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Theme :

Sentiment Analysis for Arabic Language using Advanced Deep Learning Techniques

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Thanks

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Dedications

To my dear parents: *for all their sacrifices, their love, their tenderness, their support and their prayers throughout my studies...*

To my mother: *Life without you is colorless and tasteless... May God have pity on you, my dear, and enter you into heaven. I wish you were proud of me I wish you were with me that day...*

Thank you for all your sacrifices, thank you for all your support and encouragement, thank you for being here thanks to you I give you my success, I give you the fruit of your work I am here because of you. I hope your soul is here with me... I am here because of the greatest, most beautiful, strongest and bravest woman in the whole world.

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May this work be the fulfillment of your much-alleged wishes, and the result of your unfailing support,

This work is for my mother's eyes... Thank you for always being there for me

Resumé

Ce mémoire de maîtrise se concentre sur l'analyse des sentiments pour les langues arabes à l'aide de techniques avancées d'apprentissage profond. Le but de cette étude est de développer un système intelligent capable de prédire automatiquement le sentiment d'un texte arabe basé sur le traitement du langage naturel. Les méthodes d'analyse manuelle traditionnelles sont longues, coûteuses et sujettes aux erreurs humaines. En tirant parti des progrès de l'apprentissage profond et du traitement du langage naturel, un système basé sur l'IA peut fournir des informations précises et en temps réel sur l'état émotionnel des humains, permettant aux entreprises de prendre des décisions préventives et d'optimiser la qualité de leurs produits et services. Le système proposé combine des techniques d'apprentissage en profondeur avec le traitement du langage naturel pour aider les entreprises à maintenir leurs gains et à réduire leurs pertes. Cette thèse présente la conception, la mise en œuvre et l'évaluation du système, démontrant son efficacité dans l'analyse des sentiments pour la langue arabe..

Mots clés : Intelligence Artificielle, Analyse des sentiments, Langue arabe, Traitement du langage naturel, Deep Learning, Qualité produit

ملخص

تركز رسالة الماستر هذه على تحليل المشاعر للغة العربية باستخدام تقنيات التعلم العميق المتقدمة. الهدف من هذه الدراسة هو تطوير نظام ذكي يمكنه توقع المشاعر تلقائيًا من النصوص العربية بناءً على معالجة اللغة الطبيعية. تعتبر طرق التحليل اليدوية التقليدية مكلفة وتستغرق وقتًا طويلاً ومعرضة لأخطاء الإنسان. من خلال استغلال التقدمات في التعلم العميق ومعالجة اللغة الطبيعية، يمكن للنظام القائم على الذكاء الاصطناعي توفير معلومات دقيقة وفورية حول حالة المشاعر للبشر، مما يتيح للشركات اتخاذ قرارات وقائية وتحسين جودة منتجاتها وخدماتها. يجمع النظام المقترح بين تقنيات التعلم العميق مع معالجة اللغة الطبيعية لمساعدة الشركات في الحفاظ على مكاسبها وتقليل الخسائر. تقدم هذه الرسالة التصميم والتنفيذ والتقييم للنظام، مما يبرز فعاليته في تحليل المشاعر للغة العربية

الكلمات الرئيسية: الذكاء الاصطناعي، تحليل المشاعر، اللغة العربية، معالجة اللغة الطبيعية، التعلم العميق، جودة المنتج

Abstract

This master's thesis focuses on the Sentiment Analysis for Arabic languages using Advanced Deep Learning Techniques. The aim of this study is to develop an intelligent system that can automatically predict the sentiment from Arabic text based on Natural language processing . Traditional manual analysis methods are time-consuming, costly, and prone to human errors. By leveraging advancements in deep learning, Natural Language processing, an AI-based system can provide accurate and real-time information about the sentiment status of humans , enabling businesses to take preventive decision and optimize their products and services quality. The proposed system combines deep learning techniques with Natural language processing to assist businesses in maintaining their gains and reducing losses. This thesis presents the design, implementation, and evaluation of the system, demonstrating its effectiveness in Sentiment Analysis for Arabic Language.

Keywords : Artificial Intelligence, Sentiment analysis, Arabic Language, Natural Language Processing, deep Learning, Product quality

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General Introduction

Measuring public opinion, customer feedback, and social trends in Arabic, given the rapid expansion of digital content across social media, news articles, customer reviews, and other forms of media, has become increasingly challenging. Amid such issues, the complexity of the Arabic language, with its rich morphology and multiple dialects, raises further challenges. In the case of e-commerce companies, bookstores, and movie websites, this difficulty prevents firms from effectively developing an understanding of customers, identifying needs for product changes, or measuring the success of marketing strategies. Manual analysis is not an effective method in the face of the huge number of internet users because it takes a lot of time and has a high possibility of incorrect sentiment analysis for customers, viewers, and others. Additionally, it affects the decision-making of companies, which is why getting sentiment analysis right is critical.

In this context, and faced with this problem, the objective of this end-of-studies project (ESP or PFE) is to create and implement an intelligent system based on AI to predict the sentiment to keeping the Arabic language abreast of the development of other languages in the field of Natural language processing (NLP). This system will use deep learning techniques to analyze Arabic text from a lot of platform such as social media comments and e-commerce costumers rewiers to identify the sentiment from those sources. This intelligent system will combine advances in deep learning, Natural Language processing and data cleaning to provide companies owners with the tools needed to maintain analyse there reviews and predict the sentiment. This system will enable companies and businesses monitor brand and product sentiment in customer feedback, and understand customer needs and improve their product offerings by learning what works and what doesn't and to to gain insights about how customers feel about certain topics, and detect urgent issues in real time before they spiral out of control.

This thesis is organized into four chapters:

1. The first chapter "Definition, types, importance and challenges of Sentiment Analysis " describes the importance of sentiment analysis field at the modeled scale, and the challenges of the sentiment analysis.
2. The second chapter "Literature review": This chapter covers DEEP and machine learning classification methods, as well as work related to our problematic.
3. The third chapter "Conception of the system": in this chapter we discuss the system architecture and the methods used , the natural language processing of the data.for model training: we prepare the Bilstm model and the Transformer parameters.
4. The fourth chapter "Implementation, Tests and Results" explains how the Bisltm model and the Transformer model was configured, the tools used, the division of the database, the mitrification and the results obtained by the model.

Chapter 1

Sentiment Analysis

1.1 Introduction

As communication on the internet keeps growing, social media platforms have also become powerful spaces where people can express themselves and influence millions of other persons. This constant interaction has changed almost everything about life such as social, political, commercial or cultural lives thus requiring sentiment analysis to help understand dynamics in public opinions. In a famous quote from Edward Bulwer-Lytton "The pen is mightier than the sword" he highlights the role played by free speech. Even though this freedom encourages self-expression, there are fears that if not properly used, these channels of communication may affect individual rights and even societal norms. Sentiment analysis has a special importance in multilingual settings and e-commerce since customer sentiment understanding is vital for informed decisions and effective strategies development.

1.2 Sentiment Analysis

1.2.1 Definition of Sentiment Analysis

Sentiment analysis (SA) , also known as Opinion mining (OM), is the computational study of people's beliefs, attitudes, and feelings concerning a subject. The object may stand in for people, things, or subjects. Reviews are more likely to cover these subjects. You can use either SA or OM interchangeably. They both convey the same notion. On the other hand, several researchers claimed that SA and OM had rather different ideas [MHK14] . Sentiment analysis finds and evaluates the sentiment expressed in a text, whereas opinion mining gathers and examines people's opinions about an object. As a result, the goal of SA is to gather viewpoints, determine the emotions they convey, and categorize their polarity .

1.2.2 Types of Sentiment Analysis

There Are so many types on Sentiment Analysis :

1. **Graded Sentiment Analysis :**

   Three main classes exist for sentiment analysis. Positive, negative, and neutral sentiments are key. But there are more emotions that we can extract from the SA process like happiness, sadness, anger also matter. It depends on the situation, context, and application needs. For example, on e-commerce platforms, customer product reviews show sentiment. "This product is great, delivered timely, and I'm very satisfied." The real emotion or sentiment of this costumer here is positive or happy .

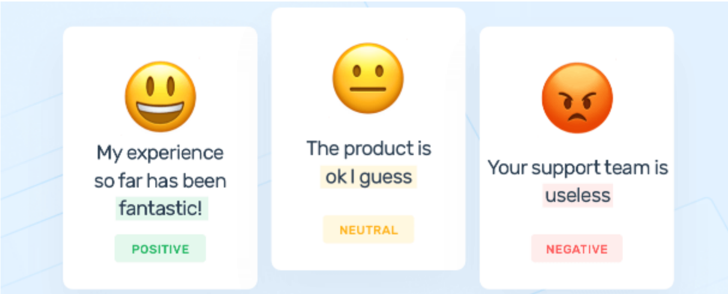

Figure 1.1 – Sentiment analysis grades [W1].

2. **Emotion Detection :**

   On the other hand, emotion detection is the process of recognizing different kinds of human emotions in text , images or audios, like anger, happiness, or depression. There are instances when terms like "emotion detection," "affective computing," "emotion analysis," and "emotion identification" are used interchangeably [PR21].

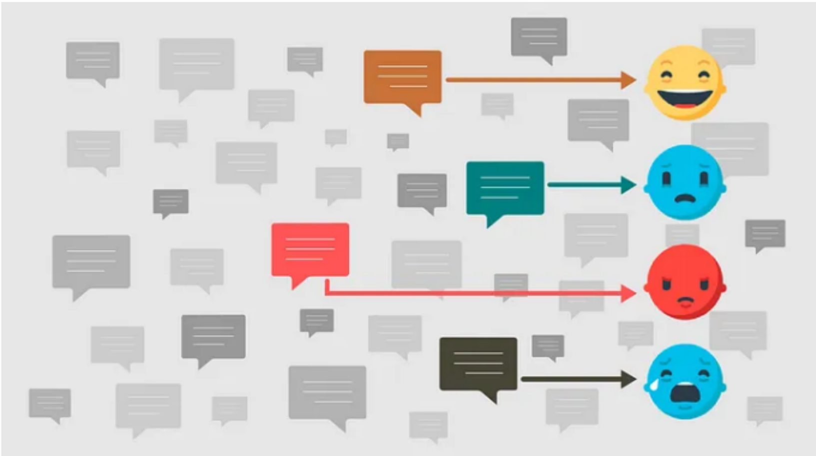

Figure 1.2 – Emotion classes in sentiment analysis [W2].

3. **Aspect-based Sentiment Analysis :**

   The term "target-based sentiment analysis," also known as "aspect-based sentiment analysis" (ABSA), describes the fine-grained handling of several sentiment analysis tasks, such as aspect extraction, aspect sentiment classification, and opinion extraction. [PXB+20]. For instance, we suppose that we have a restaurant customer feedbacks : “Waiters are very friendly and the pasta is simply average” , here we called "waiters" and "paster" as target or Aspect , "friendly" and "simply" are opinions and could be (‘Waiters’, positive, ‘friendly’) and (’Pasta’,negative, ’average’) . So compared to the traditional sentiment analysis ,(ABSA) provides more details , for example for a given product or service (ABSA) extract :
   - What aspects are people talking about ?
   - Do people like or dislike each aspect ?
   - and for what reason ?

4. **Multilingual sentiment analysis :**

   The birth of the Internet meant people started voicing their views on all sorts of things like products, services, happenings, and politics through sites, blogs, and social media in myriad languages , So they added another type of sentiment analysis called " Multilingual sentiment analysis". Analyzing opinions in multilingual texts is multilingual sentiment analysis (MSA). This creates hurdles like language differences, cultural nuances, linguistic subtleties, plus resource-constrained tongues lacking quality data. Resource-constrained languages suffer from a dearth of well-curated or suitably tagged data for effective use [Kan24].

1.2.3 Sentiment Analysis Levels

In order to use sentiment analysis, we must first establish the text that will be examined in the particular study under consideration. Sentiment analysis is typically conducted on three levels:

1. **Document level :**

   It determines the polarity of an entire text (classify a review as positive, negative, or neutral). It works best when a single person writes the document and expresses only one view on a single entity[Ber20].

2. **Sentence level :**

   It establishes the polarity of every sentence in a text by classifying the subjectivity of the sentence (i.e., whether it is objective or subjective) and the mood of the sentence (i.e., whether it is positive or negative) [Ber20].

3. **Aspects/ Features level :**

   Compared to the other levels, it does a finer analysis. It is predicated on the notion that an opinion consists of a sensation and a target. It finds and extracts elements of the object that the opinion holder has commented on, and it ascertains if the opinion is neutral, positive, or negative. This degree of study enables one to distinguish between the aspects that the texts' writers find appealing or objectionable, which facilitates the decision of potential courses of action [Ber20].

1.2.4 Sentiment Analysis Domain of Application :

Here are some well-known sentiment analysis application domains and use cases:

1. **Sentiment Analysis in Social media :**

   Web 2.0 has brought about changes in the social media landscape. Online social media platforms are not just for the creation, sharing, and expression of personal content; businesses may also utilize them for communication, understanding, and improvement by connecting with others on social media and using the internal information they provide to better serve their customers' emotions [DK19] . Acquire opinions and insights regarding your goods and services. People express their thoughts and sentiments on social media about a range of significant issues, including the Palestinian predicament.

   The amount of people using social media is growing daily (Figure 1.3). On social

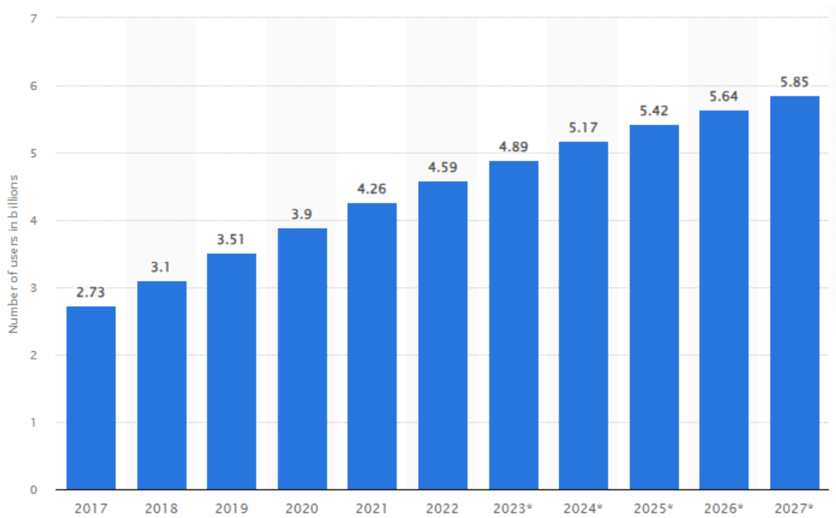

Figure 1.3 – Number of social media users worldwide from 2017 to 2027 [W3].

media, a wide range of content is shared and posted, including text, audio, video, and image formats. Additionally, sentiment analysis techniques are important for analyzing large amounts of data generated on social media, helping individuals and organizations to understand the sentiments and opinions of the general public

Better decision-making and response strategies based on their use the enlightened sensitivity is possible for these methods.

2. **Sentiment Analysis in Business and E-commerce :**

Electronic commerce, sometimes referred to as e-commerce, encompasses a wide range of online financial activities involving the buying and selling of goods and services Refers to any transaction in which the parties engage electronically rather than electronically be physically involved by ground connection or direct physical contact . Generally, e-commerce refers to the process of buying and selling goods or services over the Internet, or any transaction concerning ownership or rights to use goods or services through electronic communications networks .
Although widely recognized, this commentary lacks the detail to capture recent developments in this relatively new and sophisticated marketing phenomenon.
E-commerce refers to the use of electronic communication and digital information processing technologies in business. It is about building, transforming and redefining relationships to create value between or among departments, and between organizations and individuals .

Sentiment analysis techniques play a crucial role in analyzing vast quantities

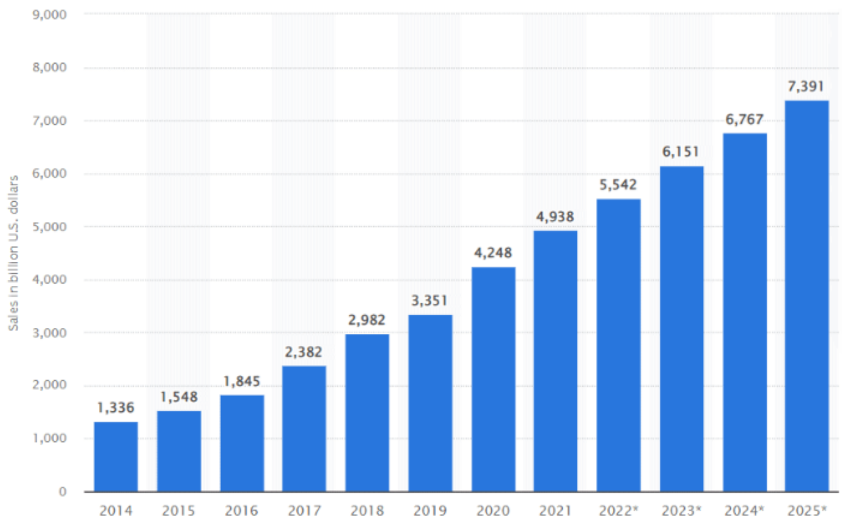

Figure 1.4 – The growth of e-commerce sales worldwide from 2014 to 2027 [W4].

of data generated on e-commerce platforms such as "Amazon," "WooCommerce," "BigCommerce," and "eBay." These techniques assist individuals and companies in comprehending the public’s opinions on products or services, enabling them to make better decisions and develop response strategies based on the insights gained from these methods.

