artificial Neural Network (ANN) is a kind of machine learning algorithm that is based on the design and operation of biological neurons in the human brain. The algorithm is made up of networked nodes, or neurons, that process and transmit data in a manner that is similar to how biological neurons work. ANNs have been effectively employed in a variety of domains, including image identification, natural language processing, and finance. They are used to identify patterns in data, make predictions, and carry out other activities.[14]

### 2-2- Architecture

An artificial neural network's (ANN) architecture is defined as the configuration of the network's neurons and the connections that connect them. Layers of nodes, or neurons, connected by weighted links make up an artificial neural network (ANN). The input layer, the hidden layer(s), and the output layer are the three most typical types of layers in ANNs.



*Figure 5- Artificial Neural Network Architecture*

The initial layer of the network, known as the input layer, is in charge of taking in data. The number of input variables is the same as the number of neurons in the input layer. At the input layer, each neuron stands for a single input variable.

The hidden layer or layers process the input data in between the input and output layers. The difficulty of the problem being handled determines the number of hidden layers and neurons in each layer. Several hidden layers in deep neural networks have demonstrated greater performance in numerous applications.

The network final layer, known as the output layer, is responsible for creating the network output. The quantity of output variables affects how many neurons are present in the output layer. At the output layer, each neuron stands for a single output variable.

Weighted linkages serve as a representation of the connections between the neurons in each layer. The strength of the connection between the neurons is determined by the weight attached to each link. These weights are modified during training in order to reduce the discrepancy between expected and actual production.

There are many different ANN architecture types, each with their own special properties and uses, including feedforward neural networks, recurrent neural networks, convolutional neural networks, and others. [15]

Overall, an ANN's performance and suitability for a given task are significantly influenced by its architecture.

### **3-Cost Function** [16]

The cost function in artificial neural networks (ANNs) is a gauge of how well the network does on a specific job. It is a mathematical function that computes a numerical number to indicate the error or loss of the network's predictions by taking as inputs the network output and the desired output. The objective of training an ANN is to reduce the inaccuracy or loss of the network's predictions in order to minimize the value of the cost function.

Depending on the particular task and the network's topology, ANNs can employ a variety of cost function types. Several typical cost functions are:

**Mean squared error (MSE):** This is a well-liked cost function for regression issues where predicting a continuous value is the main objective. The average squared difference between the anticipated value and the actual value is calculated by MSE.

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \tag{1}$$

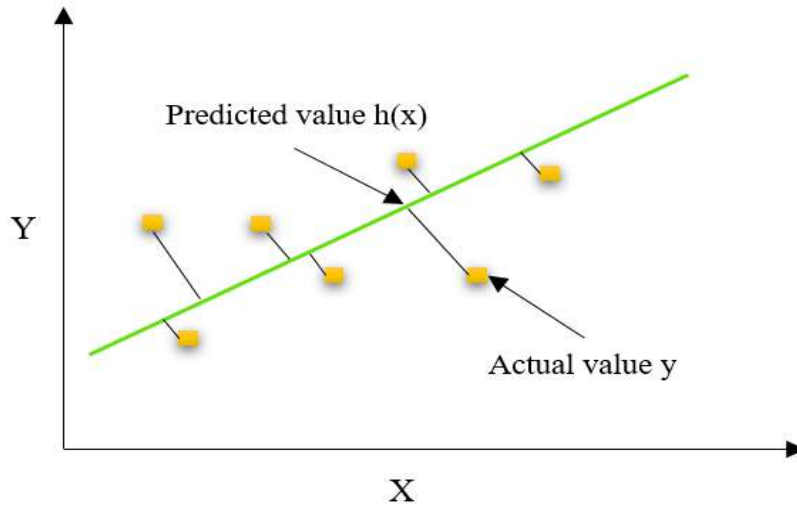


Figure 6- Mean squared error (MSE)

**Binary cross-entropy:** When attempting to forecast one of two outcomes in binary classification tasks, this cost function is applied. The difference between the expected probability of the positive class and the actual probability is measured by binary cross-entropy.

$$H_p(q) = -\frac{1}{N} \sum_{i=1}^N y_i \cdot \log(p(y_i)) + (1 - y_i) \cdot \log(1 - p(y_i)) \tag{2}$$