1.3 The Importance of The Sentiment analysis :

The field of sentiment analysis has seen substantial expansion in recent years, driven by its wide-ranging applications in both business and social settings. The following are crucial factors that highlight the significance of Sentiment Analysis (SA) and provide a response to the question "Why Sentiment Analysis?":

1.3.1 Understanding Opinions and thoughts in business :

Sentiment analysis plays an important role for businesses, allowing them to monitor reviews and feedback from customers and consumers about their products or services [KP14][ea22b][KDM16]. It thus allows them not only to identify the opinions expressed, but also to improve their marketing strategies, to rectify the anomalies reported, to resolve problems promptly and to improve their products or services, with the aim of offering an experience more satisfactory customer[RPR21][PJK23].

1.3.2 Unlocking Marketing Insights:

In the context of marketing, information extracted through sentiment analysis proves valuable for activities such as business analysis, predicting fluctuations in foreign exchange markets, designing decision support systems and the construction of marketing intelligence [RR15][YN23]. As a result, sentiment analysis plays a central role in decision-making, adapting to customer requirements, and creating more effective marketing strategies.

1.3.3 Enhancing Healthcare Through Sentiment Analysis:

The analysis of sentiment in the medical field is also beneficial for clinical research and the detection of adverse effects of treatments on the physical and mental health of patients [ea16b][ea19c]. On a broader scale, it contributes to public health monitoring by identifying changes in individual behavior, which enables forecasting and preventing future problems [DM22][ea22c]. This is valuable in times of health crises and pandemics, such as the COVID-19 pandemic. In these circumstances, studies of large volumes of data collected online provide valuable information on disease, reactions to vaccines, acceptance of treatments, shortages in the market, and objections to the use of certain medicines[ea19b][ea22a].

1.3.4 Empowering Disaster Response:

Sentiment analysis and public opinion monitoring during natural disasters allows government officials and emergency responders to respond appropriately and effectively [ea16a][RAB18][ea19a][SK22]. This vigilance is not limited to large-scale events, because the collection of information disseminated by individuals on social media platforms, regarding social situations and calls for help, has deep human meaning[ea16a].

1.4 The Challenges of Sentiment Analysis :

Sentiment analysis has multiple problems, including high computational expenses, informal writing styles, and linguistic variances. We examine the issues that arise more commonly in sentiment analysis when dealing with specific forms of sentiment structure. Some notable obstacles encountered in sentiment analysis include [WRK22].

1.4.1 Language Issue :

In Sentiment Analysis , English is often utilized due to the availability of resources such as lexicons, dictionaries, and corpora. However, academics are drawn to employing Sentiment Analysis with languages other than English, such as Arabic, Chinese, German, and so on. Consequently, researchers encounter a difficulty in constructing resources such as lexicons, dictionaries, and corpora for these languages [CGP15].

1.4.2 Fake Opinion :

often known as a Fake Review, refers to fraudulent or deceptive evaluations that mislead readers or customers by giving them with dishonest critical or good opinions about a certain thing, with the intention of damaging its reputation. These spam messages render sentiment analysis ineffective in multiple domains. The opinion mining field encounters a societal problem, nevertheless, despite this obstacle, sentiment analysis (SA) has achieved advancements [CGP15].

1.4.3 Neutral reports of events:

Prior to describing the events or situations, the speaker must indicate their emotional disposition, as it is ambiguous whether these reports are intended to convey emotional bias or assume a negative emotional state (such as happiness, anger, cheerfulness, or sadness) [AMLN19].

1.4.4 Sarcasm :

Sarcasm is a prevalent occurrence in social media and poses challenges for analysis, both for automated systems and often for people as well. The impact it has on sentiment is significant, however it is often disregarded in social media analysis due to its perceived complexity. Although there are a few existing systems capable of detecting sarcasm, very little research has been conducted on examining the impact of sarcasm on sentiment in tweets and integrating it into automated tools for sentiment analysis [MG14].

1.5 Conclusion :

This chapter presents an outline of sensitivity evaluation (SA). The number one goal is to offer insights into semantic evaluation and sensitivity evaluation. We start by way of describing sensory analysis and describing several types to facilitate expertise. Following the advent, we have a look at areas where sentiment evaluation unearths application, together with e-trade structures and social media, with relevant information to spotlight the significance in those contexts. Furthermore, we delve into the importance of sensitivity evaluation in extraordinary industries and illustrate its relevance via actual-world cases. Furthermore, we shed light on challenges to the sensitivity evaluation process, consisting of handling Sarcasm , faux opinion , and language trouble . In the next bankruptcy, we will discover the sentiment evaluation in extra detail, imparting a complete know-how of its strategies, techniques, and trends.

Chapter 2

Machine Learning and Deep Learning

2.1 Introduction

The manifestations of intelligence typically involve comprehending a situation and effectively solving difficulties, especially when the problem-solving skill is adequate to provide multiple answers for the given problem. Intelligence is also evident in the decision-making process, where the most suitable solution for the present problem is chosen [Ber20].

While the machine has the capability to solve difficulties, it remains uncertain whether it can acquire the ability to comprehend a specific problem and make the appropriate decision to solve it. How closely can machine capabilities approximate those of human beings? In 1956, a symposium held at Dartmouth University delved into these inquiries and resulted in the emergence of the word 'AI' [Jam06], which stands for Artificial Intelligence.

Artificial intelligence focuses on the study of intelligent behavior in machines, encompassing perception, reasoning, learning, communication, and action in complex environments. Therefore, AI has two main objectives: to develop machines that can perform these tasks as well as or better than humans, and to understand this behavior whether it is exhibited by machines or humans [Nil98].

In addition to these goals, the conclusion, that rather than teaching computers everything they need to know how to carry out jobs. They might be able to learn on their own, and the recent development of the internet was one of the most significant breakthroughs that caused machine learning to arise and accelerate the advancement of artificial intelligence.

2.2 Machine Learning

2.2.1 Definition

"Machine Learning is a field of study that gives computers the ability to learn without explicitly being programmed.," according to Arthur Samuel's 1959 definition [Sam67].

In general, machine learning is a relatively new use of artificial intelligence (AI) that gives computers the capacity to autonomously learn from experience and get better at it without explicit programming. The concept is to provide machines with access to data so they can learn on their own. This is predicated on the machines' ability to comprehend the structure of data and transform it into models that humans can comprehend and use [Mas15].

In contrast to conventional computing methods, machine learning is a contemporary science (discipline within computer science) that focuses on pattern identification, data mining, statistical inference, and predictive analytics to extract insights and forecasts from data. Computers can be trained on data inputs using machine learning algorithms, which then employ statistical analysis to produce numbers that fall within a predetermined range. Consequently, machine learning makes it easier for computers to create models from sample data so that data inputs can be used to automate decision-making processes. When insights from vast, varied, and dynamic data sets need to be found, it works incredibly well [Ber20].

2.2.2 Phases

Machine learning usually occurs in three phases , each of which will be defined below:

1. **The Training:** the training phase, in which the model is trained by comparing the input that is provided with the expected output using the training data.
2. **The Testing:** In this testing phase, the quality and estimation of the learning model's properties—such as error, recall, and precision—are used to gauge its effectiveness.
3. **The Application:** The model is finally subjected to real-world data during the application phase, from which conclusions must be drawn.

2.2.3 Methods

Machine learning techniques are often categorized into two groups: Supervised Learning for classification and regression , Unsupervised Learning for clustering . Additionally machine learning methods include reinforcement learning and deep learning are two more machine-learning techniques , they are categorized as shown in the following figure:

1. **Supervised Learning :** The machine learning task of supervised learning involves using sample input-output pairs to train a function that maps an input to an output. From labelled training data, which consists of a collection of training instances, it infers a function. The machine learning algorithms that require external aid are known as supervised algorithms. The train and test datasets are separated from the input dataset. An output variable from the train dataset needs to be categorized or forecasted. Every algorithm picks up some sort of pattern from the training dataset and uses it to predict or classify data from the test dataset [Mah20]. The following

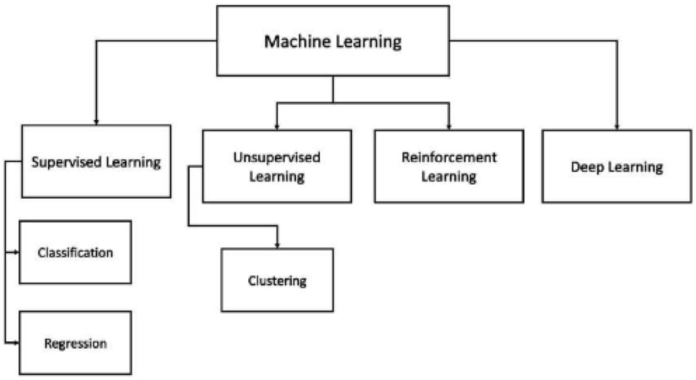

Figure 2.1 – Machine Learning Methods [[Ber20]].

figure shows the workflow of supervised machine learning algorithms:

Some of the popular supervised learning applications are Natural Language Pro-

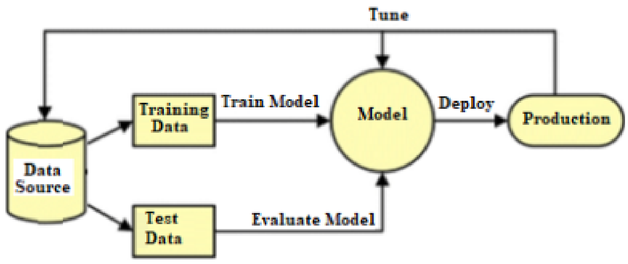

Figure 2.2 – Supervised learning Workflow [Mah20].

cessing, Image classification, predictive analysis, pattern recognition, spam detection, Speech/Sequence processing and Sentiment analysis (On social media).

Supervised learning uses classification algorithms and regression techniques to develop it different models and algorithms, therefore it is further divided into Classification and Regression :

- **Classification:** Classification is when the computer program learns and build experience from the input data given to it as supervised learning, and then uses this learning to classify new observations, where the process is to find the features that will help to separate data into different classes.

  The goal is to predict a class label, depending on the training feature, the class label will be represented as a choice from a predefined list of possibilities in the multiclass classification, such as in speech recognition, handwriting recognition, biometric identification, document classification.

  On the other hand there is the binary classification , it's like trying to answer the yes/no question, or in identifying if the person is male or female, also in sentiment analysis by detecting if the text is positive or negative , having two label class possibility. Here is some of classification algorithms : Decision Tree , Random Forest , Naive Bayes ,Neural Network .

Decision Tree : the decision tree is defined as a supervised learning model that hierarchically maps a data domain onto a response set. It divides a data domain (node) recursively into two subdomains such that the subdomains have a higher information gain than the node that was split. We know the goal of supervised learning is the classification of the data, and therefore, the information gain means the ease of classification in the subdomains created by a split. Finding the best split that gives the maximum information gain (i.e., the ease of classification) is the goal of the optimization algorithm in the decision tree-based supervised learning [SS16]. Another definition of the decision tree is a graph to represent choices and their results in form of a tree. The nodes in the graph represent an event or choice and the edges of the graph represent the decision rules or conditions. Each tree consists of nodes and branches. Each node represents attributes in a group that is to be classified and each branch represents a value that the node can take [Mah20].

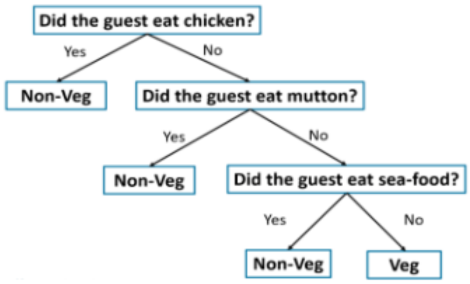

Figure 2.3 – Example in decision Tree .

Random Forest : A supervised classification approach that can be applied to regression and classification issues is the Random Forest Classifier [Pav00]. This classifier is referred to as an overall classifier because it uses multiple classification algorithms either the same or different to categorize things. Since each decision tree is a single classifier and the objective prediction is based on the majority voting method, it involves, as its name implies, establishing a forest of decision trees, the more trees in the forest, the more exact the findings.
Moreover, Breiman's concept and random feature selection, or "bagging" [Bre94], are combined to create the random forest classifier, which is made up of a huge number of individual decision trees that function as an ensemble with random sampling. The more decision trees that are taken into consideration, the more precise the result will be when it comes to making precise predictions by averaging or modalizing their output.

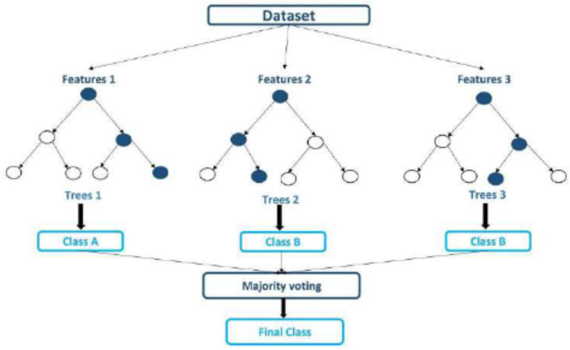

Figure 2.4 – Random Forest explication .

Additionally, Breiman defines [Bre99] a random forest as “A random forest is a classifier consisting of a collection of tree structured classifiers h(x,Ok), k=1, ... Where the Ok are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input x”.According to this definition, every tree in the forest is dependent on the values of a random vector that is separately sampled and has the same distribution for every tree. When the number of trees in a forest increases, the error for forests converges to a limit. The forest is able to proceed in the right path as a collective because the trees shield one another from their individual mistakes. While some trees may make wrong judgments, many other trees will make the right ones [Ber20].

Naive Bayes : It is a classification method predicated on the independence of predictors and the Bayes Theorem. To put it simply, a Naive Bayes classifier makes the assumption that a feature’s presence in a class is independent of the existence of any other feature. The primary industry that Naïve Bayes addresses is text classification. It is mostly employed for classification and clustering purposes, depending on the conditional likelihood of occurrence [Mah20].

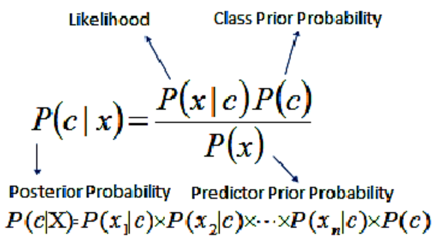

Figure 2.5 – Naive Bayes Formula .

Neural Network : It is a network of connected pieces, it is known as a artificial neural network. The biological nerve systems studies served as the basis for these components. Put another perspective, neural networks are an attempt to develop devices that mimic the functioning of the human brain by utilizing biologically inspired components [PP94].

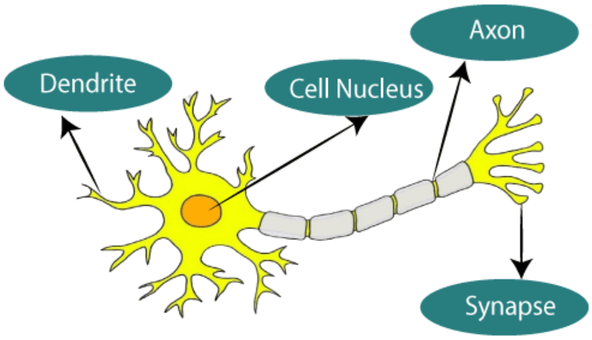

Figure 2.6 – Human's brain Cell [W5].

Relationship between Biological neural network and artificial neural network:

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

Table 2.1 – Comparison between Biological and Artificial Neural Networks [W5].

An artificial neural network (ANN) consists of several layers: a layer of input, one or more a concealed layer(s), and an output layer. The attributes (x1, x2 . . . ,xn) in the input layer as independent components represented in vector . The network uses the activation function that can be assigned to each weight (Wi) that represent the importance of each input attribute , and this converts the weighted inputs into non-linear transformation, which helps the network to learn to understand the complex patterns and relationships. The hidden layer(s) learn feature representation through the input data and then produce the (Y) response which is only interpreted by the problem definition. The choice of the type of a activation function, architecture of the network and a optimization algorithm changes network performance and ability to learn from data drastically.

- **Regression :**
  A supervised learning method called regression is used to forecast continuous responses[FKL+13]. To forecast a continuous value, such a wage, price, or weight, regression models are utilized. It is one of the most significant and widely used machine learning and statistics techniques; it enables the creation of predictions from data by figuring out how elements in the data relate to the output, which is continuous and observed. There are other models that can be employed, including Random Forest, Polynomial, Support Vector

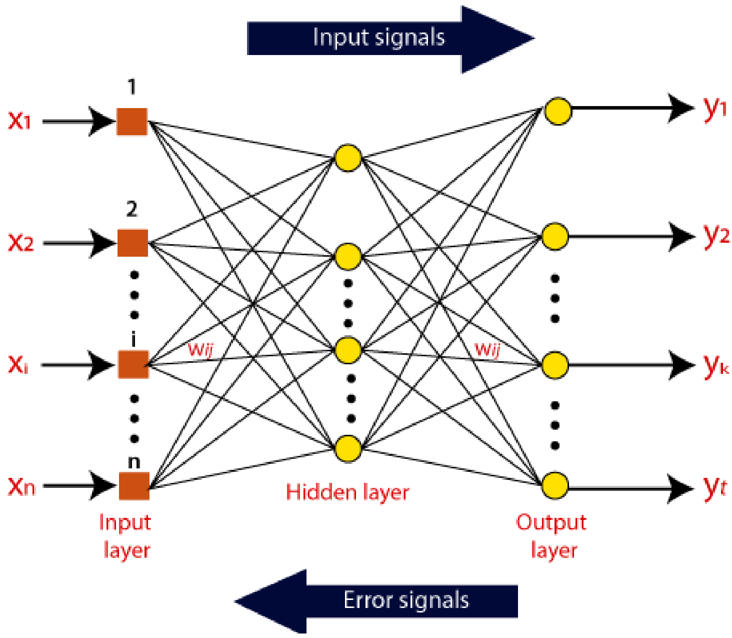

Figure 2.7 – Artificial neural network layers [W5].

[AK15], and Decision Tree regressions. The most basic model is the Simple Linear regression[Wei05].Regression is a very powerful statistical technique that can be used to generate insights on consumer behavior, understanding business, and factors influencing profitability. It is used in a vast array of applications, from predicting stock prices or person age to understanding gene regulatory networks. As an illustration, Dean[Dea09]proposed use Simple Linear Regression to evaluate the effectiveness of the Montreal Protocol in lowering atmospheric chlorofluorocarbons in order to address a worldwide environmental issue. He developed a straightforward linear equation to forecast the atmospheric concentrations by modeling the rate of change during intervals that correspond to the periods before and after the Montreal Protocol was put into effect.

2. **Unsupervised Learning :**

   Unsupervised Learning Techniques: with these methods, the learning algorithm is left to identify similarities between its input data because the training data is not labeled.It makes an effort to group the supplied dataset into clusters or classes. The input dataset consists of unprocessed data without any target results or class labels. Unstructured datasets lacking class labels, optimization criteria, and feedback are referred to as raw data [SMS20]. Unsupervised learning seeks to identify natural divisions within the dataset. Intelligent preprocessing and feature extraction systems can benefit from the application of unsupervised learning approaches. One of the most popular unsupervised learning techniques is clustering.

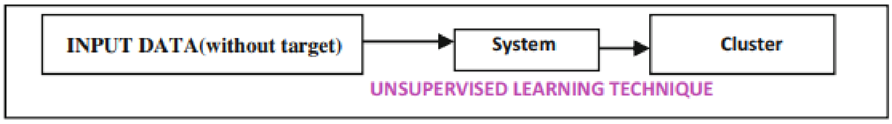

Figure 2.8 – Unsupervised learning techniques.

Clustering refers to the act of dividing data points into clusters based on their proximity to each other in a way that data points in the same cluster are more similar as compared to those in different clusters. This is a technique in supervised learning that lies under the supervision of the unsupervised branch which focuses on the extraction of information from unlabeled data points and not as like that of supervised learning in which we have a target variable.

Clustering tries to get individuals that are similar from a very big set or several different data sets. It computes the similarity score to check whether the points having higher similarity score should be grouped together, the similarity score can be computed using metrics like, the Euclidian distance or cosine distance, etc.

The most popular and widely used algorithms in machine learning are, K-means Clustering Algorithm ,Mean-Shift Clustering Algorithm, Hierarchical Clustering, K-NN (k nearest neighbors),and many others.

3. **Reinforcement Learning :**

It is a method of machine machine learning that depends on rewarding desired behaviors or punishing undesirable behaviors. In this way, it makes the robot capable of making appropriate decisions or actions by taking advantage of its awareness of the environment surrounding it. It is based on the principle of trial and error.
three three major composite make up the reinforcement learning :
Agent: the learner and the decision maker .
Environment: where the agent learns and decides what actions to perform.
Action: a set of actions which the agent can perform .

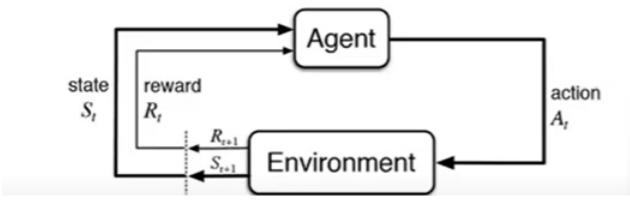

Figure 2.9 – Reinforcement learning, agent and environment interactions.

the goal is defined optimal policy in the sense of maximizing the expected value of the total reward over any no successive steps starting from the current state . One of the reinforcement learning algorithm is Q-learning algorithm .

- **Q-learning algorithm :**
  It is a model free reinforcement learning algorithm to learn the value of an action in a particular state it does not require a model of the environment (hence " model-free") and it can handle problems with the stochastic transition and rewards without requiring adaptations.

$$Q^{new}(s_t,a_t) \leftarrow \underbrace{Q(s_t,a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \overbrace{\bigg(\underbrace{\underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1},a)}_{\text{estimate of optimal future value}}}_{\text{new value (temporal difference target)}} - \underbrace{Q(s_t,a_t)}_{\text{old value}}\bigg)}^{\text{temporal difference}}$$

Figure 2.10 – Q-learning algorithm formula.

2.3 Deep Learning

2.3.1 Definition

By using a hierarchy of concepts, deep learning is a type of machine learning that lets computers learn from experience and comprehend the world. The computer taught itself how to handle and absorb data [Kim16].

It operates on a network of synthetic neurons that are modeled after the human brain. The neurons in this network are arranged in tens or even hundreds of layers, each of which receives and processes data from the layer above it.

Neural networks and deep learning differ in the depth of the model; deep learning is a term for intricate neural networks. It has to do with feature extraction and transformation, which try to establish a connection between inputs and the corresponding neural responses that the brain produces. Elaborate patterns of how information can flow across the model confer complexity. The most popular deep learning algorithms are : Convolutional Neural Network (CNN) , Recurrent Neural Networks (RNN) , Long short term memory Networks (LSTM) , Transformers .

2.3.2 Convolutional Neural Network

A convolutional neural network (CNN) is a type of deep learning model using convolutional layer to discover high-level features in the data corresponding to the areas of interest. These kernels are used to filter the input data and generate features pushed through non-linear transformations and pooling operations to reduce dimensionality and keep necessary

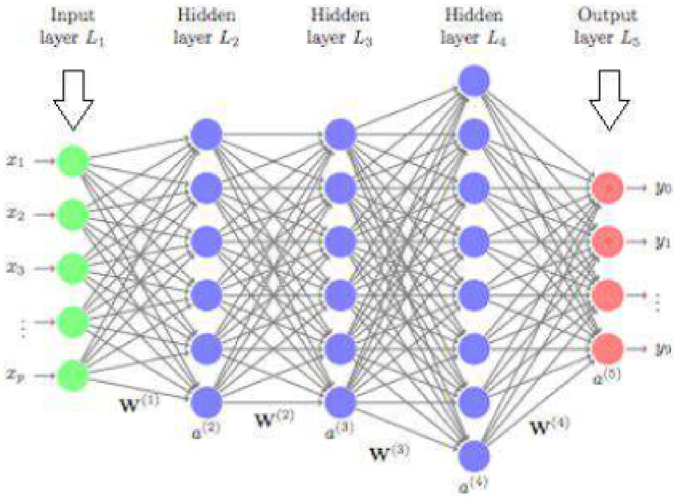

Figure 2.11 – Deep neural network architecture.

information. CNNs are particularly relevant in a number of machine learning applications, including but not limited to natural language processing, speech recognition as well as sentiment analysis where data input cannot be limited to images only.

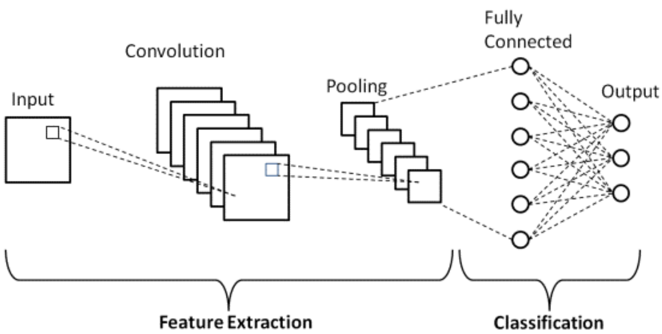

Figure 2.12 – Convolutional Neural Network architecture diagram [W6].

2.3.3 Recurrent Neural Networks

Sequence models are the machine learning models that input or output sequence of data . sequential data includes text streams , audio clips , video clips , time series data etc. Recurrent neural Networks (RNNs) is a popular algorithm use it in sequence models.

Sequential data is whenever the point in the data set are depend on the other points in the data set the data is said to be sequential data .a common example of these is a Time series such as a stock price or a sensor data where each point represent an observation of the certain point in time there are other example of sequential data like sequences Gene sequences and weather data.

Recurrent neural networks are a type of artificial neural network designed to process sequential data such as time series or natural language . they have feedback connections that allow them to retain information from previous time steps enabling them to capture temporal dependencies , this makes RNNs well-suited for tasks like language modeling , speech recognition and sequential data analysis. RNNs is best suited for sequence data it can handle arbitrary inputs (x)/outputs (y) lengths. Recurrent neural networks

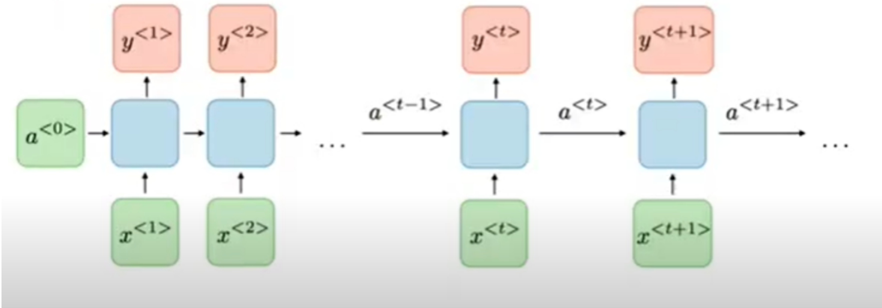

Figure 2.13 – Recurrent Neural Networks diagram .

are employed in sequence classification to predict sentiment, as seen in the figure below, which is an example of a movie review:

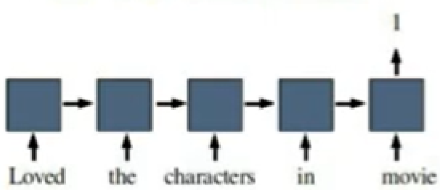

Figure 2.14 – example of an RNN .

1. **Long-Short Term Memory :**

   What a LSTM network is called is a form of recurrent neural network (RNN) architecture, the essence of which is to eliminate the problem of a vanishing gradient at the same time as appropriately capturing long-term dependencies in sequence data. In contrast to ordinary RNNs that tend to struggle to store information over long term sequences due to the vanishing gradients, LSTM networks have additional memory cells which use gating mechanisms to control the data flow over time. At the core of an LSTM network are memory cells, each equipped with three gating units: the input gate, nudge gate, and output gate. The gates monitor what goes in and out of the memory cell, as well as what takes place inside it during the learning process, and the rest of the system then selects what to keep and what to forget based on current needs. Along with all of this, LSTM networks apply activation functions and cell state updates to the flow of information which also overcomes the issue of gradient vanishing.

   Information about the gates in LSTM networks and memory cells enable recognition and understanding of time-delayed pattern relationships in sequential data which in

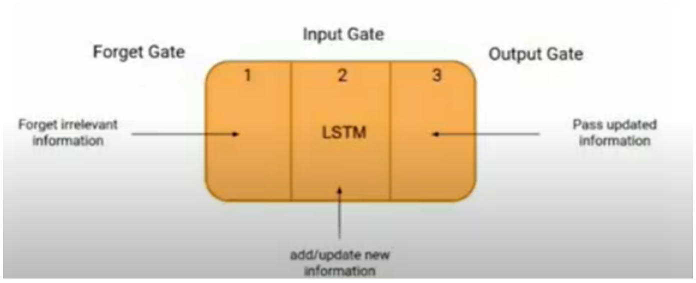

Figure 2.15 – LSTM Architecture .

various tasks, like e. g. natural language processing and speech recognition or time series prediction, can be done fast by using them.

2. **Transformers :**

"Attention is All You Need" here, [VSP+17] proposes a novel type of self-attending neural network, a fully autonomous Transformer architecture. Peculiar from RNNs and CNNs mostly based on, the Transformer architecture is only interested in capturing self-attention dependencies in input and output sequences.
Key concepts in the Transformer architecture include:

- **Parallelism :**
The Transformer model architecture allows the operations to take place in a parallel way across different positions in a sequence, making both training and inference times faster comparing to the RNN case.
- **Attention Mechanism :**
Self-attention - a process of attention scores being computed between each pair of input tokens and output tokens - eventually helps the model to focus on the significance of each token in the entire sequence.
- **Advantages Over LSTM and RNN :**
Transformers, however, are characterized by better long range dependencies treatment, easier training, better parallelization and they provide an alternative compared to RNNs and LSTMs.
- **Impact on the AI Field :**
By virtue of the newly-developed Transformer architecture, the field of artificial intelligence has recently undergone a dramatic transformation and especially in natural language processing tasks this model has demonstrated substantial attraction to and gaining widespread use.
The Transformer architecture, in general, presented extraordinary superiority in different sequence modeling tasks and it is considered to be one of the major bricklayers of the modern AI and its applications.

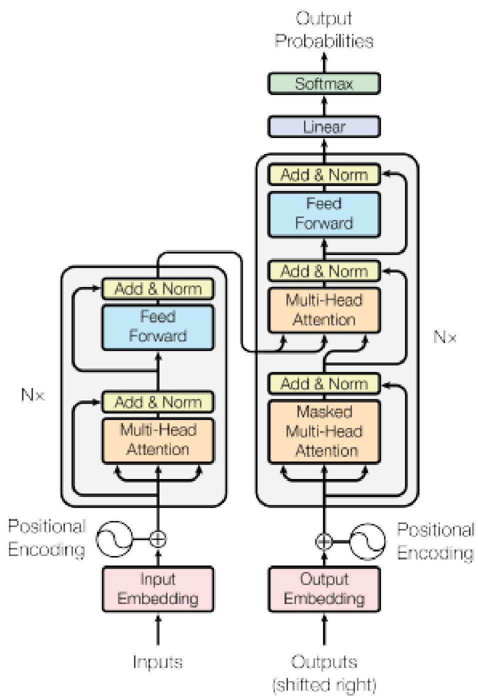

Figure 2.16 – Transformer model architecture [VSP+17].

2.4 Related Works

Arabic sentiment analysis as a field has observed its share of exponential surge in the last few years as Arabic sentiment analysis systems become the necessity in various fields such as social media monitoring, customer feedback analysis, and market research. This is the part where we discuss the major works that were research papers and so they contributed to sentiment analysis for Arabic text. The methods these works adopt differ, as there is a lot between machine learning approaches, dictionaries-based techniques, deep learning and hybrid models. We will regard the works of researchers to find out the current level of the Arabic sentiment analysis methods used and present the challenges and ways to be looked into as areas of future research.

Authors	**Titles**	**Datasets**	**Methods and Tools**	**Results**
[HTEM18]	Sentiment Analysis of Arabic Tweets using Deep Learning	Arabic Sentiment Tweets Dataset (ASTD) with 10,000 tweets distributed among 4 classes (positive, negative, neutral and objective) they removed the objective class	CNN (3 sub-models) and LSTM using AraVec and Word2Vec models, and two features: the number of words and the length of words	- CNN: **Accuracy:** 64.30%, **F1-score:** 64.09% - LSTM: **Accuracy:** 64.75%, **F1-score:** 62.08%
[AQ23]	Sentiment Analysis of Arabic Tweets on Online Learning During the COVID-19 Pandemic: A Machine Learning and LSTM Approach	the "Madrasti" platform for online education in Saudi Arabia with 100,000 Arabic tweets	Using SMOTE and random under-sampling method to balance the dataset, the classification with KNN, RF, SVM, and LSTM	- The highest F1-score was recorded with RF, achieving **86%** using SMOTE and **79%** with under-sampling - LSTM: **Accuracy:** 52.9%
[EVA+23]	Sentiment Analysis of Arabic Reviews Using Deep Learning and Word Embeddings: A Comparative Study	HARD (Hotel Arabic Reviews Dataset) 981,143 reviews and LARB (Large-Scale Arabic Book Reviews) 63,000 reviews,	CNN, LSTM, hybrid CNN-LSTM, and Word embeddings used: Word2Vec, fastText	- CNN **Accuracy:** (**94.69%**) - LSTM **Accuracy:** (**94.63%**) - LSTM/CNN **Accuracy:** (**94.63%**)

Table 2.2 – Summary of Works on Sentiment Analysis for Arabic Language.