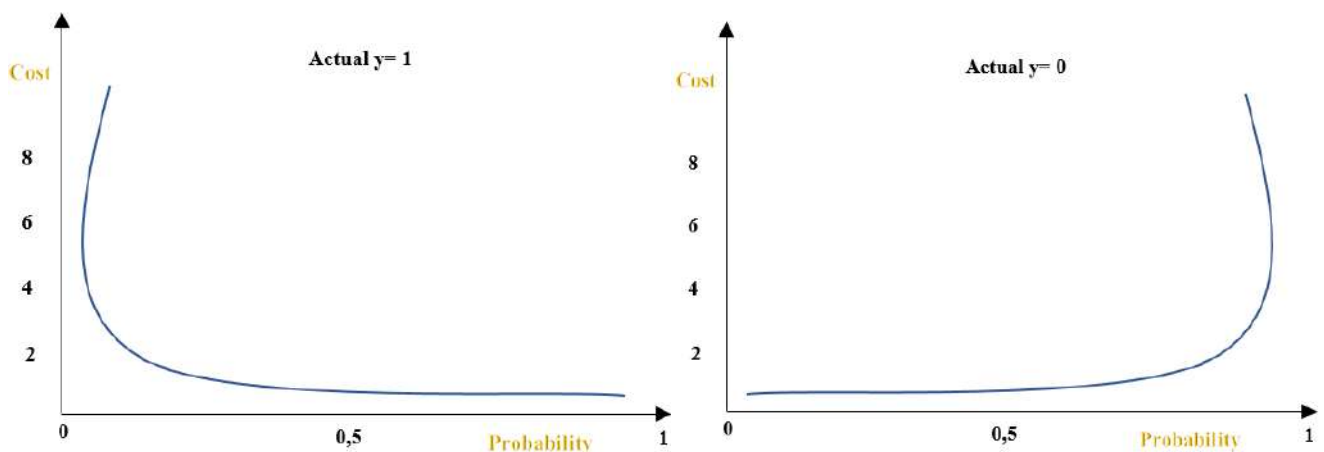


Figure 7- Binary cross-entropy

**Categorical cross-entropy:** This cost function is used to anticipate one of several potential outcomes in multi-class classification problems. The difference between the actual probability distribution and the projected probability distribution is measured by categorical cross-entropy.

$$CCE = -\sum_{i=1}^N y_i \cdot \log(y'_i) \quad (3)$$

An ANN's performance can be significantly impacted by the cost function that is selected because it affects how the network is trained and how it handles failures. It is crucial to select a cost function that is appropriate for the given task and to keep an eye on the network's performance while it is being trained to make sure it is moving closer to lowering the cost function.

#### 4-Backpropagation Algorithm

Artificial neural networks (ANNs) are trained using the popular supervised learning algorithm backpropagation. It is a form of gradient descent algorithm that updates the network weights using the calculus chain rule. The error between the network's anticipated output and the actual output is reduced through backpropagation.

The backpropagation algorithm propagates the error backwards across the network, starting at the output layer and proceeding toward the input layer. The algorithm uses the chain rule to calculate the error gradient with respect to each weight in the network, and then updates the weights in the direction of the error-minimizing negative gradient.

Backpropagation algorithms come in a variety of forms, including batch, mini-batch, and stochastic gradient descent. Mini-batch and stochastic gradient descent compute the gradient for a subset of the data, whereas batch gradient descent computes the gradient for the full dataset.[17]

Although backpropagation is an effective approach for training ANNs, it has certain drawbacks, such as overfitting and getting stuck in local minima. To overcome these concerns, researchers have suggested a number of modifications and extensions, including momentum, adaptive learning rates, and regularization techniques.[18]

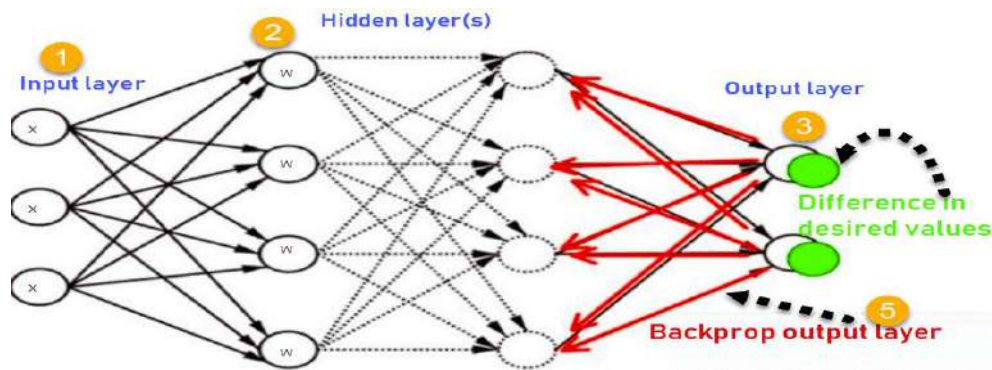


Figure 8- Backpropagation Algorithm

## 5-ANN Evaluation Metrics

Depending on the precise task and objectives, there are various approaches to assess an artificial neural network (ANN) performance. Here are a few typical approaches:

**Accuracy:** For classification issues, this statistic is most frequently employed. It is the proportion of samples that were correctly categorised to all samples.

**Precision:** This is the proportion of true positives (TP) to the total of both true and false positives (FP). It provides a rough estimate of the proportion of the expectedly positive samples that are in fact positive.

**Recall:** The ratio of true positives (TP) to the total of true positives plus false negatives (FN) is what determines this. It provides information on the proportion of positive samples that were really anticipated to be positive.

**F1 score:** This combination of recall and precision offers a fair evaluation of performance.[19]

**Confusion matrix:** For a classification problem, this matrix displays the quantity of true positives, true negatives, false positives, and false negatives. It can be used to compute a number of evaluation measures, including F1 score, recall, accuracy, and precision.

**Receiver operating characteristic (ROC) curve:** In a binary classification problem, this is a plot of the true positive rate (TPR) against the false positive rate (FPR) for various threshold values. For various threshold values, it offers a method to display the trade-off between sensitivity (TPR) and specificity (1-FPR).