Authors	Titles	Datasets	Methods and Tools	Results
[MK19]	Deep Learning Approaches for Arabic Sentiment Analysis	Corpus of 40,000 labeled Arabic tweets spanning several topics.	Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Recurrent Convolutional Neural Network (RCNN). Word2Vec embedding model, specifically the Continuous Bag of Words (CBOW) model. Pre-trained CBOW model called Aravec	**CNN:** **Accuracy:** 75.72% **Recall:** 74.60% **Precision:** 78.03% **F-score:** 75.06% **LSTM:** **Accuracy:** 81.31% **Recall:** 80.92% **Precision:** 81.99% **F-score:** 81.25% **RCNN:** **Accuracy:** 78.46% **Recall:** 77.38% **Precision:** 80.27% **F-score:** 77.86%
[AQ22]	Arabic Sentiment Analysis of Eateries' Reviews Using Deep Learning	Reviews obtained from eateries in Qassim, Saudi Arabia	Long Short-Term Memory (LSTM)	**LSTM:** **Accuracy:** 82.98%
[Alh20]	Arabic Sentiment Analysis using Deep Learning for COVID-19 Twitter Data	10 millions tweets related to COVID-19	SVM, SGRU,SBGRU, AraBert	**SVM:** **Accuracy:** 77.92% **SGRU:** **Accuracy:** 82.08% **SBIGRU-5:** **Accuracy:** 81.59% **AraBERT:** **Accuracy:** 85.41% **Ensemble model :** **Accuracy:** 90.21%

Authors	Titles	Datasets	Methods and Tools	Results
[AADE19]	Sentiment Analysis of Saudi Dialect Using Deep Learning Techniques	the Saudi Tweets	LSTM and Bi-LSTM, SVM , specifically the Continuous Bag of Words (CBOW) model	**LSTM:** **Accuracy:** 92% **Bi-LSTM:** **Accuracy:** 94% **SVM:** **Accuracy:** 86.4%
[MAA+23]	Arabic Sentiment Analysis of YouTube Comments: NLP-Based Machine Learning Approaches for Content Evaluation	Arabic comments on youtube	- N-gram ranges and TF-IDF methods for features extraction . - SVM, RF, LR, KNN, DT, and NB	**SVM:** **Accuracy:** 94.38% **Random Forest (RF):** **Accuracy:** 91.77% **Logistic Regression (LR):** **Accuracy:** 93.75% **KNN:** **Accuracy:** 92.48 % **Decision Tree (DT):** **Accuracy:** 84.10% **Naïve Bayes (NB):** **Accuracy:** 94.62%

Authors	Titles	Datasets	Methods and Tools	Results
[GME+24]	Arabic sentiment analysis of Monkeypox using deep neural network and optimized hyperparameters of machine learning algorithms	Arabic text containing sentiments related to Monkeypox	- Support Vector Machines (SVM), Naive Bayes, Random Forest. -Deep Neural Networks (DNN) with Leaky ReLU. - - Hyperparameter Optimization	**SVM,NB,RF:** **Accuracy:** 92% **DNN:** **Accuracy:** 92%
[BBFK23]	Sentiment Analysis on Algerian Dialect with Transformers	Algerian Arabic text extracted from YouTube channels	- BERT Model.	**BERT** **F1-score:** 78.38% **Accuracy:** 81.74%

2.5 Conclusion

In short, this chapter has thoroughly looked at, Ai, machine learning as well as deep learning where sentiment analysis has been over-viewed in the context of the Arabic language. We selectively presented a table with the most relevant research papers; each sub-field in the field of sentiment analysis for Arabic was represented with different aspects and perspectives.
As for now, the successive part will pass throughout summary of that literature to presenting our design and model for sentiment analysis in Arabic context. In the next chapter, we will focus on methodology, techniques and breakthrough of our approach. And we will explain everything based on foundations of this chapter. Unlike other sentiment analysis models, through painstaking trial and error and evaluation we aim to demonstrate the precision and relevance of our model in analyzing the hidden sentiments embedded in Arabic language data.

Chapter 3

Sentiment Analysis System

3.1 Introduction

In the previous chapters, we discussed the importance of sentiment analysis, the many uses of the technique in different fields and the problems involved in the correct analysis of sentiments from text data. Besides, we also walked through the North, machine learning and deep learning methodologies, studied their usefulness in sentiment analysis tasks, especially in the field of natural language processing. The methodology was followed by a detailed review of the related works in which we learned about the existing approaches and methodologies used in the sentiment analysis of the Arabic texts.

Drawing upon the insights gleaned from this state-of-the-art study, we propose a comparative analysis between two prominent models: The Bidirectional Long Short-Term Memory (BiLSTM) model and the Transformer model are the two most advanced models discussed in this chapter. The Transformer model appeared due to the visionary paper "Attention is All You Need," which led to the development of a new architecture that changed the way of thinking for the artificial intelligence.

This chapter is mainly about natural language processing (NLP) techniques and systems and the ways to solve some problems with these techniques. We focus on the limitations of the traditional methods and the problems with these methods, such as BiLSTM. The limitation, such as the inability to capture the long-range dependencies and the low efficiency in the processing of large amounts of text data, contributed to the rise of the Transformer model to sentiment analysis.

The objective of this paper is to highlight the reasons of the development of various NLP and the revolutionary influence of the Transformer architecture, thus, we will provide a detailed explanation of the reason of our comparative analysis. By this, we seek to find the basic strengths and weaknesses of both the BiLSTM and Transformer models in the context of sentiment analysis, especially in the Arabic language processing tasks, as these are the two models that are the best in the field of natural language processing for the

Arabic language.

Lastly, this chapter becomes a lead-in to our comparative analysis, which will be a detailed comparison of the capacity and the performance of these two significant models in the domain of sentiment analysis for the Arabic e-commerce sites. We will learn through hard analysis and experimentation what the best and the most robust methods of sentiment analysis are and how to adapt them to the special features of the Arabic text data.

3.2 System objective

The aim of this system is to create an Arabic language model that can anticipate sentiment from evaluations and feedback in many domains, and to compare the two models that have been constructed, Transformer and BiLSTM.

3.3 System Architecture

In this section, we illustrate the main components of our system. First, the text pass through a preprocessing and cleaning phase, to remove unwanted symbols and tokens. Then, the text are prepared to be ready for the training phase. We train two deep learning models, a BiLSTM model and an Transformer model. After training both models with different preprocessing , we selected the best of the two trained models that yield the highest Accuracy. The following model represents the general structure of our system:

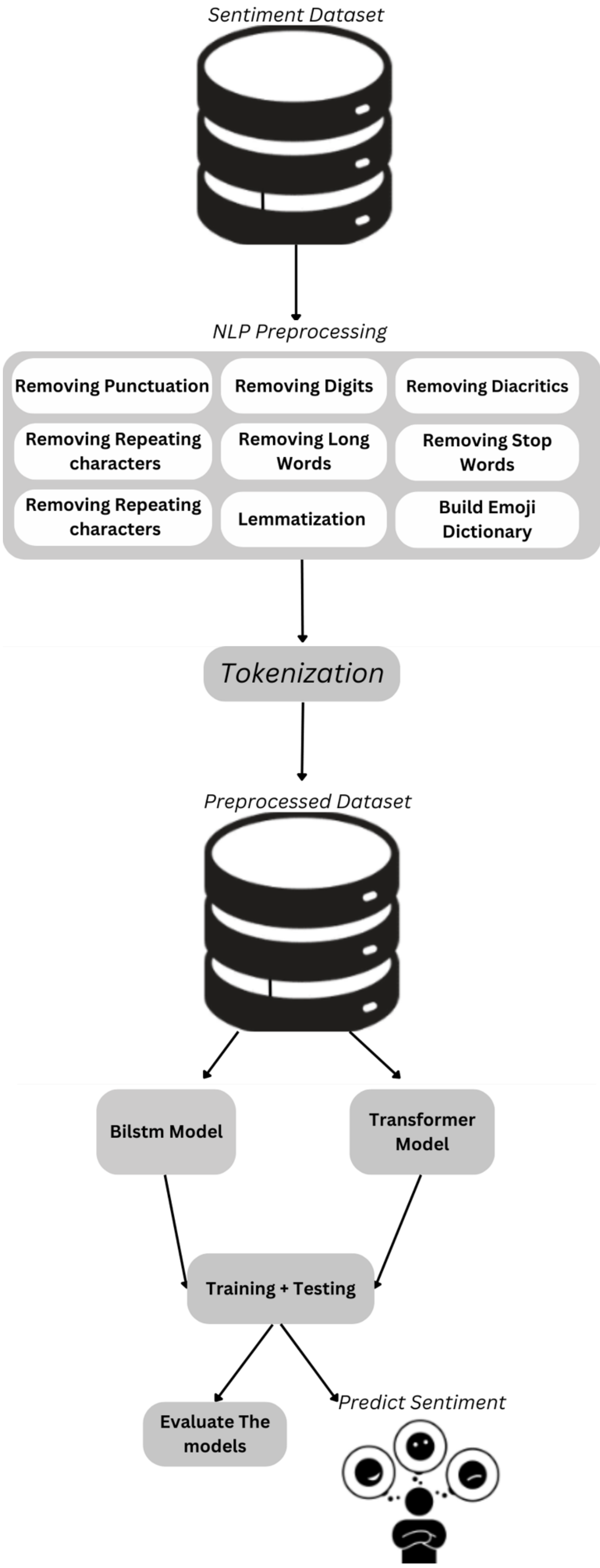

Figure 3.1 – System Architecture.

3.3.1 Data Collection

Our dataset consists of diverse Arabic text from reviews, devised in :

The training dataset : consists of 32,036 rows and two columns: **"review_description"** captures opinions—these reviews may include English text or emojis, and the **"rating"** column provides a numerical dimension: -1 for negative, 0 for neutral, and 1 for positive sentiments.

The test dataset : contains only the **"review_description"** and an **"id"** column.

3.3.2 Data Preprocessing and Cleaning

In our models for sentiment analysis of Arabic, we suggest two preprocessing methods. Firstly, we substitute emojis with their textual meanings from an emoji dataset, which is a way for machines to understand them as words. Besides this, we also get rid of the emojis completely, hence, the text input is simplified and that is what enables the machine to understand it better. The preprocessing steps improve the machine's accuracy in terms of understanding human language .

1. **Removing Punctuation:**

   Punctuation marks, such as **"! , . : () ; % _ - ... "** and many others, typically lack meaningful significance in text data. Therefore, removing them is a crucial preprocessing step to reduce noise and simplify the text , As shown in (Figure 3.1).

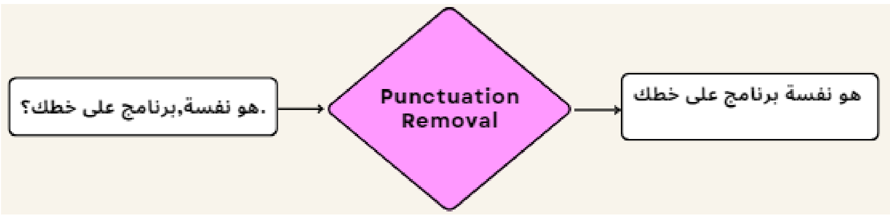

Figure 3.2 – Removing Punctuation Process .

2. **Removing Digits :**

   In text data, the digits 0 through 9 usually have no real value. In order to reduce noise, concentrate more on the text content, and make the sentiment extraction process simpler, eliminating them is an essential preprocessing step. As shown in (Figure 3.2).

3. **Removing Diacritics :**

   Diacritics are small marks that are added to Arabic letters to represent vowels or to disambiguate (Shadda , Fatha , Damma , Kasra , Sukun , Tanween) , Removing them from Arabic text in sentiment analysis simplifies the text, reduces noise, and improves consistency and efficiency of sentiment analysis models by focusing

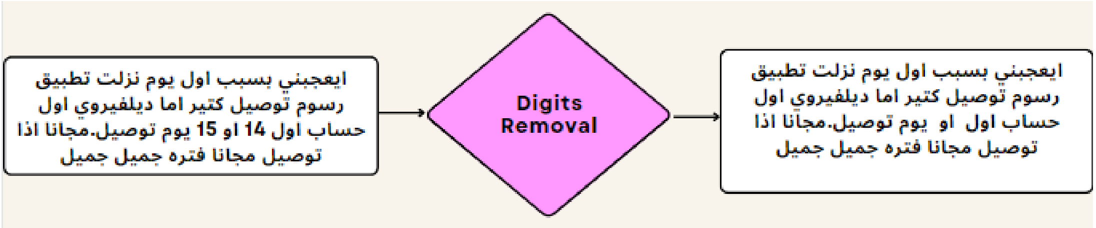

Figure 3.3 – Removing Digits Process .

on sentiment-bearing words and enhancing interpretability and normalize the text .(Figure 3.3) show the process.

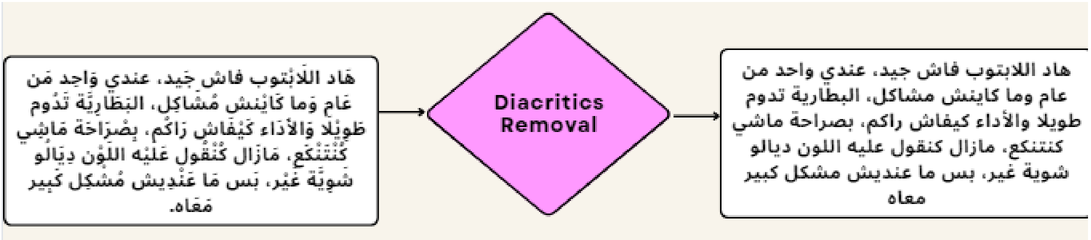

Figure 3.4 – Removing Diacritics Process .

4. **Removing Repeating characters :**

   Thus, the removal of the repeating characters makes the text normalized, readable, less noisy, and more meaningful by the elimination of the redundant character sequences that are not useful for the text message, hence, the text becomes cleaner and easier to use for sentiment analysis models. For example:

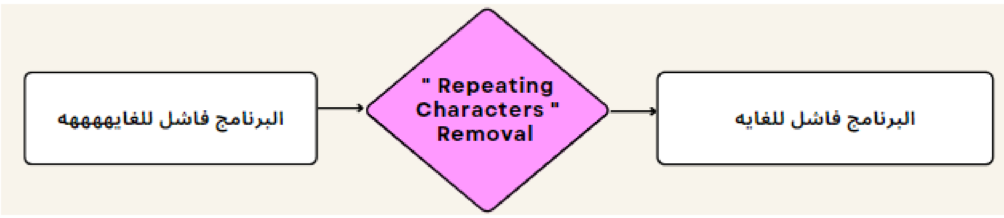

Figure 3.5 – Removing repeating Characters Process .

5. **Removing Long Words :**

   When lengthy words are erased of a text, text processing activities such as sentiment analysis and text classification become easier and less complicated. The text is made shorter to make it more understandable and to solve many problems caused by the limited usage of big words in the training set such as data sparsity, and to improve the model efficiency. Here, we start with a limit of 15, which in other words, if the length of the word exceeds 15, we remove it.

6. **Removing Stop Words :**

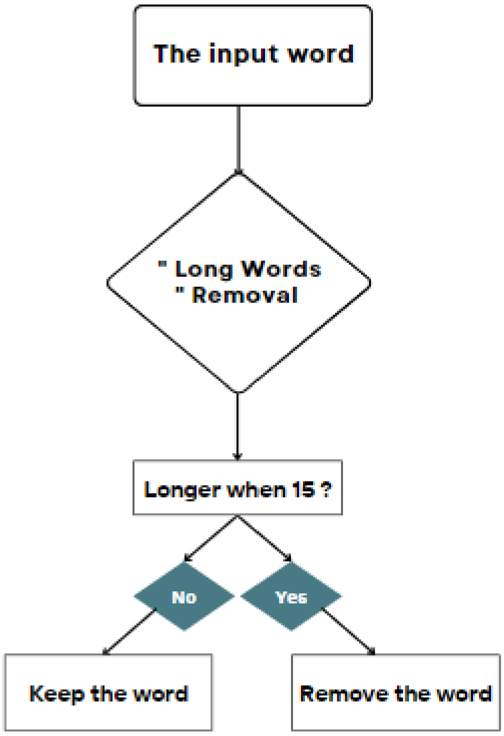

Figure 3.6 – Long words removing Process .

First, we take the lists of stop words for English, Arabic and French languages from the NLTK (Natural Language Toolkit) library. Subsequently, these stop words lists are joined to form a united list. After that, we select the particular words that we want to keep in the text data and put them in a set called "words_to_keep" set. The most common way of texturing is done by the words that have special meanings which we want to keep during the text processing. The existing stop word list is replaced with the new one, which is the set difference between the combined stop words list and the "words_to_keep" set. This way of removing the words specified in the "words_to_keep" set from the combined stop words list, the new stop words list is made which excludes these specific words.

7. **Build Emoji Dictionary :**

   In this section, we created a dictionary that maps emojis to their meanings and textual explanations. The dictionary is based on an emoji dataset that has two rows: text and emoji. In order to store the mapping between the emoji and its description,. For the first scenario, we create a function to replace the emoji with its description. For the second scenario, we create a function to delete the emojis from the text to see the difference between the functions replace and delete in the models preference.So we trained our models first with a training dataset where we replaced the emojis with their meaning, and then we trained them with a training dataset where we deleted the emojis to see if there was an improvement in the model's performance or not.

8. **Lemmatization :**

   Lemmatization is a natural language processing (NLP) technique used to reduce words to their base or root form by their meaning in the text in a smart way, in contrast to stemming. The main purpose of lemmatization is to group together different forms of a word so they can be analyzed as a single item.
   We made the lemmatize._word function that can lemmatize one word from a sentence in English or Arabic language – first we identify the language of the word. Assuming the word is English, it is then translated to Arabic and subjected to a list of stopwords; the remaining ones are then lemmatized. In the case of an Arabic word the procedure is lemmatization without translation. The second lemmatize._multilingual._text function is used to lemmatize a multilingual text for each word by creating an empty list, splitting the text into words, using the lemmatize._word function on the words in the list, and finally converting the list back to a text. It also facilitates more appropriate lemmatization of multilingual texts thus improving sentiment analysis.

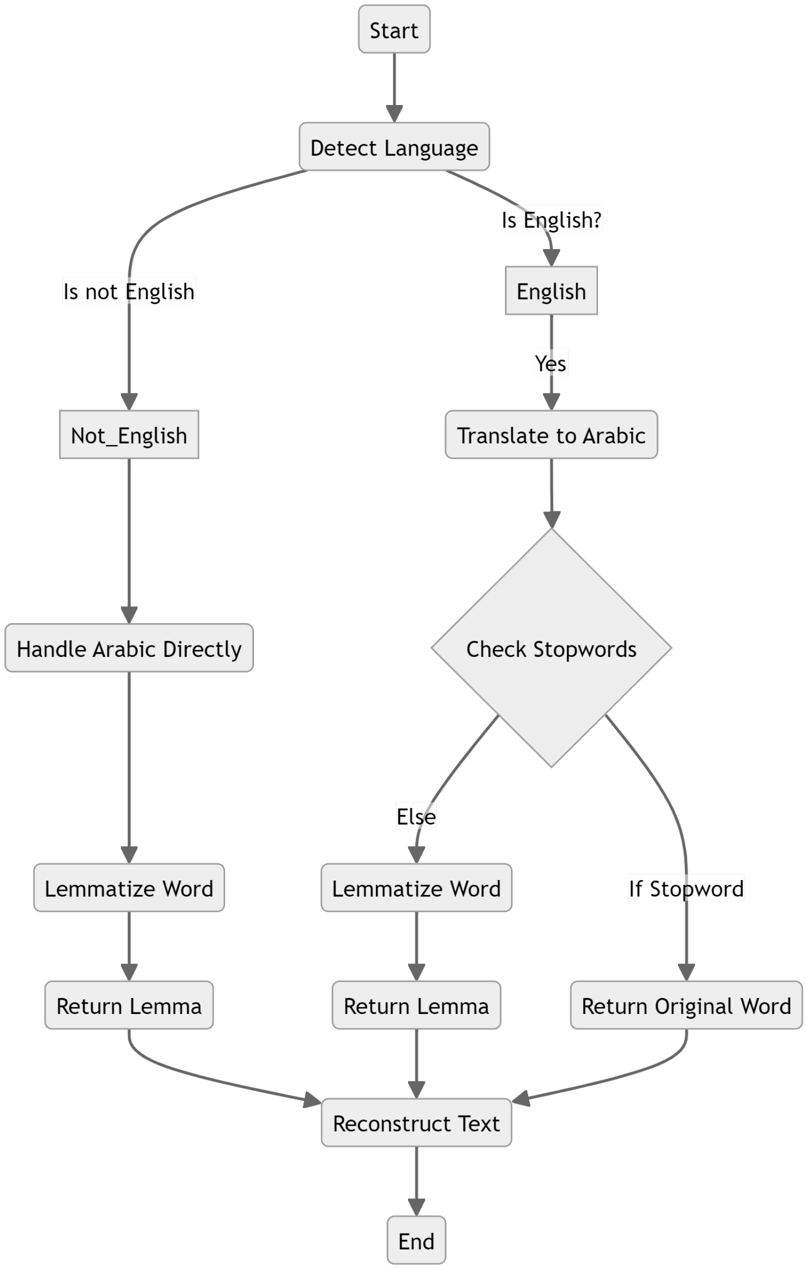

Figure 3.7 – Lemmatization Process.

3.3.3 BiLSTM model Architecture

Bilstm, or bidirectional LSTM, is an advanced type of RNN (recurrent neural network) that contains two layers: the forward layer, which processes the input sequences from left to right, and the backward layer, which processes them from right to left.

The intuition behind this approach is that by processing data in both directions, it gives the ability to better understand relationships between sequences (e.g., knowing the following and the first words in a sentence).

1. **Tokenization :** Tokenization is the process of converting text into tokens or words, where each unique word is assigned a unique integer identifier (token). This is an

important step to prepare the text data for our Bilstm model.

2. **Convert Text to sequence :** This converts each review into a sequence of integers, where each integer corresponds to a word's index in the tokenizer's vocabulary. We want all sequences to be of the same length to ensure consistency when feeding data into the BiLSTM model so we set 100 as max length of the sequences.

3. **Padding Sequences :** Here we padded the sequences to ensures that all sequences have the same length by padding shorter sequences with zeros (or truncating longer ones). In our case we fixed the maximum sequence length by 100.
This preprocessing is essential for enabling text data into a neural network as these models are adequate to work on only when given fixed sized inputs. in our case we need to pre-process the data for further applying it to the embedding layer and the Bidirectional LSTM model in the context of a sentiment analysis task.

4. **Build BiLSTM model :**The layers of the model will be defined in this section.

   - **Embedding Layer:**

     The embedding layer is the first layer, where a trainable vector is assigned to every word. These vectors have a tendency to self-adjust after sufficient training so that words with comparable meanings have similar vectors. After processing these sequences, the data is then sent to bidirectional LSTM layers.

   - **First Bidirectional LSTM Layer:**

     We built The forward LSTM layer with 64 nodes , processes the input sequence x1,x2,...,xt to produce the forward hidden states ht and Ct is the cell state at time step t . The forward layer processes the input sequences from the start to the end.

$$h_t = \text{LSTM}_{\text{forward}}(x_t, h_{t-1}, C_{t-1}) \tag{3.1}$$

   - **Second Bidirectional LSTM Layer:**

     We built The backward LSTM layer with 32 units , processes the input sequence x1,x2,...,xt to produce the forward hidden states ht and Ct is the cell state at time step t. The backward layer processes the input sequences from the end to the begin.

$$(h_t, C_t) = \text{LSTM}_{\text{backward}}(x_t, h_{t+1}, C_{t+1}) \tag{3.2}$$

   - **Concatenation:**

     At each time step t, the hidden states from the forward and backward LSTM are concatenated to form the final output ht.

$$h_t = [h_t(Forward); h_t(Backward)] \tag{3.3}$$

- **Two Dropout Layers:**

  Dropout is a regularization technique that randomly sets a fraction (0.2 or 20.%) of input units to 0 at each update during training to prevent overfitting.

- **Dense Layer:**

  Dense layer with 32 units and relu (rectified linear unit) activation function.This layer adds non-linearity and helps in learning complex representations.

- **Output Layer:**

  Dense layer with 3 units and softmax activation function , The softmax activation is used for multi-class classification. It outputs a probability distribution over the 3 classes (e.g., for sentiment analysis: positive, neutral, negative).

Then we trained the BiLSTM model with the preprocessed train dataset.

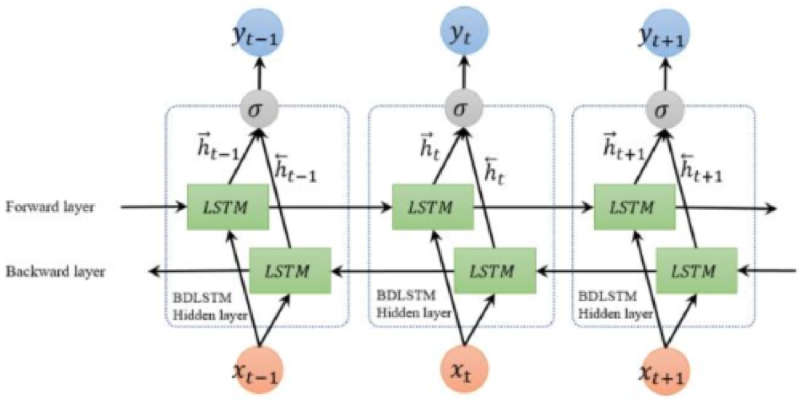

Figure 3.8 – BiLSTM Architecture [CKPW18].

3.3.4 Transformer model Architecture

Transformers are a form of semi-supervised learning they are pre-trained in a semi-supervised manner , and they are fine tuned through the supervised training to get them to platform better.

Transformers use something called attention mechanism and this provide context around items in the input sequence.

The Transformer attempts to identify the context that bring meaning in each words in the sequence , the attention mechanism give the Transformers a huge leg up over algorithms like RNN's that must run in sequence , Transformers run multiple sequences in parallel and this speeds up the training time.

We developed our model based on the Transformer model architecture of the famous paper "Attention is all you need "[VSP+17].

1. **Tokenization :** tokenizer is a vocabulary with words and it's IDs, tokenization is an important phase in the transformers models , used to divide the sequence of text into words called tokens then convert them to integers according to them ID's.

Figure 3.9 – Tokenization Process.

2. **Embedding :** In this step the input ID is represented by a vector of random numbers with a fixed dimension of 512. The transformer model is supposed to improve this vector's ability till the extent that it gives us an accurate expression and meaning of the word.

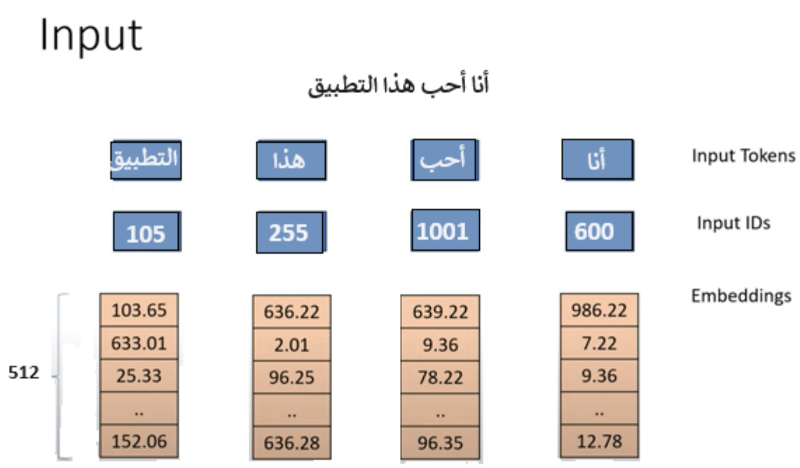

Figure 3.10 – Embedding Process.

3. **Positional Encoding :** The main idea of positional encoding in transformers is to assign each word in a sequence a vector that reflects its position within that sequence. This vector helps the model understand the sequential order of words, crucial for Sentiment analysis task .
In transformers, the positional encoding vector is calculated one time differently based on whether the word's position index is even or odd:

- For even positions, the formula used is :

$$PE(pos, 2i) = \sin\left(\frac{pos}{10000^{2i/dimension_{\text{model}}}}\right) \tag{3.4}$$

- For odd positions, the formula used is :

$$PE(pos, 2i+1) = \cos\left(\frac{pos}{10000^{2i/dimension_{\text{model}}}}\right) \tag{3.5}$$

When we combine the embedding vector (meaning) with the positional encoding (position) vector it give us the meaning of the word in relation to its position in the sentence (Encoder Input).

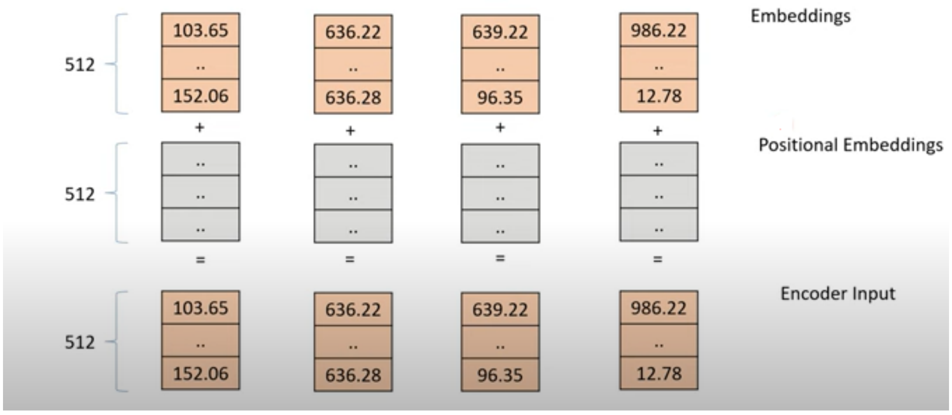

Figure 3.11 – Encoder Input.

4. **The Encoder :** There are ten layers in our encoder that are the same. Two sublayers make up each layer. A two feed-forward network that is simple and fully connected based on position is the second mechanism, while a multi-head self-attention mechanism is the first. After layer normalization, we use a residual connection around each of the two sub-layers. Three of the four matrices that the input encoder matrix was transferred into were named Query (Q), Key (K), and Value (V) are the Multi-head Attention layer's inputs; the Normalization layer receives the fourth copy.

   - **Multihead Attention layer :**
     The multi-head attention mechanism is a crucial component of the Transformer model based on the self attention mechanism. It allows the model to focus on different parts of the input sequence simultaneously by computing multiple sets of attention weights.
     We provided a detailed explanation of how multi-head attention works :

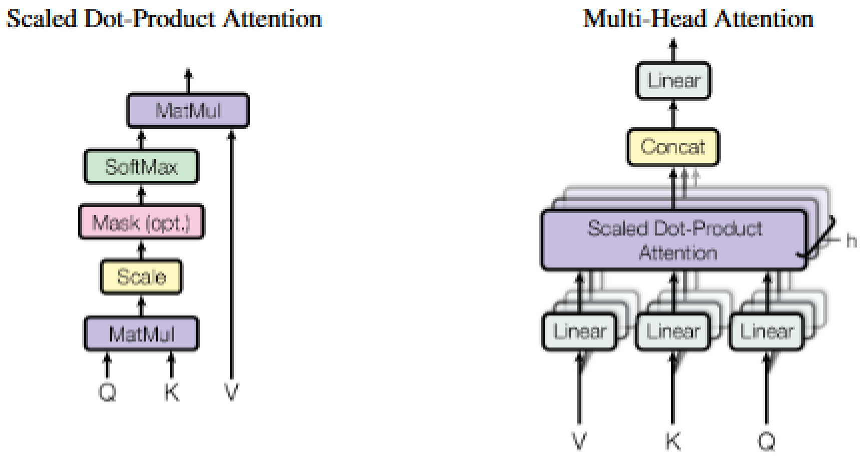

Figure 3.12 – Multihead Attention Process [VSP+17].

- Linear Projections for Queries, Keys, and Values: First , the Q,V,K matrices should multiplied with W_Q,$W_V$and W_k weight matrices to give weight for each word in the sequence to define the relationships and dependencies between the words in the sequence, facilitating the computation of attention scores that determine how much focus should be placed on each word when processing the sequence.

$$Q = X \cdot W_Q \tag{3.6}$$

$$K = X \cdot W_K \tag{3.7}$$

$$V = X \cdot W_V \tag{3.8}$$

- Scaled Dot Product Attention: The input consists of queries and keys of dimension d_k (from the Key matrix), and values of dimension d_v (of Value matrix). We compute the dot products of the query with all keys, divide each by $\sqrt{d_k}$, and apply a softmax function to obtain the weights on the values. In practice, we compute the attention function on a set of queries simultaneously, packed together into a matrix Q. The keys and values are also packed together into matrices K and V [VSP+17].

We compute the matrix of outputs as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{3.9}$$

Instead of performing a single attention function with d model-dimensional keys, values and queries, it's better to use multihead attention with 8 heads , withe this formulars :

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h) \cdot W^O \tag{3.10}$$

$$\text{where head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \tag{3.11}$$

- **Feed Forward Neural Network (FFN):**
  Here we applied two fully connected layers with a ReLU activation in between.

$$\text{FFN}(x) = \text{ReLU}(xW^{(1)} + b^{(1)})W^{(2)} + b^{(2)} \tag{3.12}$$

  Where W are weight matrices and b are bias vectors.

5. **The Decoder :** A stack of N = 10 identical layers also makes up the decoder. The decoder adds a third sub-layer to each encoder layer in addition to the first two, and this sub-layer handles multi-head attention over the encoder stack's output. Like the encoder, we use residual connections surrounding every sub-layer and then layer normalization. furthermore the multihead attention mask. This masking makes sure that the predictions for location i can only rely on the known outputs at positions less than i, along with the fact that the output embeddings are offset by one position [VSP+17].

   - **Masked Multihead Attention :**
     It based on the Causal Model which means "The model must not be able to see the future words".
     Masked multi-head attention in transformers , especially in the decoder part, guarantees that in any sequence generation task, such as text translation, the prediction of each token does not depend on the information that comes later. This causal masking ensures that sequence generation is both conditional and realistic, while its autoregressive nature is vital for training and performance in sequence modeling.

   Overall, while the basic components (multihead attention, feed-forward networks, normalization) are similar between encoder and decoder layers, the specific application of cross-attention and causal masking in the decoder distinguishes it as specialized for sequence generation tasks.

Then we trained our Transformer model on the prepocessed train dataset.