**Mean squared error (MSE):** When attempting to predict a continuous output variable, this metric is frequently used. The average squared difference between the expected and actual values is what is measured.[20]

These are merely a few illustrations of artificial neural network evaluation metrics and procedures. The specific task and goals determine the metric to use. To provide accurate evaluation results, it's also crucial to employ the proper cross-validation and hyperparameter tweaking approaches.

## 6-Advantages and Disadvantages of Artificial Neural Networks (ANN)

### 6-1- Advantages

Artificial neural networks have gained enormous popularity in recent years due to their precision in simulating complicated data and tasks as well as their capacity to mimic the pattern-recognition abilities of the brain. Additionally, it has a number of benefits, such as requiring less formal statistical training, having access to a variety of training algorithms, and being able to implicitly detect complex nonlinear relationships between dependent and independent variables.

- ✓ **Storing information on the entire network:** The information is stored across the network, as with traditional programming, rather than in a database. The disappearance of some data in one place does not prevent the network from operating.
- ✓ **Ability to work with incomplete knowledge:** After ANN training, the data can provide results even with incomplete information. The loss of performance here depends on the importance of the missing information.
- ✓ **Having fault tolerance:** Corrupting one or more cells of ANN will not prevent it from generating results. This feature makes networks fault tolerant.
- ✓ **Having a distributed memory:** In order for an ANN to learn, it is necessary to identify examples and teach the network according to the desired output by showing them to it. The success of the network is proportional to the instances chosen, and if events are not fully visible to the network, the network may produce erroneous output.
- ✓ **Gradual corruption:** Over time, the network slows down and relatively deteriorates. A network problem does not immediately cause corrosion.
- ✓ **Ability to make machine learning:** Artificial neural networks analyze activities and make selections with the aid of using commenting on comparable activities.

- ✓ **Parallel processing capability:** Artificial neural networks have the numerical strength to perform multiple tasks at once. [21]

## 6-2- Disadvantages

Artificial neural networks have numerous benefits, they also have significant disadvantages. Due of their complexity, neural networks need a lot of data to be trained. It can take a lot of money and time to do this. Additionally, neural networks are prone to overfitting, which is when they recognize patterns in the data that aren't really there. This could produce unreliable outcomes. Additionally, there are a number of drawbacks to artificial neural networks that need to be addressed, including:

- ✓ **Hardware dependence:** The structure of artificial neural networks necessitates processors with parallel processing capabilities. Consequently, the creation of such equipment is reliant on this specific requirement.
- ✓ **Unexplained behaviour of the network:** ANN's chief issue lies in its inability to explain the how's and whys behind the probing solution it generates, thereby diminishing confidence in the network.
- ✓ **Determination of proper network structure:** Designing the structure of artificial neural networks is not governed by any set guidelines. It is only through trial and error and experience that an appropriate network architecture can be formulated. [21]
- ✓ **ANN Over fitting Likely:** ANNs are susceptible to overfitting during the training phase. One of the main reasons for this is the fact that the size and structure of ANNs are typically determined through a process of trial and error.[22]
- ✓ **Difficulty of showing the problem to the network:** Artificial neural networks, or ANNs, are designed to process numerical data. As a result, any issues must first be converted into numeric values before being fed into an ANN. It's worth noting that the display mechanism is a crucial element that affects the network's overall efficiency. Ultimately, the user's proficiency in navigating such mechanisms plays a significant role in determining how well the ANN performs.
- ✓ **The duration of the network is unknown:** Upon completion of training, the network is condensed to a specific sample means error value. However, this particular value does not guarantee the best possible outcome.[21]

- ✓ **Size and Structure Chosen by Trial and Error:** The size and structure of the ANN are usually chosen empirically and by trial and error. The choice of ANN size and structure is crucial to obtain an accurate solution.[22]
- ✓ **Black Box Solution:** ANN itself is a black box solver. That said, once a solution is found, it can be difficult to Figure ure out how that solution was achieved.
- ✓ **Science artificial neural networks:** People born in the middle of the 20th century is developing rapidly. In modern times, we explore the benefits of artificial neural networks and the problems of using them. It should not be forgotten that ANN networks, as a growing branch of science, are gradually eliminating their shortcomings while their advantages are increasing day by day. This means that artificial neural networks have become an integral part of our lives and are becoming more and more important. [21]
- ✓ According to the authors of the book "Deep Learning for Coders with Fastai and PyTorch," layer-by-layer or even node-by-node weight comparisons can provide mathematical insights. Combined with visualization, ANNs can be made easier to understand. Jeremy Howard and Sylvan Gugger highlight: "There is a wealth of research showing how to overhaul deep learning models and derive valuable insights from them".[23]

Advantages	Disadvantages
<b>Ease and simplicity of use</b>	Not fully accurate
<b>Change , alter to unknown circumstances</b>	Large complexity of network structure (quite intricate).
<b>It can model difficult function</b>	The ANN needs the training to operate and become productive
<b>It may be implemented in any situation and application</b>	Huge time form processing large ANN

*Table 2: Some Advantages and Disadvantages of ANN*

## 7-Conclusion

The sophisticated models known as analytical neural networks (ANNs) can be used in a variety of situations. Although they have applications in a variety of fields, including medicine, security/finance, governance, agriculture, and analyse reviews, several notable uses of ANNs have already been recognized.