3.4 BiLSTM VS Transformer

Bidirectional Long Short-Term Memory (BiLSTM) networks have been a powerful tool for natural language processing (NLP) tasks, but they have some limitations that

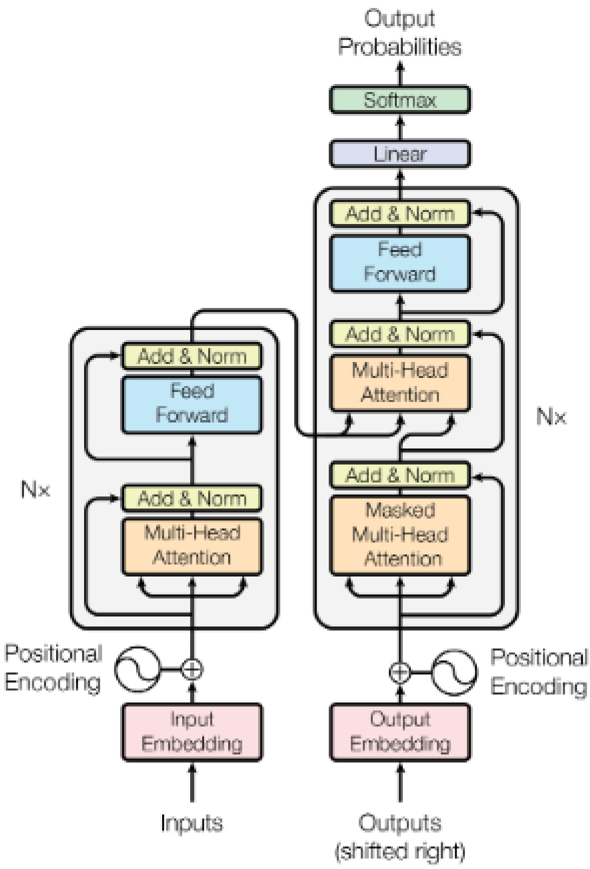

Figure 3.13 – The Transformer model Architecture [VSP+17] .

transformers address. Here's a breakdown of the limitations and why transformers offer advantages

3.4.1 Limitation of BiLSTM :

Here are some limitation of the biLSTM againts of the Transformers :

- **Limited Context:** BiLSTM is only able to solely incorporate context in terms of words in a limited number of words ahead (future) or behind (past). In long and complicated sentences, this may make it difficult for it to recognize the long-term structure and interdependencies [YWT+17].
- **Sequential Processing:** The BiLSTM in particular work sequentially, which implies that they operate on the input word by word. This can be quite time consuming and sometimes very slow in processing large quantities of text information.
- **Vanishing/Exploding Gradients:** LSTMs have an issue of Gradient vanishing/exploding where gradients which are used during training to implement the state change could vanish or explode when computed over large intervals[HS97].

3.4.2 Advantages of Transformers:

Here is some advantage of the Transformers againsts the Bilstm :

- **Attention Mechanism:** The most important thing about the Transformers is that they use an attention mechanism that enables the decoder to take into consideration only the portions of the input sequence which are relevant to the current word being produced. This makes them capable of capturing long range dependencies with higher precision than what BiLSTMs can offer[VSP+17].
- **Parallel Processing:** Transformers have the input sequence's entire memory mapped to all of its members, which enables both training and inference to happen efficiently at a faster rate than the LSTMs [VSP+17].
- **Better Handling of Long Sequences:** Some models such as LSTMs have limitations when dealing with sequences of text, and because of the attention mechanism and parallel processing transformers are more suitable in this case [VSP+17].

3.5 Conclusion

We have proposed two approaches that make it possible to classify the sentiment of humans from comments, reviews, and feedback. We started with a preprocessing step that allows us to improve the text quality and precision in order to make the task easier for our classifiers Bilstm and Transformer. To compare these two methods with two different preprocessing scenarios (replace the emojis with their meaning and delete the emojis),, and we discussed some Bilstm limitations, such as limited context, and the new concept behind the Transformers.
In the next chapter, we will compare the results of these two models with the best model for the task of sentiment analysis in Arabic.

Chapter 4

Implementation, Testing and Results

4.1 Introduction

This chapter concentrates on the actual implementation of our system, outlining the important procedures, the tests that were run, and the outcomes that were attained. It's time to realize our vision by bringing our plans and ideas to life, having defined the design and basic concepts in the preceding chapters.

We will start by thoroughly outlining the steps involved in putting our system into place, emphasizing the technological decisions and instruments that were made, the bases that were employed, and the values of the parameters that were set. We'll discuss about the technical elements, the difficulties faced, and the strategies used to get beyond these barriers.

4.2 Models Parameters

Whichever kind of artificial intelligence application, achieving acceptable performance depends critically on the model parameterization stage.

We conducted multiple experiments and experimentally tuned the parameters to get the best possible results. We carefully examined our data and came up with the following numbers to optimize our systems:

4.2.1 Bidirectional Model Parameters

We noted that the best parameters for a good classification for our BiLSTM model are:

-The size of the vocabulary, which is the total number of unique words in the tokenized texts plus one.

-The size of the dense embedding, which is set to 100.

-The maximum length of input sequences, which is set to 100.

-The number of units in the first LSTM layer, set to 128.

-The dropout rate, set to 0.2.

-The number of units in the second LSTM layer, set to 64.

-The number of units in the dense layer, set to 3 (corresponding to the three sentiment categories).

-The activation function, set to softmax for multi-class classification.

-The loss function, set to categorical_crossentropy.

-The optimizer, set to Adam with a learning rate of 0.001.

-The number of epochs for training, set to 10.

-The batch size for training, set to 32.

-The fraction of the training data to be used as validation data, set to 0.2.

4.2.2 Transformer Model Parameters

We noted that the best parameters for a good classification for our Transformer model are:

-The size of the vocabulary, which is the total number of unique words in the tokenized texts plus one.

-The number of encoder layers,set to 10.

-The number of decoder layers,set to 10.

-The number of attention heads,set to 8.

-The size of the embedding, which is set to 512.

-The fully connected Dimension, set to 32.

-The maximum sequence length,set to 128.

-The activation function, set to softmax for multi-class classification.

-The loss function, set to categorical_crossentropy

-The optimizer,set to Adem with learning rate:1e-4.

-The number of epochs for training,set to 15.

-The batch size for training,set to 64.

-The fraction of the training data to be used as validation data, set to 0.2.

4.3 Hardware Tools

The experiments were carried out on a laptop running Windows 11. The computer in question is equipped with an Intel(R) Core(TM) i5-8250U CPU, clocked at 1.60 GHz 1.80 GHz and 4 GB of memory. For the implementation of the algorithms, we used the Python language within the Jupiter and Google Colab development environment.

4.4 Software Tools

4.4.1 Development environment

Jupyter : For collaborative computing in all programming languages, there is free software, open standards, and online services. For creating and sharing computer documents online, the Jupyter Notebook was the first tool developed. The experience is document-focused, simplified, and easy to use [W7].

4.4.2 Programming language

Python : Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built in data structures, combined with dynamic typing and dynamic binding, make it very attractive for Rapid Application Development, as well as for use as a scripting or glue language to connect existing components together. Python's simple, easy to learn syntax emphasizes readability and therefore reduces the cost of program maintenance. Python supports modules and packages, which encourages program modularity and code reuse. The Python interpreter and the extensive standard library are available in source or binary form without charge for all major platforms, and can be freely distributed [W8].

4.4.3 Description of the libraries used

- **Scikit-learn :** Scikit-learn is a free Python library for machine learning. It is developed by numerous contributors, notably in the academic world by French higher education and research institutes such as Inria and Telecom ParisTech [W9].
- **Pandas :** The library for data analysis and working with data sets is named Pandas. It is designed with built-in modules for analyzing data, cleaning data, exploring data, and manipulating data. The name "Pandas" is an acronym for "Panel Data" as well as a play on "Python Data Analysis" and was started by Wes McKinney in 2008. With the support of Pandas, we are able to analyze big data and derive certain conclusions based on theories of statistics. Another task of Pandas is to resculpt data sets that may be dusty and unusable, making them neat, clean, and useful. This

is because, in data science, dealing with large amounts of data and information is the key way of dealing with the havoc it brings [W10].

- **NLTK :** The natural language toolkit is one of the most popular tools for developing applications in the programming language of Python that contains tools for working on natural language data. Over 50 corpora and lexical resources such as WordNet are available through complex APIs, there are a set of text processing libraries for classification, tokenization, stemming, tagging, parsing, semantic reasoning, and others, several industrial-strength NLP libraries' wrappers, and an active referencing to the forum. NLTK is open source and is compatible with the Windows, MAC OS X and Linux operating systems [W11].
- **CSV :** The most favorite format used for import and export of spreadsheets and databases is called CSV — Comma Separated Values. RFC 4180, standard that aims to describe CSV format in detail, was created relatively recently, although CSV format was in use for many years before. This is because there is no capped standard as to what constitutes a good kind of data, there are always fine distinctions that distinguish one set of data used and produced by multiple applications. The differences highlighted above can make it inconvenient to process CSV files originated from various sources. But though the delimiters and quoting characters are different, most of the case are similar in the fact that you can write a single module that can handle the data efficiently and isolate the fact of reading/writing the data from the programmer [W12].
- **Keras :** Keras is designed to operate as an API and it is rightfully so, it is designed for human use and not machines. Keras follows best practices for reducing cognitive load: it has a stable and clear interface for many users and demands fewer actions from the user, and it gives precise and call-to-action error messages. Another strong feature of Keras is that it provides highest priority for creating good documentation as well as developer references [W13].
- **Tansorflow :** TensorFlow is a free and open-source software library for machine learning and artificial intelligence , A library to build neural networks on graph data (nodes and edges with arbitrary features), including tools for preparing input data and training models.It was developed by the Google Brain team for Google's internal use in research and production [W14].
- **Numpy :** Numpy is a Python package for an efficient operation for high-level scientific computing, mainly along with multi-dimensional arrays. It also contains features that enables its functioning in domains as linear algebra, fast fourier transform, and matrices. It was developed in 2005 by Travis Oliphant, who did this work in order to enhance and advance the Python programming language. These are free software, created under the Open-Source project and you are very welcome to use

it. NumPy is an abbreviation of Numerical Python although, it's also known as Numeric Python [W15].

- **Matplotlib :** Matplotlib is a versatile library for generating clear and shiny static, animated, and interactively generated plots in Python. This was said about Matplotlib and it can be generalized to most mathematical tools because Matplotlib makes easy things easy and hard things possible [W16].

4.5 Evaluation metrics

- **Accuracy :** In classification, the accuracy metric is an important measurement to validate the model. Accuracy, or the rate of correct predictions, corresponds to the proportion of correct predictions among all predictions made. It is the number of true positives and true negatives predicted by the model divided by the total number of data points. The accuracy is calculated using the following formula:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.1}$$

Where:

  - TP = True Positives
  - TN = True Negatives
  - FP = False Positives
  - FN = False Negatives

This formula helps in determining how well the model is performing by considering both the correctly identified positive and negative instances.

- **Precision :** Precision is a measure of user performance in classification and automatic learning that evaluates the model's ability to correctly identify positive examples among all positive predictions. The names of the words and the faux positives are divided by the names of the voices to calculate the precision. In these terms, it is necessary to provide exact positive results for all positive predictions. The level of accuracy indicates that the model is capable of producing a viable combination of faux positives, which is generally desirable. However, high precision can increase the false negatives because this model has a negative class that is positive. The precision is calculated using the following formula:

$$\text{Precision} = \frac{TP}{TP + TN} \tag{4.2}$$

- **Recall :** In classification and machine learning, Recall is a performance metric used to evaluate the ability of a model to identify all positive examples among all positive

real examples.
The calculation is obtained by dividing the number of true positives by the sum of true and false negatives. In other words, it calculates the appropriate positive rate for each positive real-world example. The recall is calculated using the following formula:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4.3}$$

- **F1-score :** The F1 score is a harmonic average of precision and recall. It is used to consider both precision and recall, placing more emphasis on uneven classes. A value of 1 on the F1-score indicates perfect classification, while a value of 0 indicates poor classification. Therefore, a higher F1 score means that the classification model performs better in terms of precision and recall. The F1-score is calculated using the following formula:

$$\text{Recall} = \frac{2.(Precision.Recall)}{Precision + Recall} \tag{4.4}$$

4.6 Testing Results

In this section we will talk about the outcomes of the two developed models, the Transformer model and the Bilstm model:

4.6.1 The Testing Dataset

We searched a number of times before we were able to locate a dataset with enough reviews of a well-known Arabic company called Talabat. Talabat is an online food ordering service that assists users in finding restaurants in their neighborhood, narrowing down their options by cuisine, perusing menus, and placing orders with the option of paying online or with cash on delivery [W17]. From it, we were able to gather almost 40.000 reviews, both favorable and negative, as well as natural.

4.6.2 Testing BiLSTM and Transformer models

In this section, we will discuss the results of the BiLSTM model in two different cases:

- **Case 1:** Employing Preprocessed Dataset with Emoji dictionaries At this point, the dataset had been processed before utilizing dictionaries of emotions through which we were able not only maintain but also understand emoticons based on our text. It may also include something about how important interpretation will increase true results when analyzing sentiments as conveyed by them depending upon situation-specific context.

- **Case 2:** Managing Preprocessed Set without Emoticons When we got to the second instance, we had removed emoticons from the data set. It only looks at the written word and does not consider sentiments communicated through emoticons. This makes language easier but has a possibility of taking away signal value contained in the emoticon.

1. **BiLSTM model :** We assessed the performance of our BiLSTM model in both cases to consider the effect of emojis on sentiment analysis accuracy. The obtained results were closely examined with respect to standard evaluation metrics such as accuracy, precision, and F1-score. Here are the results:

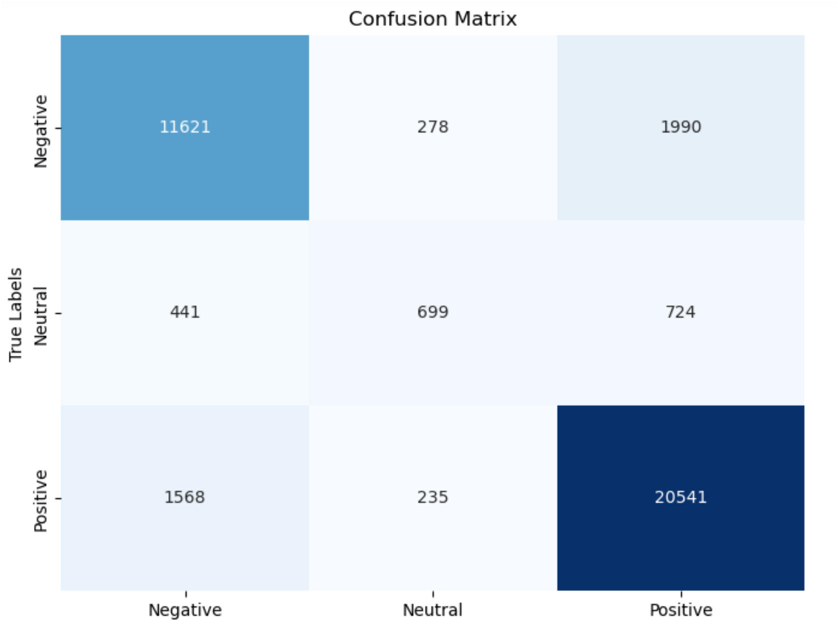

Figure 4.1 – The confusion Matrix for BiLSTM model.

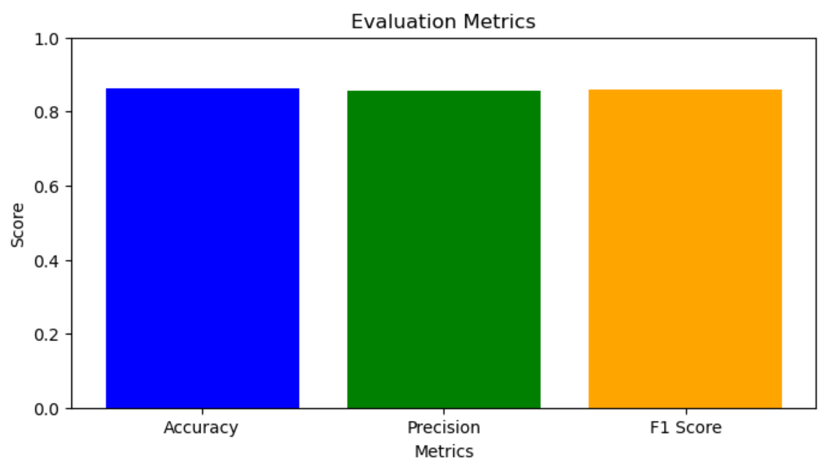

Figure 4.2 – The Evaluation metrics plots for BiLSTM model.

2. **Transformer model:** We assessed the performance of our Transformer model in both cases to consider the effect of emojis on sentiment analysis accuracy. The obtained results were closely examined with respect to standard evaluation metrics such as accuracy, precision, and F1-score. Here are the results:

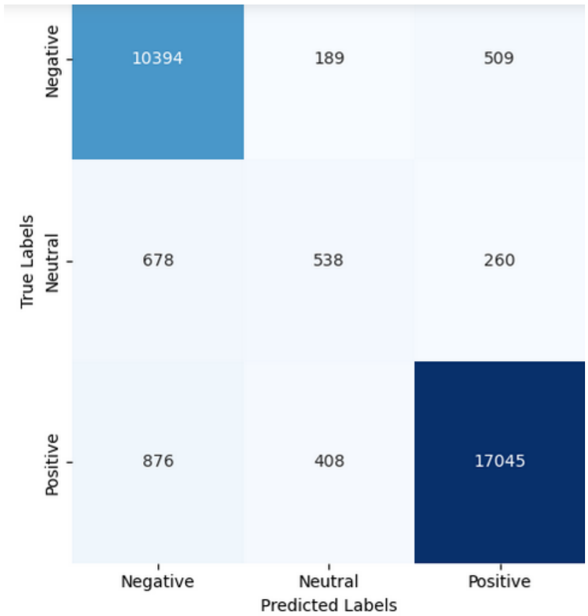

Figure 4.3 – The confusion Matrix for Transformer model.

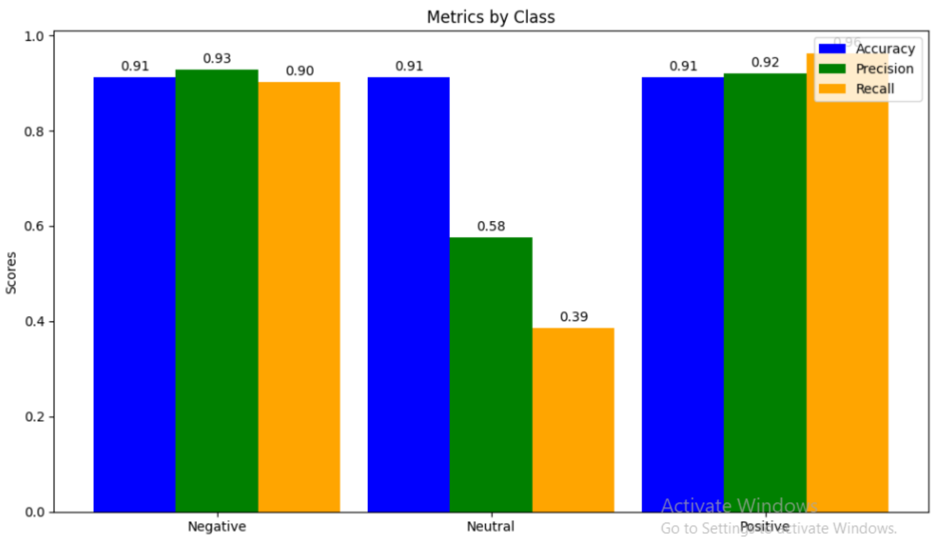

Figure 4.4 – The Evaluation metrics plots for Transformer model.

So in the metrics plot for the models in the first case, as discussed earlier, we noticed that the "neutral" class alters the metric values significantly. This is because the number of reviews classified as "neutral" is comparatively small relative to the number of negative and positive reviews. That is why the precision, accuracy, and F1-score for the "neutral" class is more likely to be lower than for other classes: many similar instances to learn from are fewer, and more often the model classifies them as something else, causing an increased number of errors.

4.7 Results Comparison

In this section, we will compare the two models in the two cases. The following table shows the obtained results:

- **Case 1:**

Metric/Model	Transformer	BiLSTM
Training Accuracy	0.9599	0.9312
Testing Accuracy	0.9194	0.8586
Testing Precision	0.9070	0.8539
Testing F1 Score	0.9085	0.8547

Table 4.1 – Comparison of Transformer and BiLSTM models across the first case.

Regarding accuracy, precision, and f1score, the transformer model outperforms the biLSTM model in the first instance.

- **Case 2:**

Metric/Model	Transformer	BiLSTM
Training Accuracy	0.96	0.9312
Testing Accuracy	0.86	0.8370
Testing Precision	0.8641	0.8382
Testing F1 Score	0.8619	0.8376

Table 4.2 – Comparison of Transformer and BiLSTM models across the second case.

Based on our results, when using all the models for examining SA in Arabic text, the highest F-score was obtained where we apply the Transformer model with preprocessing involving an emoji dictionary. This is because emojis provide more contextual information which can be utilized while Transformer allows for learning long-range dependencies and complex sentiment patterns. Integrating emojis further improves the model by increasing the accuracy, precision, F1-score while decreasing the R-squared score more compared to other blends.

As it was also mentioned, emoji dictionaries have a great positive impact towards the BiLSTM model but its performance is worse than the performance of the Transformer. For safety reasons, emojis were removed from the data set, and this reduced the performance of the BiLSTM model but not to a major extent.

In conclusion, it can be said that the Transformer model with the inclusion of emo-preprocessing reveals the best results in the sentiment analysis and helps to minimize the problem of the class imbalance, as well as including positive and negative sentiment indicators which can be found in emojis. Altogether, the combination provides an important information for businesses and organisations dealing with the analysis of Arabic text.

4.8 Conclusion

In more details, this chapter discussed the manner in which our proposed sentiment analysis system for Arabic text was performed, the tools that were employed and the specific settings that were applied. In the experimental analysis, we employed a carefully prepared dataset for the evaluation of our system. But I think the most challenging part was the development of the ground truth repository for each review to spend much time of concentrated effort in order. Doing this, we obtained the results that can be considered rather satisfying, which testifies to the efficiency of the working sentiment analysis system. The success rates of the test reviews' sentiment have been handled efficiently thus implying the feasibility of the proposed approach in distinguishing between different Arabic texts' sentiments. It also paves the way for further enhancement of this method in other facets of system causing its flexibility to work on other types of sentiment analysis tasks.

General Conclusion

This dissertation explored in depth the use of artificial intelligence (AI) for Sentiment analysis in Arabic language. We presented an intelligent AI-based system that uses two deep learning techniques to automatically predict the sentiment from an arabic text.This system provides businesses with the opportunity to take faster decision and make measures,to improve their product offerings. The results obtained by our Transformer model demonstrated its effectiveness which give a better result against the Bilstm model in predict sentiment analysis in arabic comments , reviews and feedbacks, which confirms its potential to improve the gain in companies and control the market a, and shows the limitation of our Bilstm model. The combination of deep learning, Natural Language processing and data analysis has developed a two models capable of accurately identifying sentiment in Arabic language. businesses can thus be alerted quickly, allowing them to take appropriate measures to improve there services.

However, it should be emphasized that our system presents opportunities for improvement and future research for Arabic language. An interesting perspective would be to explore new dictionary that specific for Arabic dialects would allow our system to be further tested and validated against a wider variety of real-world scenarios. This would also improve its robustness and ability to predict sentiment from a dataset with different Arabic countries dialects.

In conclusion, the use of AI for sentiment analysis has strong potential to improve the gains of companies and controlling the market. Our intelligent AI-based system represents a significant advancement in this field, providing an automated and precise solution for predict sentiment in Arabic language with her complexity. However, future work, including exploration of new datasets and comparison with deep learning algorithms, is needed to continue improving the performance and accuracy of sentiment analysis in different Arabic dialects. These developments will help businesses practices and improve the products and services quality in satisfying costumers, while providing new research perspectives for even more effective use of artificial intelligence in modern sentiment analysis.

Bibliography

[AADE19] Rahma M Alahmary, Hmood Z Al-Dossari, and Ahmed Z Emam. Sentiment analysis of saudi dialect using deep learning techniques. In *2019 International Conference on Electronics, Information, and Communication (ICEIC)*, pages 1–6. IEEE, 2019.

[AK15] Mariette Awad and Rahul Khanna. Support vector machine. In *Efficient Learning Machines*, pages 70–82. ApressOpen, first edition, 2015.

[Alh20] Sarah Alhumoud. Arabic sentiment analysis using deep learning for covid-19 twitter data. *International Journal of Computer Science and Network Security*, pages 132–138, 2020.

[AMLN19] Ameen Abdullah Qaid Aqlan, B Manjula, and R Lakshman Naik. A study of sentiment analysis: concepts, techniques, and challenges. In *Proceedings of International Conference on Computational Intelligence and Data Engineering: Proceedings of ICCIDE 2018*, pages 147–162. Springer, 2019.

[AQ22] Leen Muteb Alharbi and Ali Mustafa Qamar. Arabic sentiment analysis of eateries' reviews using deep learning. *Ingénierie des Systèmes d'Information*, 27(3), 2022.

[AQ23] Shahd Ebrahim Alqaan and Ali Mustafa Qamar. Sentiment analysis of arabic tweets on online learning during the covid-19 pandemic: A machine learning and lstm approach. *Ingénierie des Systèmes d'Information*, 28(6), 2023.

[BBFK23] Zakaria Benmounah, Abdennour Boulesnane, Abdeladim Fadheli, and Mustapha Khial. Sentiment analysis on algerian dialect with transformers. *Applied Sciences*, 13(20):11157, 2023.

[Ber20] Israr Berrim. Sentiment analysis in arabic tweets. Master's thesis, University of Kasdi Merbah, Ouargla, Algeria, 2019/2020.

[Bre94] Leo Breiman. Bagging predictors. Technical Report 421, University of California, Berkeley, California 94720, 1994. Accessed 11/03/2020.

[Bre99] Leo Breiman. Random forests–random features. Technical Report 567, University of California, Berkeley, California CA 94720, 1999. Accessed 06/05/2024.

[CGP15] Chandni Nav Chandra, Sarishty Gupta, and Renuka Pahade. Sentiment analysis and its challenges. *International Journal of Engineering Research & Technology*, 4(03):968–970, 2015.

[CKPW18] Zhiyong Cui, Ruimin Ke, Ziyuan Pu, and Yinhai Wang. Deep bidirectional and unidirectional lstm recurrent neural network for network-wide traffic speed prediction. *arXiv preprint arXiv:1801.02143*, 2018.

[Dea09] Nelson Dean. Using simple linear regression to assess the success of the montreal protocol in reducing atmospheric chlorofluorocarbons. *Journal of Statistics Education*, 17(2), 2009.

[DK19] Zulfadzli Drus and Haliyana Khalid. Sentiment analysis in social media and its application: Systematic literature review. *ELSEVIER*, 2019.

[DM22] Asmita De and Sushruta Mishra. Augmented intelligence in mental health care: Sentiment analysis and emotion detection with health care perspective. *Augmented Intelligence in Healthcare: A Pragmatic and Integrated Analysis*, pages 205–235, 2022.

[ea16a] Ghazaleh Beigi et al. An overview of sentiment analysis in social media and its applications in disaster relief. *Sentiment Analysis and Ontology Engineering: An Environment of Computational Intelligence*, pages 313–340, 2016.

[ea16b] W. Christian Crannell et al. Pattern-matched twitter analysis of us cancer-patient sentiments. *Journal of Surgical Research*, 206(2):536–542, 2016.

[ea19a] Cheng Zhang et al. Social media for intelligent public information and warning in disasters: An interdisciplinary review. *International Journal of Information Management*, 49:190–207, 2019.

[ea19b] Eleonora D'Andrea et al. Monitoring the public opinion about the vaccination topic from tweets analysis. *Expert Systems with Applications*, 116:209–226, 2019.

[ea19c] Francisco Javier Ramírez-Tinoco et al. Use of sentiment analysis techniques in healthcare domain. *Current Trends in Semantic Web Technologies: Theory and Practice*, pages 189–212, 2019.

[ea22a] Hui Yin et al. Sentiment analysis and topic modeling for covid-19 vaccine discussions. *World Wide Web*, 25(3):1067–1083, 2022.

[ea22b] Praveen Ranjan Srivastava et al. Analyzing online consumer purchase psychology through hybrid machine learning. *Annals of Operations Research*, 2022.

[ea22c] Shailesh Hinduja et al. Machine learning-based proactive social-sensor service for mental health monitoring using twitter data. *International Journal of Information Management Data Insights*, 2(2):100113, 2022.

[EVA+23] Nasrin Elhassan, Giuseppe Varone, Rami Ahmed, Mandar Gogate, Kia Dashtipour, Hani Almoamari, Mohammed A El-Affendi, Bassam Naji Al-Tamimi, Faisal Albalwy, and Amir Hussain. Arabic sentiment analysis based on word embeddings and deep learning. *Computers*, 12(6):126, 2023.

[FKL+13] Ludwig Fahrmeir, Thomas Kneib, Stefan Lang, et al. *Regression: Models, Methods and Applications*. Springer-Verlag, Berlin Heidelberg, first edition, 2013.

[GME+24] Hasan Gharaibeh, Al Mamlook, Rabia Emhamed, Ghassan Samara, Ahmad Nasayreh, Saja Smadi, Khalid MO Nahar, Mohammad Aljaidi, Essam Al-Daoud, Mohammad Gharaibeh, et al. Arabic sentiment analysis of monkeypox using deep neural network and optimized hyperparameters of machine learning algorithms. *Social Network Analysis and Mining*, 14(1):1–18, 2024.

[HS97] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

[HTEM18] Maha Heikal, Marwan Torki, and Nagwa El-Makky. Sentiment analysis of arabic tweets using deep learning. *Procedia Computer Science*, 142:114–122, 2018.

[Jam06] Mor James. Dartmouth artificial intelligence conference. the next fifty years. *AI Magazine*, 27(4):2006, 2006.

[Kan24] Mohamed Raouf Kanfoud. *Analyse des sentiments dans un contexte multilingue à l'aide de techniques d'apprentissage automatique et de traitement automatique des langues*. PhD thesis, 2024.

[KDM16] K L Santhosh Kumar, Jayanti Desai, and Jharna Majumdar. Opinion mining and sentiment analysis on online customer reviews. *2016 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, pages 1–4, 2016.

[Kim16] Kwang Gi Kim. Book review: Deep learning. *Healthcare informatics research*, 22(4):351, 2016.

[KP14] Daekook Kang and Yongtae Park. Review-based measurement of customer satisfaction in mobile service: Sentiment analysis and vikor approach. *Expert Systems with Applications*, pages 1041–1050, 2014.

[MAA+23] Dhiaa A Musleh, Ibrahim Alkhwaja, Ali Alkhwaja, Mohammed Alghamdi, Hussam Abahussain, Faisal Alfawaz, Nasro Min-Allah, and Mamoun Masoud Abdulqader. Arabic sentiment analysis of youtube comments: Nlp-based machine learning approaches for content evaluation. *Big Data and Cognitive Computing*, 7(3):127, 2023.

[Mah20] Batta Mahesh. Machine learning algorithms-a review. *International Journal of Science and Research (IJSR).[Internet]*, 9(1):381–386, 2020.

[Mas15] Reza-Amini Massih. *Apprentissage machine de la théorie à la pratique*. Edition Eyrolles, 75240 Paris Cedex 05, 2015.

[MG14] Diana G Maynard and Mark A Greenwood. Who cares about sarcastic tweets? investigating the impact of sarcasm on sentiment analysis. In *Lrec 2014 proceedings*. ELRA, 2014.

[MHK14] Walaa Medhat, Ahmed Hassan, and Hoda Korashy. Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, 2014.

[MK19] Ammar Mohammed and Rania Kora. Deep learning approaches for arabic sentiment analysis. *Social Network Analysis and Mining*, 9(1):52, 2019.

[Nil98] Nils J. Nilsson. *Artificial Intelligence: A New Synthesis*. Morgan Kaufmann Publishers, San Francisco, CA 94104-3205 USA, 1998. [Online]. 493p. Available at https://books.google.dz/books?id=GYOFSd6fETgC&printsec=frontcover&dq=Artificial+Intelligence:+A+New+Synthesis&hl=fr&sa=X&ved=2ahUKEwiWlp3MvsvrAhVkxoUKHbKCBpoQuwUwAHoECAUQCg#v=onepage&q=Artificial%20Intelligence%3A%20A%20New%20Synthesis&f=false (accessed 18/06/2020).

[Pav00] YU.L Pavlov. *Random Forest*. Ridderprint BV Ridderkerk, The Netherlands, first edition, 2000. Accessed 06/05/2024.

[PJK23] Seyoung Park, Junegak Joung, and Harrison Kim. Spec guidance for engineering design based on data mining and neural networks. *Computers in Industry*, 144:103790, 2023.

[PP94] Phil Picton and Phil Picton. *What is a neural network?* Springer, 1994.

[PR21] Nandwani Pansy and Verma Rupali. A review on sentiment analysis and emotion detection from text. *Social Network Analysis and Mining*, 2021.

[PXB+20] H. Peng, L. Xu, L. Bing, F. Huang, W. Lu, and L. Si. Knowing what, how and why: A near complete solution for aspect-based sentiment analysis. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(05):8600–8607, 2020.

[RAB18] J. Rexiline Ragini, P.M. Rubesh Anand, and Vidhyacharan Bhaska. Big data analytics for disaster response and recovery through sentiment analysis. *International Journal of Information Management*, 42:13–24, 2018.

[RPR21] Kumar Ravi, Aishwarya Priyadarshini, and Vadlamani Ravi. Opinion mining-based conjoint analysis of consumer brands. *Smart Computing Techniques and Applications*, pages 227–239, 2021.

[RR15] Kumar Ravi and Vadlamani Ravi. A survey on opinion mining and sentiment analysis: Tasks, approaches and applications. *Knowledge-Based Systems*, 89:14–46, 2015.

[Sam67] Arthur Samuel. Some studies in machine learning: Using the game of checkers. *IBM Journal*, pages 601–617, November 1967.

[SK22] Fahim K. Sufi and Ibrahim Khalil. Automated disaster monitoring from social media posts using ai-based location intelligence and sentiment analysis. *IEEE Transactions on Computational Social Systems*, pages 1–11, 2022.

[SMS20] K Sindhu Meena and S Suriya. A survey on supervised and unsupervised learning techniques. In *Proceedings of international conference on artificial intelligence, smart grid and smart city applications: AISGSC 2019*, pages 627–644. Springer, 2020.

[SS16] Shan Suthaharan and Shan Suthaharan. Decision tree learning. *Machine Learning Models and Algorithms for Big Data Classification: Thinking with Examples for Effective Learning*, pages 237–269, 2016.

[VSP+17] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.

[Wei05] Sanford Weisberg. *Applied Linear Regression*. John Wiley & Sons, Hoboken, New Jersey, third edition, 2005.