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## **CHAPITRE III: Developed Model**

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## 1-Introduction

In recent years, neural networks, a kind of artificial intelligence (AI), have gained popularity for their capacity to scan vast volumes of data and spot patterns. Neural networks can be very helpful for businesses to assess customer emotion and preferences when it comes to product ratings. In order to process natural language and recognize significant elements and attitudes conveyed in product reviews, neural networks can be trained. Businesses can learn which features of their products are most valued and which ones want development by examining this data. Businesses who receive a lot of product reviews may find this particularly helpful because neural networks can swiftly assess this data and offer insights that are tough to obtain manually.

Additionally, false reviews may be recognized and eliminated from the data set using neural networks, guaranteeing that companies have access to accurate and trustworthy information about their products. In this situation, applying neural networks to product reviews presents fascinating opportunities for comprehending consumer behavior and enhancing product quality, which will ultimately result in improved customer experiences and higher sales.

## 2- Problem to be Solved

Semantic analysis of product reviews is a typical task in machine learning and natural language processing (NLP). In order to comprehend the ideas, experiences, and attitudes expressed by consumers about a certain product or service, it entails assessing the sentiment and extracting insightful information from customer evaluations. Semantic analysis of product reviews, however, is not without difficulties and issues. Let's talk about a couple of them.

**Sentimental Evaluation:** Semantic analysis of product reviews includes sentiment analysis as a core component. It is difficult to determine a review's sentiment precisely, whether it be good, negative, or neutral. However, the inclusion of sarcasm, vagueness, and subjective wording in evaluations makes sentiment analysis difficult. A big problem is creating models that can manage these complexities well.

**Understanding the Context:** A product review's context is essential for thorough analysis. Reviews of products frequently make mention of certain characteristics, features, or user experiences. However, it might be challenging to comprehend the context and link it to the

pertinent mood, particularly when reviews are extensive or cover a wide range of topics. Another difficulty is extracting precise sentiments for various features of a product.

**Handling Opinion Variations:** Different users may use different linguistic terms or vocabularies to describe thoughts that are similar. For instance, one user can comment that "The camera quality is outstanding," while another might say, "The camera is amazing." It is a challenging undertaking that calls for strong modeling techniques to capture these variations and convert them to a consistent sentiment representation.

**Data Sparsity and Unbalanced Datasets:** Gathering labeled data for training sentiment analysis models can be an expensive and time-consuming procedure. Finding a balanced dataset with an equal number of favorable, negative, and neutral evaluations can be difficult in some situations. Additionally, some feelings could be less common than others, leading to unbalanced statistics. To create models that effectively represent the emotion distribution and generalize well, it is essential to address data imbalance and sparsity.

**Domain Adaptation:** When used in a different domain, sentiment analysis models developed for one domain may not perform as well. Different product categories or industries may use language, vocabulary, and emotional expressions that differ greatly from one another. To achieve reliable sentiment analysis across many product domains, strategies for domain adaptation, transfer learning, or fine-tuning models using domain-specific data must be developed.

**Handling Multi-modal Data:** Product feedback frequently includes modalities other than text, such as photographs, videos, or audio. Additional difficulties arise when analyzing multi-modal data and merging data from many modalities to fully comprehend sentiment. Research is still being done on creating models that successfully integrate and fuse data from several modalities.

**Real-time Analysis:** To track customer sentiment and act quickly, many firms need to analyze product reviews in real-time. It can be difficult computationally to do sentiment analysis on a huge number of evaluations in real-time while retaining high accuracy and efficiency. For practical applications, it is crucial to develop scalable, effective systems that can manage real-time analysis.

## 3-Model implementation

### 3-1-Language and tools

#### a-Python

Due to its adaptability, simplicity, and extensive ecosystem of libraries and frameworks, Python is a widely used programming language in the field of machine learning. It is the best option for creating and putting into practice machine learning algorithms due to its intuitive syntax and readability. Many libraries, like NumPy, Pandas, and Matplotlib, are available in Python and offer strong capabilities for data manipulation, analysis, and visualization. Additionally, Python has strong support for well-known machine learning frameworks like TensorFlow, PyTorch, and scikit-learn, enabling academics and practitioners to quickly create and hone sophisticated machine learning models. Python has established itself as the go-to language for machine learning tasks thanks to its simplicity, significant community support, and wide range of libraries, enabling developers to explore and experiment in the fascinating subject of artificial intelligence.

#### b-IDE

Google Colab is a web-based platform provided by Google that offers a free cloud-based environment for AI development and collaboration. It is particularly useful for AI development due to its integration with popular machine learning libraries such as TensorFlow and PyTorch. With Google Colab, you can write and execute Python code in a Jupyter Notebook-like interface, which allows for interactive data analysis and experimentation. It provides access to powerful GPUs and TPUs, enabling faster computation for training complex AI models. Additionally, Colab allows you to save and share your notebooks, making it convenient for collaboration and knowledge sharing in AI development projects. Overall, Google Colab is a convenient and accessible tool for AI developers, providing the necessary resources and infrastructure to develop and experiment with AI models without the need for expensive hardware setups.

#### c-Different Libraries

- ✓ **Pandas** is a well-known Python package that is frequently used for data analysis and manipulation. Data structures and methods are offered that make it simple to organize, modify, and study datasets. Pandas is a go-to tool for preprocessing and preparing data for machine learning tasks because of the straightforward DataFrame object's ability to make complicated processes like indexing, merging, and filtering data simple.

- ✓ Python-based **Keras** is an API for high-level neural networks. It provides a simple and straightforward interface for creating and refining deep learning models. Because Keras is built on top of TensorFlow, developers may take advantage of TensorFlow's capabilities while also taking advantage of Keras's simplicity and ease of use. By offering pre-built layers and models that are easily customizable and extendable, it streamlines the process of building neural networks.
- ✓ A robust machine learning package called Scikit-learn (**sklearn**) provides a variety of methods and tools for various applications like classification, regression, clustering, and dimensionality reduction. It offers a consistent API and a wide range of functions for jobs including data preprocessing, model choice, and assessment. Scikit-learn is renowned for being straightforward and effective, making it a useful tool for both inexperienced and seasoned machine learning practitioners.
- ✓ A potent open-source framework for creating and training machine learning models, especially deep learning models, is called **TensorFlow**. It offers a customizable and expandable ecosystem for building neural networks and running complicated computations. Automatic differentiation, distributed training, and model deployment capabilities are just a few of the features and tools that TensorFlow has to offer. Due to its broad community support, thorough documentation, and compatibility with a variety of hardware platforms, it has experienced substantial growth in popularity.
- ✓ Python's **Pickle** module is used for deserializing and serializing objects. It enables the transformation of objects into a stream of bytes that may be stored to a file or sent over a network. In machine learning, pickle is frequently used to save trained models to disk or send them between computers. It offers a practical method for stably storing models, making it possible to reuse or distribute them for prediction tasks without having to retrain the models first.

These libraries, including Pandas, Keras, scikit-learn, TensorFlow, and Pickle, form a powerful ecosystem in Python for machine learning. Together, they enable data manipulation, model development, training, and deployment, making Python a preferred language for building and implementing machine learning solutions.

### 3-2-Dataset

#### a-Description

“The Amazon reviews polarity dataset [24] is constructed by taking review score 1 and 2 as negative, and 4 and 5 as positive. Samples of score 3 is ignored. In the dataset, class 1 is the negative and class 2 is the positive. Each class has 1,800,000 training samples and 200,000 testing samples the files train.csv and test.csv contain all the training samples as comma-separated values the CSVs contain polarity, title, text. These 3 columns in them, correspond to class index (1 or 2), review title and review text. polarity - 1 for negative and 2 for positive. title - review headin. text - review body the review title and text are escaped using double quotes ("), and any internal double quote is escaped by 2 double quotes (""). New lines are escaped by a backslash followed with an "n" character, that is "\n”.

#### b-Visualization

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3599999 entries, 0 to 3599998
Data columns (total 3 columns):
#   Column
---  ---
0   2
1   Stuning even for the non-gamer
2   This sound track was beautiful! It paints the senery in your mind so well I would recomend it even to people
dtypes: int64(1), object(2)
memory usage: 82.4+ MB
```

Figure 9- general informations about the data set

```
path = '/content/drive/MyDrive/train.csv'
df = pd.read_csv(path)
df.head()
```

2	Stuning even for the non-gamer	This sound track was beautiful! It paints the senery in your mind so well I would recomend it even to people who hate vid. game music! I have played the game Chrono Cross but out of all of the games I have ever played it has the best music! It backs away from crude keyboarding and takes a fresher step with grate guitars and soulful orchestras. It would impress anyone who cares to listen! ^_^	
0	2	The best soundtrack ever to anything.	I'm reading a lot of reviews saying that this ...
1	2	Amazing!	This soundtrack is my favorite music of all ti...
2	2	Excellent Soundtrack	I truly like this soundtrack and I enjoy video...
3	2	Remember, Pull Your Jaw Off The Floor After He...	If you've played the game, you know how divine...
4	2	an absolute masterpiece	I am quite sure any of you actually taking the...

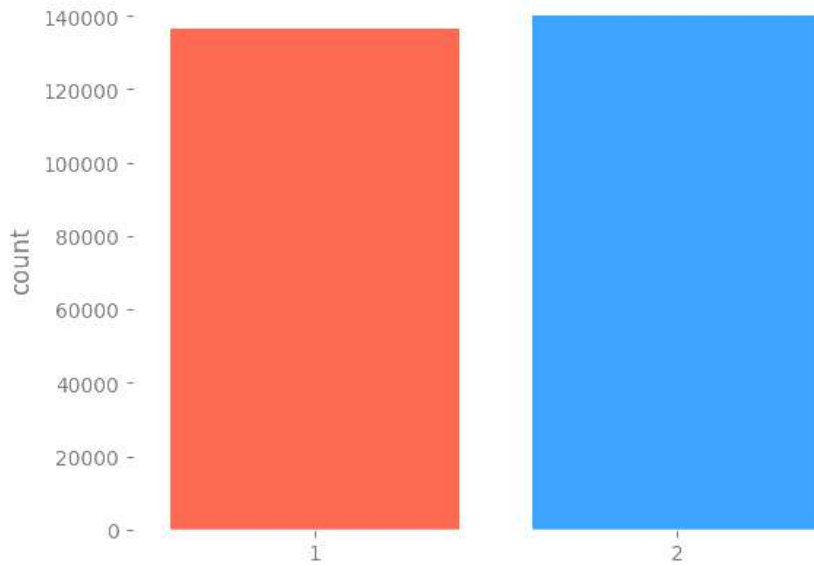
Figure 10- data sample from the data set

```
x = df.iloc[:(int)(len(df.iloc[:,2])/13),2]
y = df.iloc[:(int)(len(df.iloc[:,0])/13),0]
```

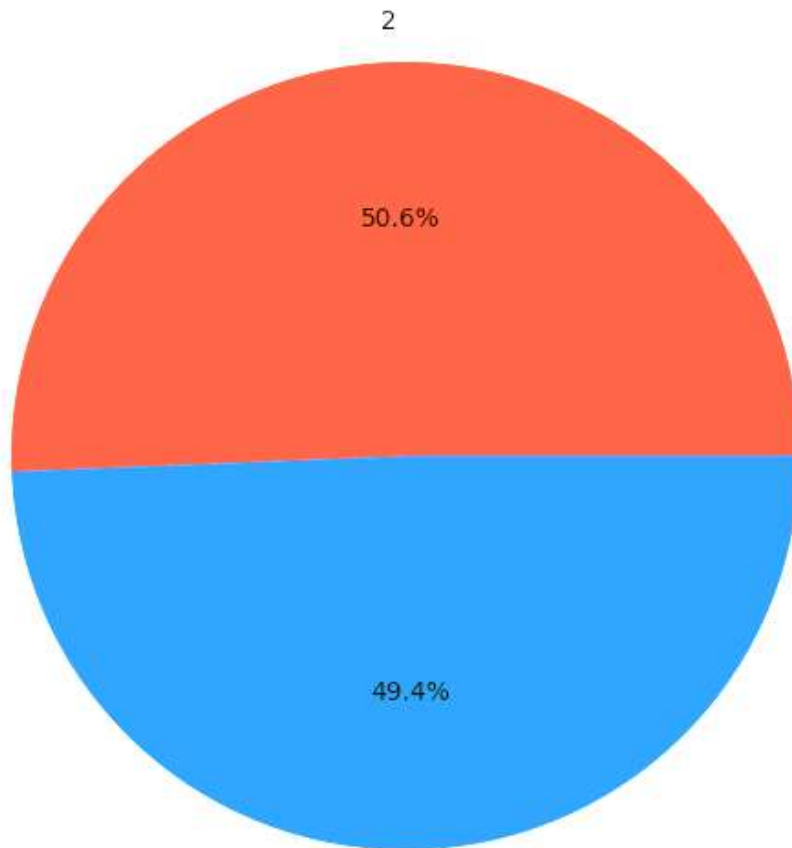
*Figure 11- splitting the data*

```
[11] sns.countplot(x=y, data=df)
```

<Axes: xlabel='2', ylabel='count'>



*Figure 12- positive and negative reviews chart*



*Figure 13- positive and negative reviews circle*

### c-Pre-processing

Before using any machine learning or natural language processing techniques, the dataset must first go through a number of data transformations and cleaning stages known as preprocessing in semantic analysis. Preprocessing aims to improve the quality and efficiency of the semantic analysis models by putting the data in a format that is acceptable for analysis. Here are a few typical semantic analysis preprocessing steps:

**Text cleaning** involves deleting any unused or distracting text data elements, including HTML tags, special characters, punctuation, and numerals. It assists in making sure the data is organized and consistent for subsequent analysis.

**Tokenization:** Tokenization is the process of breaking the text up into tokens or words. By dividing the text into manageable chunks, this phase makes it simpler to process and analyze. The fundamental building pieces for later analysis processes are tokens.

**Stop Word Removal:** Stop words are frequently used terms in a language (such as "and," "the," and "is") that have no semantic significance. Eliminating stop words decreases the complexity of the data and gets rid of extraneous noise that could impede analysis.

**Lowercasing:** By changing all text to lowercase, you can assure uniformity and avoid word repetition as a result of case insensitivity. Additionally, it normalizes the text and simplifies the terminology.

**Lemmatization and stemming:** are methods for condensing words to their root or basic form, respectively. While lemmatization converts words to their canonical forms (e.g., "better" becomes "good"), stemming strips words of their prefixes and suffixes, resulting in terms like "running" becoming "run" These methods assist in managing word variants and limiting the vocabulary.

**Eliminating Noise or Irrelevant Words:** Occasionally, the dataset contains words or phrases that don't really add anything to the semantic analysis. The accuracy and emphasis of the analysis can be improved by eliminating such noise or extraneous terms, which are frequently discovered through domain expertise or dataset analysis.

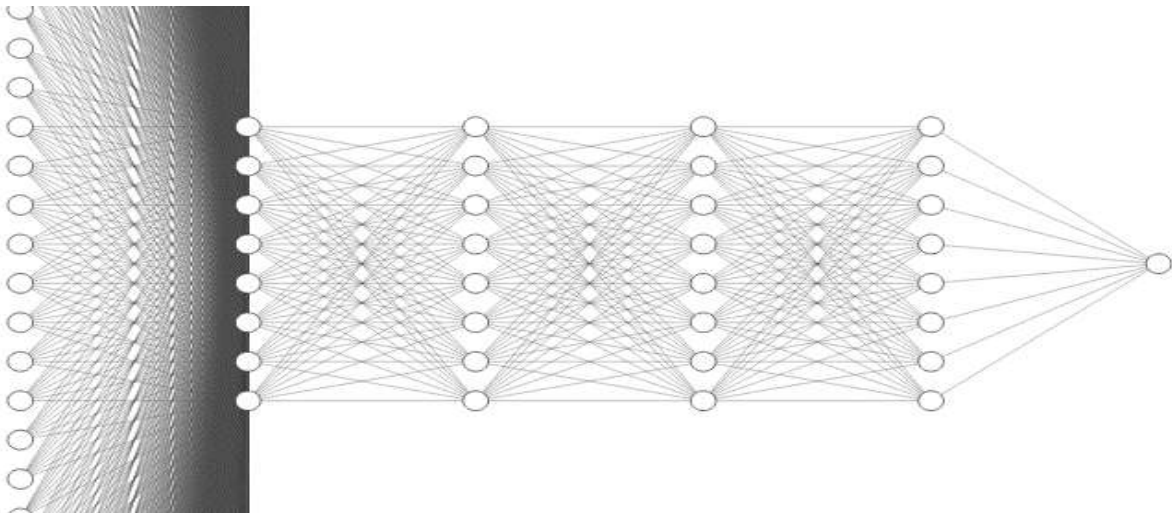
**Handling Rare Words or Outliers:** Infrequently occurring rare words or outliers may not give enough data for analysis or may cause noise. Such uncommon words can be changed or eliminated to enhance the quality of the analysis's findings.

**Vectorization:** A fundamental stage in semantic analysis is the transformation of text data into numerical vectors. Text data can be represented quantitatively using methods like bag-of-words (BoW) or term frequency-inverse document frequency (TF-IDF), which capture the significance of words within the context of the full dataset.

Preprocessing is a crucial phase of semantic analysis since it raises the caliber and efficiency of later analysis methods. Preprocessing guarantees that the dataset is in an appropriate format for training and using machine learning models for semantic analysis tasks by cleaning, converting, and lowering the dimensionality of the data.

### 3-3-ANN-based Model

#### a-Approach



*Figure 14- Model Architecture*

In the input layer we have **2250** neurons, and we have **4** hidden layers with **8** neurons, finally we have 1 neuron in the output layer, look at (**figure 14**).

#### b-Training

Training is the process of instructing a machine learning model to recognize patterns and predict outcomes from the preprocessed information. In order to reduce the discrepancy between the anticipated outputs and the actual outputs (labels) of the training data, it is necessary to feed the preprocessed data to the model and iteratively change the model's parameters. Throughout this training process, the model picks up knowledge from the input features and their corresponding labels. By learning from the patterns and relationships seen in the training data, the objective is to give the model the ability to generalize and make precise predictions on new, unknown data.

Training typically involves selecting an appropriate machine learning algorithm, defining evaluation metrics, splitting the data into training and validation sets, and iteratively optimizing the model's parameters through techniques like gradient descent or backpropagation.

```

training ...
Epoch 1/7
3462/3462 [=====] - 26s 5ms/step - loss: 0.6488 - accuracy: 0.8189
Epoch 2/7
3462/3462 [=====] - 20s 6ms/step - loss: 0.4689 - accuracy: 0.8347
Epoch 3/7
3462/3462 [=====] - 18s 5ms/step - loss: 0.4481 - accuracy: 0.8377
Epoch 4/7
3462/3462 [=====] - 19s 5ms/step - loss: 0.4358 - accuracy: 0.8386
Epoch 5/7
3462/3462 [=====] - 19s 6ms/step - loss: 0.4316 - accuracy: 0.8391
Epoch 6/7
3462/3462 [=====] - 18s 5ms/step - loss: 0.4304 - accuracy: 0.8386
Epoch 7/7
3462/3462 [=====] - 21s 6ms/step - loss: 0.4288 - accuracy: 0.8388
training complete !

```

*Figure 15- Training the Model*

### c-Testing

The evaluation procedure that follows model training is referred to as testing in the context of developing AI models. It entails evaluating the trained model's performance, accuracy, and generalization abilities using new or unrelated test data. The main objective of testing is to evaluate the model's ability to make predictions or carry out the required action on new data.

Here are some essential elements of testing in the creation of AI models:

**Test Dataset:** Testing is conducted using a distinct dataset from the training set. Idealized real-world settings and a wide range of samples that the model is anticipated to handle should be covered by this test dataset.

**measures for Performance Evaluation:** A number of measures are employed to assess the model's effectiveness when applied to test data. The measurements selected rely on the particular work at hand and the issue that has to be resolved. Accuracy, precision, recall, F1 score, mean squared error, and area under the curve (AUC) are examples of common evaluation measures.

**Assessment of Generalization:** Testing reveals how effectively the model generalizes to fresh, untested data. It evaluates if the model has discovered significant patterns and is capable of making precise predictions outside of the samples it was trained on. To guarantee the model's dependability and performance in real-world circumstances, generalization is a critical component.

**Overfitting Detection:** Testing is used to determine whether a model has overfit the training set of data. When a model performs well on training data but struggles to generalize to new data, it is said to be overfit. Overfitting can be identified and necessary corrections, such as regularization

methods or gathering more varied training data, can be done by evaluating the model's performance on the test data.

**Hyperparameter Tuning:** Testing is frequently used to adjust the model's hyperparameters. Hyperparameters, which include the learning rate, batch size, and number of layers in a neural network, are configuration options that regulate the learning procedure. On the basis of test data, various combinations of hyperparameters can be tested in order to improve model performance.

**Iterative Refinement:** The testing phase of model creation is iterative. It aids in discovering the model's flaws, restrictions, or potential improvement areas. Test findings help engineers improve the model's architecture, tweak hyperparameters, or add extra preprocessing steps to improve performance and correct any flaws.

As testing reveals the model's performance, generalization capability, and possible areas for improvement, it is vital for the development of AI models. Thorough testing makes sure the model is trustworthy, accurate, and able to produce the intended outcomes in practical applications.

#### d-Evaluation

Analyzing an AI model's performance, efficacy, and strengths and flaws are all part of the evaluation process. The model's performance on particular tasks is evaluated, and this information is useful for deciding where to deploy the model and where it can benefit from refinement.

Using accuracy metrics we get **83%**.

Using precision metrics we get **84%**.

```
evaluating ...
1731/1731 [=====] - 5s 3ms/step - loss: 0.4273 - accuracy: 0.8386
evaluating complete !
evaluating ...
1731/1731 [=====] - 5s 3ms/step - loss: 0.4213 - precision: 0.8412
evaluating complete !
```

*Figure 16- Evaluation the Model*

## 4-Difficulties and Perspectives

During the development of this project one of the major difficulties we encountered was the limitation of the hardware, the model requires a lot of RAM to load all the data set around 30GB, that forced us to use a part of the data set not all of it. Other than that the model's maximum accuracy is around 84%, and you have to manually find the best architecture for the ANN model.

We can solve the last two problem using a new ANN model which called Long Short-term Memory Recurrent Neural Network LSTM.

## **5-Conclusion**

In conclusion, utilizing neural networks in product review analysis can be a game changer for firms. Businesses may obtain important insights into customer sentiment and preferences, discover areas for improvement, and ultimately deliver better goods and customer experiences by using the power of Artificial Intelligence. Product reviews have become an important source of information for consumers, and employing neural networks to analyze this data guarantees that businesses have access to reliable and accurate information.

As technology advances, the potential applications of neural networks in product assessments are unlimited, and businesses who leverage this technology will have a substantial competitive advantage. In conclusion, utilizing neural networks to analyze product reviews is an interesting concept with the potential to revolutionize how businesses function and engage with their customers.

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## **GENERAL CONCLUSION**

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## General Conclusion

As a result of reading this manuscript, you now have a better understanding of the incredible ability of semantic analysis in understanding the sentiments stated in product reviews. We have looked at the critical roles played by artificial neural networks, coding, and implementation approaches, as well as machine learning, in obtaining insightful information from the massive amounts of textual data that are accessible on online platforms.

Businesses can easily categorize reviews as good, negative, or neutral by automating sentiment analysis using machine learning techniques. Through automation, businesses may better respond to consumer input, address issues, and use positive feedback to enhance their goods and services while also saving time and money.

Artificial neural networks have demonstrated their value in identifying the subtleties and complicated patterns seen in product reviews. Sentiment analysis has undergone a revolution as a result of their capacity to learn from and adapt to massive datasets, giving organizations a better grasp of customer views and preferences. The adaptability of neural networks enables more precise sentiment classification, enabling businesses to make data-driven decisions and successfully customize their offers to satisfy client expectations.

The necessity of using the right tools, frameworks, and programming languages was emphasized in the third chapter's discussion of the practical aspects of coding and implementation. Businesses may create trustworthy and effective sentiment analysis systems that scale to accommodate high review volumes by implementing robust methodologies for data pretreatment, model validation, and deployment.

Semantic analysis is set for greater improvements as we move to the future. More advanced sentiment analysis methods that can comprehend context, sarcasm, and irony in reviews will be made possible by ongoing research and innovation in machine learning and artificial neural networks. Additionally, the combination of deep learning and natural language processing techniques shows promise for even more precise sentiment analysis outcomes.

In conclusion, the investigation into the use of machine learning for semantic analysis of product reviews has yielded useful insights into the significance of comprehending consumer attitudes. Businesses may make wise decisions, increase customer happiness, and gain a competitive edge in the ever-changing market by utilizing the power of textual data. Understanding

emotions will be essential to developing winning company strategies and long-lasting client relationships as we traverse the digital world.

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