[WRK22] Mayur Wankhade, Annavarapu Chandra Sekhara Rao, and Chaitanya Kulkarni. A survey on sentiment analysis methods, applications, and challenges. *Artificial Intelligence Review*, 55(7):5731–5780, 2022.

[YN23] Mehdi Yekrangi and Nikola S. Nikolov. Domain-specific sentiment analysis: An optimized deep learning approach for the financial markets. *IEEE Access*, 11:70248–70262, 2023.

[YWT+17] Hua-Lei Yin, Wei-Long Wang, Yan-Lin Tang, Qi Zhao, Hui Liu, Xiang-Xiang Sun, Wei-Jun Zhang, Hao Li, Ittoop Vergheese Puthoor, Li-Xing You, et al. Experimental measurement-device-independent quantum digital signatures over a metropolitan network. *Physical Review A*, 95(4):042338, 2017.

Webographie

[W1] , Sentiment Analysis: A Definitive Guide. https://monkeylearn.com/sentiment-analysis/, Last access : 29/03/2024.

[W2] , From Sentiment Analysis to Emotion Recognition: A NLP story https://medium.com/neuronio/from-sentiment-analysis-to-emotion-recognition-a-nlp-sto Last access : 29/03/2024.

[W3] , https://www.statista.com/statistics/278414/number-of-worldwide-social-netwo Last access : 02/04/2024.

[W4] , https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sale Last access : 02/04/2024.

[W5] , https://www.javatpoint.com/artificial-neural-network, Last access : 06/05/2024.

[W6] , https://jokerpt.medium.com/binary-image-classifier-cnn-using-tensorflow-a3f Last access : 06/05/2024.

[W7] , https://jupyter.org/, Last access : 29/05/2024.

[W8] , https://www.python.org/doc/essays/blurb/, Last access : 29/05/2024.

[W9] , https://www.researchgate.net/publication/336113323_Building_Machine_Learning_and_Deep_Learning_Models_on_Google_Cloud_Platform_A_Comprehensive_Guide_for_Beginners, Last access : 29/05/2024.

[W10] , https://www.w3schools.com/python/pandas/default.asp, Last access : 29/05/2024.

[W11] , https://www.nltk.org/, Last access : 29/05/2024.

[W12] , https://docs.python.org/3/library/csv.html, Last access : 29/05/2024.

[W13] , https://keras.io/, Last access : 29/05/2024.

[W14] , https://www.tensorflow.org/, Last access : 29/05/2024.

[W15] , https://www.w3schools.com/python/numpy/numpy_intro.asp#:~:text=NumPy%20is%20a%20Python%20library,NumPy%20stands%20for%20Numerical%20Python., Last access : 29/05/2024.

[W16] , https://matplotlib.org/, Last access : 29/05/2024.

[W17] , https://www.talabat.com/about, Last access : 09/06/2024.

Start-up Annex

Project Presentation

The project idea (proposed solution)

- The business area of the project is the service field, and the focus is on e-commerce-related sites.
- The genesis of the idea for the project stems from realizing the difficulties that are encountered by the owners of companies in deciphering the observations and sentiments of customers regarding their products, especially in Arabic reviews.
- This is done by designing a web service that would fit into the context of e-commerce.
- Users enter different customer opinions, and our service determines the tone of the entered text and offers a statistical summary of the analysis.
- It will start with a pilot run on specific electronic commerce sites as a way of developing the service.

The proposed values

- A customer engagement is increased by harnessing an ability to analyse emotions and preferences in real time.
- This emphasizes Arab customer feedback data monitoring and analysis for better marketing and customer services targeting techniques.
- The propositions for the Arabic sentiment data include getting the optimal business outcomes with the support of broad-spectrum Arabic sentiment data for enhancing the performance and satisfaction of clients.
- Integrated and plug-and-play mechanism enable e-commerce platforms harness Arabic sentiment in an effortless manner.

Work team

Laraissia Lina Yassamine: has skills in Web services and artificial intelligence and sentiment analysis.

Farou Brahim: has skills in the field of IT and project management.

- Laraissia Lina Yassamine's role is responsible for the development of the web service, building the conception, and implementing the testing interface for users.
- Farou Brahim's role: Lead the project.

The project's objectives

Short term: Start the sentiment analysis service as well as gain a fan base in Algerian markets of e-commerce platforms.

Medium term: Introduce the service that will help Algerian e-shopping websites gain a thorough understanding and analysis of the customer's attitude towards the services or products offered.

Long term: Master a dominant market share the sentiment analysis services for Arabic language spread across ecommerce sites and in view of this, seek to have great sales adoption in the next five years.

Project completion schedule

Phase	**1m**	**2m**	**3m**	**4m**	**5m**	**6m**
Preliminary studies: Analysis of the local market, Choice of business model	*	*				
Service development			*	*	*	
Testing and launch	*					
Marketing and promotion						*

Table 1.3 – Project Completion Schedule

Innovative Aspects

- Launch of the first ever such platform in Arabic-speaking markets, and utilization of latest in machine learning and Artificial Intelligence to ensure exacting sentiment analysis while interacting in e-commerce mediums.

- Agents about the need to develop unique algorithms to deciphering the hard coding of Arabic expressions and distinctive dialects present in a customer complaint.
- Introducing additions of sentiment analysis tools that include real-time analysis to help businesses understand customer sentiments at the right time to inform their customer relation and marketing approaches.
- Combining the sentiment analysis results with actual social media feeds, formal customer reviews, etc. , so that the client gets a truly global snapshot of consumer sentiment.
- Development of interactive front-end and mobile apps that can enable easy incorporation of sentiment analysis solutions into mature e-commerce systems.
- Getting supplementary support plus localization elements for those who prefer to use the Arabic language or numerous dialects within this language.
- Attempts to empower small and medium enterprises (SMEs) with affordably fast and accurate sentiment analysis, placing them on equal footing with their well-funded competitors in the fiercely competitive e-commerce segment.
- Adoption of recommended systems from available analytical information on sentiment of customers with regard to shopping personalization.
- Enhancing the efficiency of analysis of customer reviews by utilizing more sophisticated tools for sentiment analysis, which would help to eliminate the time-consuming SPSS methodology.
- Helping firms to understand business related sentiments that can be useful to them in adjusting their processes of offering goods and services.
- Reducing the variability in the review analysis by eradicating the prospects of blunders organized by humans guaranteeing that business decisions are accurate.

Strategic Market Analysis

The Market Segment:

The potential market: Owners of Arabic e-commerce platforms seeking to understand customer sentiment.

The target market (Segment):

- Organizations that want to optimize customer satisfaction and loyalty by leveraging passions insights found by sentiment analysis.
- E-commerce solutions aimed at Arabs users. Organizations looking for statistical data on which to base decisions on marketing and communication strategies.

- Small business who requires online marketing and optimization for websites and social media platforms.
- Several departments in a given company seeking to designer products that have best shot in the market.

Measurement of Competition Intensity:

- Main gist competitors in the Arabic sentiment analysis market include Affectiva, Lexalytics, IBM Watson, and Google Cloud Natural Language Processing.
- Some strengths as follows: Competitors specialize in designing subtle sensible disposition analysis algorithms for Arabic, they spend lot of resources in Arabic language and culture research and development, integration with e-commerce sites and social networks, they have demonstrated they can offer accurate sensible disposition analysis for various Arabic dialects.
- The areas for improvement include lack of simplification of certain regional varieties of the Arabic language, spoken language, and slang as well as failure to capture rapidly evolving dialects of the language and the potential scalability issues with handling large volumes of real-time sentiment data in Arabic contexts.

Marketing Strategy:

- **Workforce Efficiency:** Utilizing sentiment analysis to reduce dependency on manual methods, thereby optimizing workforce allocation and enhancing service efficiency.
- **Promotional Campaigns:** Regular promotional offers and loyalty programs based on sentiment analysis data to attract and retain customers.

Production and organization plan

The Production Process

- Partnerships of e-commerce , e-commerce social media pages.
- Development of the service.
- Testing and deployment.
- Marketing launch.

Supply:

Companies, social media pages, etc.

Employees:

Our sentiment analysis services for e-Commerce platforms support the creation of approximately 50 career opportunities, including positions related to data analytics and customer service.

Special Discussion:

For us, key partnerships encompass collaborations with leading e-trade systems and social media systems. These partnerships are crucial because they provide get admission to to a wealth of patron comments and ideas. By operating carefully with those structures, we build collectively useful relationships that enhance consumer engagement and guide our efforts to provide accurate sentiment analysis for Arabic E-Commerce transactions.

Financial plan

Costs and Charges:

The identification of all the necessary costs and investments is essential when dealing with customers due to the broad range of fairly differentiated opinions that need to be categorized and processed. This refers to the basic costs, annual costs as well as fixed and other costs. Here are the main aspects to consider:

A) Initial Costs:

Infrastructure:

- Establishing or leasing or acquiring offices for development and administration.
- Security measures/Provisions as well as other aspects such as installing servers, computers, and network connections.
- Tech-support and monthly access fees to various cloud services for hosting and data storage.

Equipment:

- **Computers and Workstations:** Modular offices and IT workstations for coding, data processing, and other related tasks as well as administrative uses.
- **Servers and Cloud Services:** A stable, reliable, and scalable web application framework/platform for hosting the platform and store large datasets in cloud storage.
- **Networking Equipment:** The other important IT equipment for cost efficient networking include routers, switches amongst others for connectivity and communicating.

- **Software Tools:** Licenses for development tools and text mining libraries, data processing tools etc.
- **-Backup and Security Systems:** Hardware including those used to back up data, protecting it against cyber threats and to guarantee that the platform is secure.
- **Office Supplies:** Staple consumables like pens, notebooks, files and document organizers as well as office furniture including desks and chairs.

Technology:

- **Sentiment Analysis Algorithms:** The best algorithms and natural language processing tools used in the next generation of Arabic sentiment analysis machine learning models.
- **Data Management Systems:**Secure and manageable databases and data warehousing technologies, with necessary applications to contain the huge amount of customers' feedbacks and opinions.
- **Integration Tools:** Web APIs and integration tools to link the sentiment analysis platform with targeted e-commerce platforms and social networking profiles.
- **User Interfaces:** Update the web and mobile graphical user interface so that businesses can effortlessly scroll through the provided sentiment analyses.
- **Analytics and Reporting Tools:** Data processing of customer sentiment data to make available to the organization's decision makers in packages that includes analytics platforms and reporting dashboards.

B) Operational Costs:

Personnel:

- **Salaries of Employees:** These include; pay for teals regarding personnel in the development of the software, data scientist, project managers, staffs who are present to offer customers support, etc.
- **Continuing Training for Staff:** Focused training for employees to attend seminars or workshops to update the business with the development of sentiment analysis, natural language processing, and e-commerce trends.

Logistics:

- **Cloud Services and Hosting:** Ongoing expenses for cloud garage, server website hosting, and facts bandwidth.
- **Software Subscriptions:** Regular prices for keeping software licenses, sentiment analysis gear, and other vital packages.

- **Data Acquisition:** Costs related to obtaining and processing huge datasets for evaluation, inclusive of any costs for accessing outside data sources.

Marketing and Customer Service:

- **Marketing Campaigns:** mean all continuous expenditures acquiring digital marketing campaign, social media promotions, content creating, and any other advertising endeavor targeting the sentiment analysis service.
- **Customer Service Management:** refers to the expenses of handling customer support which sometimes requires responding to inquiries raised, processing complaints, and aiding in user satisfaction.

C) Other Costs:

- Liability insurance will deal with cases related to platform operations.
- Data insurance will guard against loss of data through analysis.
- Getting necessary licenses and permits for lawful operations.
- Adhering to laws on data privacy and online business.

D) Recurring Costs:

- Maintenance of equipment and vehicles.
- Renewal of licenses and permits.
- Updating and maintaining computer systems.

Methods and Sources of Obtaining Financing :

To finance this project, several methods and sources of financing can be explored:

A) Internal Financing:

- Use of the company's own funds.
- Reinvestment of profits.

B) External Financing:

Bank Loans:

- Long-term loans to cover large upfront costs.
- Lines of credit for operational costs.

Investors:

- We want to find investors who are ready to invest in new ideas meant for advancement of the Arabic Language e-Commerce platforms by use of sentiment analysis tools.
- The best thing to do is to engage in partnerships that are well thought out with these venture capitalists or owners whose niche is in technology as well as artificial intelligence.
- Introducing merchandising chances at making the sentiment analysis tool more widespread and large within digital market space.

Subsidies and Aid:

- Explore government subsidies and grants available for innovative technology companies, particularly those advancing Arabic language sentiment analysis in e-commerce.
- Participate in start-up incubators and accelerators focused on AI and data analytics to leverage mentorship, networking, and funding opportunities.

Crowdfunding: Use crowdfunding platforms to obtain funds from many small investors.

C) Obtaining Reimbursement:

A detailed payment schedule can help plan the repayment of borrowed or invested funds. This table must include:

Scheduling Repayments:

- **Payment Schedule:**
  - Details of amounts to be repaid and deadlines for each source of financing.
  - Applicable grace periods and interest rates.

- **Cash Flow:**
  - Cash flow forecasting to ensure that the company has sufficient liquidity to meet repayment deadlines.
  - Adjustment of expenses and income to avoid deficits.

Payment Table:

Date	Amount	Financing Type	Due Date	Remaining Balance
2024-07-01	1,000,000 DZD	Initial Investment	N/A	1,000,000 DZD
2024-08-15	500,000 DZD	Operational Costs	N/A	500,000 DZD
2024-09-30	750,000 DZD	Marketing Campaigns	N/A	1,250,000 DZD
2024-10-15	300,000 DZD	Software Licenses	N/A	950,000 DZD
2024-11-30	400,000 DZD	Staff Salaries	N/A	550,000 DZD

The table above is a simplified example. It is essential to keep this table up to date and to rigorously monitor sentiment analysis metrics to ensure accurate insights and to guarantee the effectiveness of the sentiment analysis model for e-commerce platforms. By following these steps, the management and enhancement of sentiment analysis for e-commerce interactions can be conducted efficiently, with precise performance evaluation and rigorous model validation.

Business Model Canvas

Key Partners

collaborations with language technology providers for algorithm enhancement, social media platforms for data access, market research firms for industry insights, digital marketing agencies for targeted campaigns, and industry associations for credibility and visibility. These partnerships can amplify the value proposition of your service and drive growth through expanded capabilities and market reach.

Key Activities

Key activities for your sentiment analysis business model include algorithm development, data acquisition and preprocessing, sentiment analysis, platform development, customer support, marketing and sales, and partnership management. These activities are essential for delivering a high-quality sentiment analysis service and driving success in the market.

Key Resources

Key resources for your sentiment analysis business model include advanced natural language processing algorithms, access to large volumes of textual data, a robust platform or software-as-a-service solution, skilled data scientists and developers, effective customer support systems, marketing and sales channels, and strategic partnerships with technology providers, social media platforms, and market research firms. These resources are essential for delivering a reliable sentiment analysis service and achieving business objectives.

Value Proportions

Our sentiment analysis service offers businesses the ability to gain valuable insights from textual data, enabling them to understand customer sentiments, improve products and services, manage brand reputation, and make informed decisions. With advanced natural language processing algorithms, customizable analytics, and seamless integration options, our platform provides actionable insights that drive growth and enhance customer satisfaction.

Customer Relationships

Our sentiment analysis service prioritizes strong customer relationships through personalized support, regular communication, and responsive assistance. We offer dedicated account managers, comprehensive onboarding, and ongoing training resources to ensure that customers receive the guidance and support they need to maximize the value of our platform. Additionally, we actively seek feedback and input from customers to continuously improve our service and tailor our offerings to their evolving needs.

Channels

Our sentiment analysis service reaches customers through multiple channels, including online platforms, social media, industry events, and strategic partnerships. We leverage digital marketing channels such as content marketing, email campaigns, and search engine optimization to generate leads and drive awareness. Additionally, we utilize direct sales efforts, referral programs, and partnerships with industry associations to expand our reach and acquire new customers.

Customer Segments

Our sentiment analysis service caters to a diverse range of customer segments, including businesses of all sizes and industries seeking to gain insights from textual data. Our flexible platform accommodates the needs of startups, small and medium-sized enterprises (SMEs), and large corporations alike, offering scalable solutions tailored to specific industry verticals such as retail, hospitality, finance, healthcare, and more. Whether analyzing customer feedback, monitoring brand reputation, or conducting market research, our service is ideal for any organization looking to leverage the power of sentiment analysis for strategic decision-making.

Cost Structure

Our cost structure for the sentiment analysis service is based on a subscription model with monthly payments, offering customers flexibility and affordability. Pricing tiers are determined by usage levels, with options for basic, standard, and premium plans tailored to the needs of businesses of all sizes. Costs cover access to the sentiment analysis platform, data processing and analysis, customer support, and platform maintenance. Additionally, customization options and add-on features are available for an additional fee, providing customers with flexibility to tailor their subscription according to their specific requirements.

Revenue Streams

Our revenue streams are primarily derived from subscription fees for access to our sentiment analysis platform, offering customers flexibility through monthly payments. Additional revenue sources include customization options, add-on features, and enterprise-level solutions, providing higher-value services and generating increased revenue per customer. Leveraging partnerships, referrals, and value-added services also contributes to maximizing revenue potential and ensuring sustainable growth.

Designed For:

Designed by:

Date:

Version: