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THESIS

Submitted in partial fulfillment of the requirements for a Master's degree

Exploring Features for Arabic Spam Detection

Field: Computer Science

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By

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Dedication

To my beloved **father**, whose unwavering support and sacrifices have made life so much easier for me. Your strength and love have been my foundation, and I am nothing without you. Your presence has been a constant source of motivation, and for that, I am eternally grateful.

To my dear **mother**, who has shaped me into the person I am today. Your nurturing care, wisdom, and endless love have guided me through every step of my journey. Your influence on my life is immeasurable, and I am forever thankful for your presence.

To my wonderful **sisters**, for always being there for me. Your support, laughter, and companionship have been my pillars of strength. Thank you for standing by my side through thick and thin, and for being a source of comfort and joy in my life.

This work is dedicated to you all, with love and gratitude.

الملخص

في السنوات الأخيرة، تم تكريس الكثير من الأبحاث لتطوير منهجيات لتحديد وإدارة مراجعات المنتجات المزيفة، خاصة باستخدام تقنيات التعلم الآلي التقليدية. ومع ذلك، فقد تحول تركيز الباحثين مؤخرًا نحو مناهج التعلم العميق لتطبيقات مرتبطة بالمراجعات المزيفة في مجموعات بيانات مراجعات المنتجات. لقد أثبت التعلم العميق أداءً متفوقًا في مجالات متنوعة، بما في ذلك كشف المراجعات المزيفة، مما يجعله مجالًا مقنعًا للتحقيق. ومع ظهور التعلم العميق كحدود جديدة في التعلم الآلي، فقد فتح آفاقًا جديدة لتحسين أنظمة كشف التزييف في منصات مراجعات المنتجات.

تقدم هذه الأطروحة تصميمًا وتنفيذًا لنظام كشف المراجعات المزيفة باستخدام معماريات التعلم العميق المبتكرة. الهدف من البحث هو تطوير حلول قوية وقابلة للتكيف قادرة على تحديد وتقليل مراجعات المنتجات المزيفة عبر المنصات عبر الإنترنت. تستكشف المنطقة المشكلة لكشف المراجعات المزيفة، وتُراجع الأعمال ذات الصلة في هذا المجال لتقديم فهم شامل لحالة الفن الحالية. يحقق نظام كشف المراجعات المزيفة القائم على التعلم العميق دقة ملحوظة، مما يُظهر فعالية المنهجيات المختارة وملاءمتها لمهام كشف المراجعات المزيفة في العالم الحقيقي في مجموعات بيانات مراجعات المنتجات. تساهم نتائج هذا البحث في تقدم مجال كشف المراجعات المزيفة وتقدم إمكانيات كبيرة لتطبيقات عملية في تحسين رضا المستخدمين والحفاظ على مصداقية المنصات عبر الإنترنت.

كلمات مفتاحية : معالجة اللغة الطبيعية، كشف الآراء العشوائية، التعلم العميق، التعلم الآلي، مراجعات المنتجات.

ABSTRACT

In recent years, significant research has been dedicated to the development of methodologies for identifying and managing spam product reviews, particularly utilizing traditional machine learning techniques. However, more recently, researchers have shifted their focus towards deep learning approaches for spam-related applications in product review datasets. Deep learning has exhibited superior performance across various domains, including spam review detection, making it a compelling area of inquiry. As deep learning has emerged as a new frontier in machine learning, it has unlocked new possibilities for enhancing spam detection systems in product review platforms.

This thesis presents the design and implementation of a spam review detection system using innovative deep learning architectures. The objective of the research is to develop robust and adaptable solutions capable of accurately identifying and mitigating spam product reviews across online platforms. The problematic area of spam review detection is explored, and related work in the field is reviewed to provide a comprehensive understanding of the current state of the art. The deep learning-based spam review detection system achieves remarkable accuracy, demonstrating the effectiveness of the chosen methodologies and their suitability for real-world spam detection tasks in product review datasets. The results of this research contribute to advancing the field of spam review detection and hold great potential for practical applications in enhancing user satisfaction and maintaining the credibility of online platforms hosting product reviews.

Keywords: Natural Language Processing, Spam detection, Deep Learning, Machine Learning, Product reviews

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General Introduction

Spam, in the context of online communication, refers to unsolicited or irrelevant messages, often sent in bulk, with the intention of advertising, phishing, or spreading malware. Spam can take various forms, including emails, text messages, comments on websites, and social media posts. It is a nuisance to users and can pose security risks to individuals and organizations.

Spam reviews are a subset of spam that specifically target online reviews and ratings of products, services, or businesses. These reviews are often fabricated or exaggerated to manipulate public perception and influence purchasing decisions. Spam reviews can artificially inflate or deflate ratings, mislead consumers, and undermine the credibility of review platforms.

Natural Language Processing (NLP) is a field of study that focuses on the interaction between computers and human language. It involves the development of algorithms and techniques that enable computers to understand, interpret, and generate human language in a meaningful way. NLP encompasses a wide range of tasks, including text classification, sentiment analysis, machine translation, and speech recognition.

Deep learning is a subfield of machine learning that involves the use of artificial neural networks with multiple layers (hence "deep") to learn from large amounts of data. Deep learning algorithms have demonstrated remarkable performance in various tasks, including image recognition, natural language processing, and speech recognition. They excel at automatically discovering intricate patterns and representations in data, without the need for manual feature engineering.

In the context of addressing the spam problem, researchers are leveraging NLP and deep learning techniques to develop more effective spam detection and filtering systems. By analyzing the content and linguistic features of messages, NLP algorithms can identify patterns indicative of spam. Deep learning models, with their ability to learn complex representations from raw data, can further enhance the accuracy of spam detection by automatically extracting relevant features from text, images, or other multimedia content.

In this thesis, we examined various methodologies for detecting spam by employing a real-world dataset. Our research delved into investigating innovative deep learning architectures customized for

spam detection. We also delved into the integration of linguistic nuances and contextual cues within machine learning frameworks. An essential aspect of our study involved rigorously assessing the efficacy of these methodologies using authentic datasets. Our overarching objective is to devise resilient and adaptable solutions capable of curtailing the proliferation of spam across online communication channels. By doing so, we aim to enhance user satisfaction and uphold the credibility of online platforms.

STATE OF ART

Presently, e-commerce platforms offer to users the opportunity to share reviews or feedback regarding their purchased products. User-generated content plays a big role in guiding potential buyers, offering insights into product experiences and opinions from fellow consumers. Moreover, manufacturers leverage online reviews to glean valuable insights for product enhancement. Opinions shared on social media platforms are becoming ever more integral for both individuals and organizations, influencing consumer choices, electoral decisions, marketing strategies, product designs, and beyond. While positive opinions often equate to financial gains and enhanced reputation for businesses and users alike, this trend unfortunately fosters a climate where individuals are tempted to manipulate the system by disseminating counterfeit opinions or critiques. These actions aim to either endorse or undermine specific products, services, organizations, individuals, or ideas, all while concealing their true motives or affiliations. However, as the user base grows, so does the volume of reviews, rendering it impractical for users or manufacturers to manually sift through every comment. Lengthy reviews further complicate the process, hindering users' ability to discern product attributes and manufacturers' capacity to identify areas for improvement. Therefore, sentiment analysis emerges as a critical tool, capable of automatically categorizing user sentiments as true or false. This process streamlines the extraction of actionable insights from a plethora of reviews, empowering users and manufacturers alike to make informed decisions based on collective opinions.

1. Sentiment analysis

1.1. Definition

Sentiment analysis, also known as opinion mining, is a sophisticated computational technique employed to analyze and decipher the sentiment conveyed within textual data, including reviews, comments, and social media posts. It involves the extraction of subjective information from text to determine whether the expressed opinion is positive, negative, or neutral. Sentiment analysis leverages advanced natural language processing (NLP) algorithms and machine learning models to automatically classify the sentiment of text data, enabling organizations to glean valuable insights into public opinion and consumer attitudes towards products, services, or topics [1].

This analytical approach has become increasingly essential in today's digital landscape, where vast amounts of user-generated content flood online platforms. By harnessing sentiment analysis, businesses can gain deeper insights into customer feedback, identify patterns in sentiment across different demographics or geographic regions, and pinpoint areas for improvement in their products or services. Moreover, sentiment analysis empowers organizations to tailor their marketing strategies and messaging to align with prevailing consumer sentiment, thereby enhancing customer satisfaction and driving brand loyalty [1].

In addition to its commercial applications, sentiment analysis is widely utilized in social media monitoring and reputation management. By tracking public sentiment towards brands, events, or public figures on social media platforms, organizations can promptly identify emerging trends, address customer concerns, and manage potential crises effectively. This proactive approach to sentiment analysis enables businesses to maintain a positive brand image and swiftly respond to evolving consumer perceptions [2]. Overall, sentiment analysis serves as a powerful tool for organizations across various industries to make data-driven decisions, improve customer engagement, and adapt their strategies to meet the ever-changing demands of the digital marketplace.

1.2. The tasks of sentiment analysis

The tasks of sentiment analysis encompass a broad array of computational processes aimed at understanding and categorizing sentiment expressed in textual data, playing a pivotal role in various applications across digital platforms [1]. In addition to sentiment classification and aspect-based sentiment analysis, sentiment analysis tasks also include opinion mining, sentiment summarization, and aspect extraction [2]. Moreover, sentiment analysis techniques are applied in other domains, such as brand monitoring, market research, and customer feedback analysis [3]. By analyzing sentiment expressed in online reviews, social media posts, and customer surveys, organizations can gain valuable insights into consumer attitudes, preferences, and trends, enabling them to make informed business decisions and enhance their products or services [4].

However, one of the critical applications within sentiment analysis is spam detection, where the focus shifts from discerning sentiment to identifying and filtering out unsolicited or irrelevant messages, such as spam emails, comments, or text messages [5]. Spam detection systems leverage techniques from sentiment analysis to automatically classify incoming messages as legitimate or spam based on their content, structure, and context [6]. By employing machine learning algorithms and natural language processing techniques, these systems can effectively differentiate between genuine user-generated content and spam, thereby enhancing the user experience and maintaining the integrity of online platforms [7].

In today's digital landscape, where the volume of user-generated content continues to surge, the importance of robust spam detection systems cannot be overstated. These systems not only protect users from unwanted content but also contribute to fostering a safer and more trustworthy online environment [8].A taxonomy of the most popular sentiment analysis tasks is presented in Figure 1.

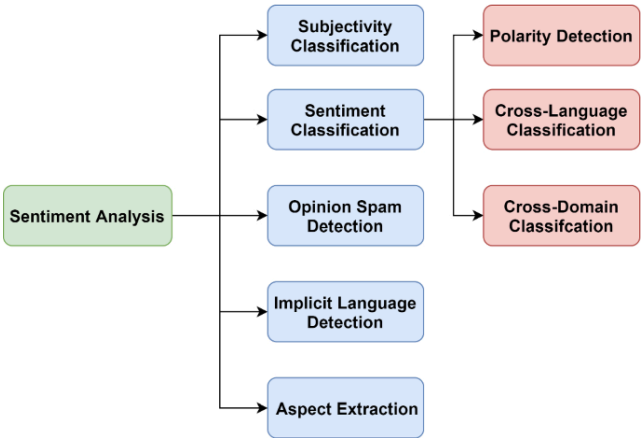

Figure 1 : The tasks of sentiment analysis

2. Spam / deceptive opinions

2.1 Definition

Termed as "opinion spammers," these individuals engage in activities known as opinion spamming [5]. Opinion spamming involves the deliberate dissemination of fake or misleading opinions with the intent to manipulate online discussions and sway public perception. This phenomenon extends beyond mere commercial interests; in social and political spheres, opinion spamming can distort perceptions and influence public opinion in ways that may contravene legal or ethical standards.

As social media continues to play an increasingly prominent role in shaping public discourse and decision-making processes, the prevalence and sophistication of opinion spamming present significant challenges for detection and mitigation efforts. Opinion spammers often exploit the anonymity and reach of online platforms to operate covertly and at scale. They employ various tactics, such as creating fake accounts, generating automated messages, or orchestrating coordinated campaigns, to amplify their influence and disseminate deceptive content.

However, despite the challenges posed by opinion spamming, detecting and mitigating such activities remain essential to uphold the integrity and credibility of social media platforms as reliable sources of information and avenues for meaningful discourse. Robust detection algorithms and proactive measures are necessary to identify and remove spam content promptly. Moreover, fostering user awareness and promoting digital literacy initiatives can empower users to recognize and counteract opinion spam effectively [5].

2.2 Types of deceptive opinions

Jindal and Liu were instrumental in laying the groundwork for understanding and addressing the pervasive issue of opinion spam within online reviews [5]. Their seminal work identified and categorized three distinct types of opinion spam, shedding light on deceptive practices that undermine the authenticity and reliability of online discourse:

Type 1 Untruthful Opinions:

This category encompasses reviews that deliberately mislead readers by providing unwarranted positive evaluations to target objects, with the intention of promoting them, or by maliciously offering negative reviews to tarnish the reputation of objects. These deceptive tactics aim to manipulate consumer perceptions and influence purchasing decisions, ultimately serving the interests of the spammers rather than providing genuine feedback to consumers.

Type 2 Reviews on Brands Only:

Unlike reviews that focus on specific products, this type of opinion spam targets brands, manufacturers, or sellers without offering substantive commentary on the products themselves. By bypassing product-specific details and focusing solely on brand-related aspects, these reviews fail to provide meaningful insights to consumers and are thus deemed as spam. Such practices detract from the authenticity of online reviews and erode consumer trust in the reliability of the information presented.

Type 3 Non-Reviews:

Non-reviews encompass two main subtypes: advertisements and irrelevant reviews devoid of opinions. Advertisements masquerading as reviews seek to promote products or services under the guise of genuine user feedback, while irrelevant reviews lack substantive opinions or commentary altogether. Both types contribute little to genuine discourse and serve to clutter online platforms with noise, making it challenging for users to discern valuable insights from spammy content.

Of these types, the second and third are categorized as deceptive opinion spam [5]. While these types may be relatively easy for human users to identify, the first type, deceptive opinion spam, poses a more significant challenge. Its deceptive nature makes it inherently difficult to detect, requiring sophisticated algorithms and techniques to differentiate between genuine and spammy content effectively. As online platforms continue to evolve and the volume of user-generated content proliferates, the need to combat deceptive opinion spam becomes increasingly imperative. By developing robust detection mechanisms and fostering user awareness, stakeholders can work together to mitigate the impact of opinion spam and uphold the integrity of online discourse, ensuring that users can trust the information they encounter and make informed decisions.

3. Detecting systems

3.1. Definition

A detecting system is a sophisticated arrangement or infrastructure devised to identify, recognize, or detect particular objects, signals, patterns, or phenomena within a given environment. It encompasses a diverse range of applications across numerous domains, including security, surveillance, medical diagnostics, environmental monitoring, and scientific research. At its core, a detecting system typically comprises an amalgamation of hardware and software components meticulously orchestrated to collect, process, and interpret data from the surrounding milieu. These components may include sensors, actuators, data acquisition modules, processing units, and decision-making algorithms [7].

Sensors serve as the frontline operatives of the detecting system, capturing raw data from the environment in various forms, such as electromagnetic signals, acoustic vibrations, chemical compositions, or physical parameters [4]. These sensors may range from simple devices like motion detectors or temperature sensors to more complex instruments such as radar systems or spectrometers, depending on the nature of the target being detected.

Once the data is acquired, it undergoes a series of processing stages where it is filtered, analyzed, and transformed into meaningful information. This process often involves the application of sophisticated algorithms and computational techniques tailored to the specific task at hand [4]. For instance, in the realm of security surveillance, image processing algorithms may be employed to detect and track the movement of individuals or objects within a video feed, while in medical diagnostics, machine learning models may be utilized to analyze medical imaging data for signs of abnormalities. The effectiveness and accuracy of a detecting system depend not only on the quality of its hardware and software components but also on the robustness of its underlying algorithms and the expertise of its designers [3]. Continuous refinement and optimization are essential to ensure that the system can adapt to evolving conditions and maintain reliable performance over time.

3.2 Spam detection systems

Spam detection systems are sophisticated mechanisms crucial for maintaining the integrity of communication channels in the digital realm. They serve as guardians against the influx of unwanted and potentially harmful messages, including spam emails, text messages, and comments, which can inundate users and undermine the usability of online platforms. These systems employ a multifaceted approach, combining various techniques and algorithms to effectively identify and filter out spam content. One of the primary techniques utilized by spam detection systems is content filtering, where the system analyzes the textual content of messages to detect patterns, keywords, or characteristics commonly associated with spam. Natural language processing (NLP) algorithms play a vital role in this process, enabling the system to parse and understand the semantics of messages, thereby distinguishing between legitimate and spammy content [4].

Behavioral analysis is another key component of spam detection systems, wherein the system monitors user behavior and interaction patterns to identify anomalies indicative of spam activity. By tracking metrics such as click-through rates, response times, and user engagement, the system can discern suspicious behaviors and flag potentially spam messages [3]. Machine learning techniques also play a significant role in spam detection, with algorithms trained on labeled datasets to recognize patterns and features characteristic of spam. These machine learning models can automatically classify incoming messages based on their content, structure, and context, thus enabling the system to adapt and evolve over time [7].

Additionally, spam detection systems often employ strategies such as blacklisting and whitelisting to filter incoming messages. Blacklists contain known spam email addresses, domains, or IP addresses, while whitelists include trusted contacts or domains. By comparing incoming messages against these lists, the system can quickly identify and block spam content [4]. By integrating these techniques and algorithms, spam detection systems can effectively mitigate the impact of spam across various communication channels, thereby enhancing user experience and maintaining the credibility of online platforms.

4. The Arabic language

4.1 Arabic

Arabic, a Semitic language with a rich history spanning millennia, holds a prominent place as one of the world's major languages, spoken by millions across the Middle East, North Africa, and beyond. Its linguistic characteristics are shaped by its unique script, grammar, and cultural significance [9]. One defining feature of Arabic is its script, which is written from right to left and comprises a beautifully intricate system of connected letters. The Arabic script, known as the Arabic alphabet, consists of 28 letters, with additional diacritical marks to indicate vowel sounds and nuances in pronunciation. This script lends itself to elaborate calligraphy, which is revered as both an art form and a means of preserving cultural heritage.

Furthermore, Arabic boasts a complex and nuanced grammatical structure, characterized by a system of roots and patterns that underlie word formation. This system allows for the derivation of countless words from a relatively small set of root letters, contributing to the language's expressive richness and versatility. Additionally, Arabic grammar encompasses intricate rules governing syntax, morphology, and verb conjugation, lending depth and precision to communication.

Arabic is also known for its vast vocabulary, which reflects the language's historical and cultural heritage. With roots extending back to ancient civilizations, Arabic has absorbed influences from diverse linguistic traditions, resulting in a lexicon that encompasses a wide range of topics, from poetry and philosophy to science and religion [10].

Arabic's influence extends beyond traditional communication channels to the digital realm, where its presence is rapidly expanding. As evidenced by the figure "The fastest growing Internet language by the

number of users," Arabic stands out as one of the fastest-growing languages on the internet, with a significant increase in the number of users [11]. This surge in Arabic usage reflects the growing importance of the language in online spaces, driven by various factors such as increased internet penetration in Arabic-speaking regions, the proliferation of Arabic content online, and the rising demand for Arabic language services and platforms.

The internet serves as a dynamic platform for Arabic speakers to engage in diverse forms of communication, including social media, blogs, forums, and e-commerce platforms [11]. This digital landscape not only facilitates communication and collaboration but also fosters the dissemination of Arabic language and culture on a global scale. Furthermore, the accessibility of online resources in Arabic enhances linguistic empowerment and promotes digital inclusion among Arabic-speaking communities worldwide.

As the Arabic language continues to gain prominence on the internet, there is a growing need for digital content and services tailored to Arabic users [11]. This includes the development of Arabic language tools, applications, and websites that cater to the linguistic and cultural preferences of Arabic-speaking audiences. Additionally, the demand for Arabic language content creators, translators, and digital marketers is on the rise, reflecting the expanding opportunities in the digital economy.

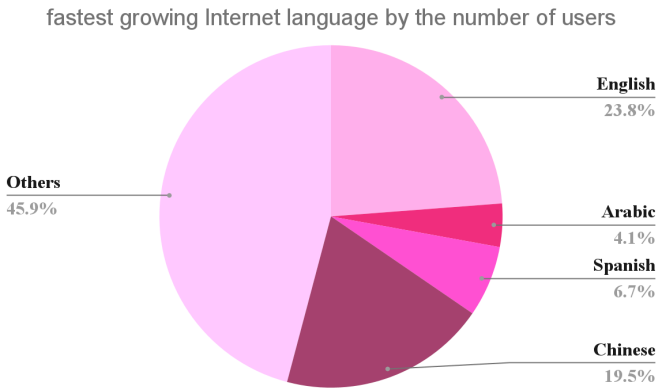

Figure 2: fastest growing internet language by the number of users [11]

5. Related works

Recent advancements in the field of natural language processing have significantly improved spam detection capabilities, particularly through the application of deep learning techniques. The Arabic language, with its complex morphology and diverse dialects, presents unique challenges for spam detection. In response to these challenges, a growing body of research has emerged, focusing on developing and refining deep learning models to effectively identify and filter out spam content in Arabic text. This comparative analysis highlights recent studies that have explored various methodologies and datasets to enhance the accuracy and efficiency of Arabic spam detection using deep learning. These works collectively contribute to a deeper understanding of the field and pave the way for more robust solutions to tackle spam in Arabic digital communications.

This table provides a summary of the 10 most recent research papers on Arabic spam detection using deep learning. It includes details such as the title, year of publication, the corpus used, and the methods applied. These studies collectively highlight the advancements and diverse approaches taken to address the challenges of spam detection in the Arabic language.

Research title	Year	Corpus used	Method employed	The results
Deep Learning-Based Arabic Text Classification for Spam Detection [12]	2017	Arabic text dataset containing spam and non-spam messages.	Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs).	Achieved competitive performance in detecting spam in Arabic-language content.
Enhancing Arabic Text Classification for Spam Detection using Bidirectional Long Short-Term Memory Networks [13]	2018	Dataset of Arabic text labeled as spam or non-spam.	Bidirectional Long Short-Term Memory (BiLSTM) networks.	Notable improvements in spam detection accuracy compared to traditional machine learning approaches.
Spam Detection in Arabic Social Media Using Convolutional	2018	Arabic social media posts annotated as spam or legitimate.	Convolutional Neural Networks (CNNs)	Demonstrated the potential of CNNs in effectively identifying spam in Arabic-language social

Neural Networks [14]				media content.
Deep Learning-Based Approaches for Spam Detection in Arabic Reviews [15]	2019	Arabic user reviews dataset with labels indicating spam or legitimate reviews.	Word embeddings, Recurrent Neural Networks (RNNs), Attention mechanisms.	Promising results in accurately identifying spam reviews in Arabic.
Character-Level Convolutional Neural Networks for Arabic Spam Detection [16]	2019	Dataset of Arabic text containing spam and legitimate content.	Character-level Convolutional Neural Network (CNN).	Robust performance in distinguishing between spam and legitimate Arabic text.
Arabic Twitter Spam Detection using Deep Learning Techniques [17]	2020	Arabic tweets labeled as spam or legitimate.	Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks.	Investigation of different neural network architectures for effective spam detection in Arabic tweets.
A Hybrid Approach for Arabic Spam Detection Using Deep Learning and Lexical Analysis [18]	2020	Diverse dataset of Arabic spam messages.	Hybrid approach combining deep learning methods with lexical analysis techniques.	Evaluation of the hybrid model's performance on Arabic spam detection, highlighting the strengths of deep learning and lexical analysis.
Arabic Email Spam Detection using Deep Learning and Semantic Analysis [19]	2021	Arabic email dataset labeled as spam or non-spam.	Deep learning-based approach combined with semantic analysis.	Exploration of semantic embeddings and neural network architectures for effective spam detection in Arabic emails.
Improving Arabic Spam Detection with Ensemble Deep Learning Models [20]	2021	Dataset of Arabic text messages containing spam and non-spam content.	Ensemble deep learning models combining different architectures.	Investigation of ensemble techniques to enhance spam detection accuracy in Arabic text.

Adversarial Learning for Robust Arabic Spam Detection [21]	2022	Arabic text dataset for spam detection.	Adversarial learning techniques for enhancing model robustness.	Examination of methods to improve deep learning model resilience to adversarial attacks in Arabic spam detection.

Table 1: summary of the most recent research papers on Arabic spam detection using deep learning

The table 1 summarizing recent research on Arabic spam detection using deep learning reveals significant advancements in the field. The studies span from 2017 to 2022, showcasing a variety of methodologies and datasets employed to tackle the unique challenges posed by the Arabic language. Key observations from the table include:

Diverse Approaches: The research papers employ a range of deep learning techniques, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Bidirectional LSTM (BiLSTM), character-level CNNs, and hybrid approaches combining deep learning with lexical or semantic analysis. This diversity highlights the experimental nature of the field, with researchers exploring various models to identify the most effective methods for Arabic spam detection.

Different Corpora: The studies utilize various corpora, from social media posts and user reviews to email messages and general Arabic text datasets. This variety indicates an effort to cover multiple facets of spam detection, addressing different sources and types of spam.

Improvement Over Time: There is a noticeable progression in the complexity and sophistication of the methods used. Earlier studies focused on basic neural network architectures, while more recent research incorporates advanced techniques such as ensemble models and adversarial learning. This evolution reflects the ongoing refinement and enhancement of spam detection capabilities.

Focus on Real-World Applications: Many studies emphasize the practical application of their findings, aiming to improve spam detection in real-world scenarios such as social media, email communication, and online reviews. This focus ensures that the research remains relevant and applicable to actual user experiences.

5.1 Advantages and Disadvantages of Spam Detection Systems for the Arabic Language

A. Advantages

Improved Accuracy with Deep Learning: Deep learning techniques, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown substantial improvements in the accuracy of spam detection in Arabic. These models can capture complex patterns and nuances in the Arabic text, leading to more effective identification of spam content.

Adaptability to Diverse Dialects: Advanced models can be trained on various Arabic dialects, enhancing their ability to understand and process the wide range of linguistic variations present in Arabic. This adaptability is crucial given the rich diversity in spoken Arabic across different regions.

Scalability and Efficiency: Deep learning models, once trained, can process large volumes of data quickly and efficiently. This scalability is essential for managing the vast amount of user-generated content on social media platforms and other online forums where Arabic is used extensively .

Automation and Reduced Human Intervention: Automated spam detection systems reduce the need for manual review, saving time and resources. They provide a consistent approach to filtering out spam, which is particularly beneficial for platforms with massive user bases and high content turnover .

Enhanced User Experience: By effectively filtering out spam, these systems enhance the overall user experience on online platforms. Users can trust the content they encounter, making these platforms more reliable and user-friendly .

B. Disadvantages

Complexity of Arabic Script: The Arabic script's complexity, including its right-to-left writing direction, connected letter forms, and extensive use of diacritical marks, poses significant challenges for text processing and model training. This complexity can lead to higher error rates in spam detection systems .

Dialects and Colloquial Variations: The presence of numerous Arabic dialects and colloquial variations makes it difficult to create a one-size-fits-all model. Each dialect has unique phonetic, morphological, and syntactic properties that must be accounted for, complicating the development of comprehensive spam detection systems .

Data Scarcity for Certain Dialects: While Modern Standard Arabic (MSA) is well-documented, there is often a scarcity of annotated datasets for many regional dialects. This lack of data can hinder the effectiveness of spam detection models, which rely on large amounts of labeled data for training .

High Computational Resources Required: Training and deploying deep learning models require significant computational power and resources. This can be a limitation for smaller organizations or researchers with limited access to high-performance computing facilities .

Evolving Nature of Spam: Spammers continually evolve their tactics to bypass detection systems. This constant evolution requires regular updates and retraining of models to keep up with new spam patterns, which can be resource-intensive and challenging to maintain .

6. Conclusion

The comprehensive review of the aforementioned research papers underscores the remarkable progress achieved in the development of spam detection systems tailored for the Arabic language. While acknowledging the substantial advancements made this far, it is apparent that there exists a wealth of opportunities for further exploration and refinement in this domain.

In my forthcoming experiments, I will leverage the insights gleaned from these studies as a foundational framework. Employing a diverse array of models, I will meticulously compare and contrast their effectiveness in detecting Arabic spam.

CHAPTER 02 : Conceptual study

1. Introduction

The preceding chapter provided a comprehensive overview of spam detection systems, focusing on their application in the context of the Arabic language. We explored various methodologies and technologies employed in the development of these systems, highlighting the significant progress made in this field. Specifically, we examined how deep learning and neural networks serve as the foundational technologies driving these advancements. This chapter aims to present the models and algorithms we will be using during our experiments for the Arabic spam detection systems. We will begin by discussing the different deep learning models and algorithms employed, outlining their roles in the detection process.

2. The Spam Detection Process

2.2 System

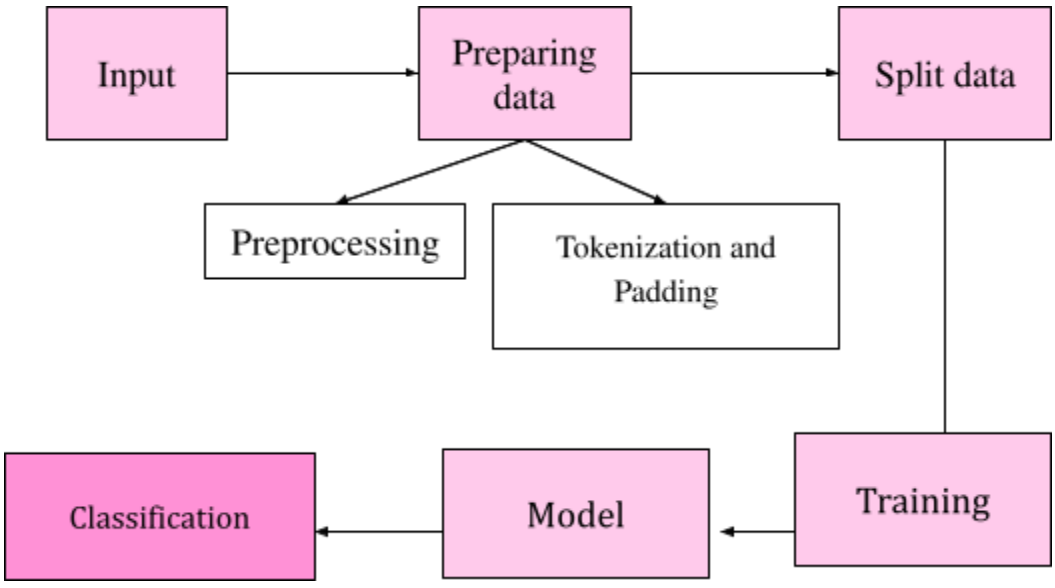

Figure 3: System architecture

2.3 Data preparation

The authors of [5] proposed a method for generating fake and deceptive positive opinions using Amazon's popular crowdsourcing service, Mechanical Turk. Subsequently, [5] employed Amazon's Mechanical Turk service to create another publicly available database of hotel reviews.

Given the absence of a suitable Arabic language database for our experiments, which would offer complete and well-structured comments, we analyzed the data from Ott et al.'s English databases. We observed that they had generated a substantial number of structured opinions, both truthful and deceptive. This observation motivated us to translate these opinions into Arabic to construct a database for our experiments. This approach was used to compensate for the lack of Arabic resources and to utilize meaningful, structured texts.

The challenges specific to Arabic data collection include the diversity of Arabic dialects, the complexity of Arabic script, and the scarcity of annotated datasets. The Arabic language, with its various dialects and formal Modern Standard Arabic (MSA), presents a unique challenge as colloquial expressions and regional variations must be accurately captured and translated. Additionally, the rich morphology and complex syntax of Arabic make it difficult to ensure consistency and accuracy in translations. These challenges highlight the necessity for developing comprehensive Arabic datasets that reflect the linguistic diversity and intricacies of the language, which is crucial for advancing research in Arabic NLP and spam detection.

	Arabic comments	English comments
Spam	إذا كنت تبحث عن فندق أنيق في وسط مدينة شيكاغو، عليك البقاء هنا. يحتوي فندق أمباسادور إيست على غرف كبيرة ومريحة وجميلة جدا، مثل منزل بعيدا عن المنزل. المكان المثالي لرجل الأعمال، وإذا كان لديك حيوان أليف صغير يمكنك إحضارهم أيضا! وأود أن تعطي هذا المكان أربعة نجوم، وسوف تبقى بالتأكيد هنا مرة أخرى.	If you're looking for a stylish hotel in downtown Chicago, you should stay here. Ambassador East Hotel has large, comfortable and very beautiful rooms, like a home away from home. The perfect place for a businessman, and if you have a small pet you can bring them too! I would give this place four stars and would definitely stay here again.
Truth	هذا الفندق كان موقع رائع، ولكن يمكنك أن تفعل أفضل بكثير للحصول على المال. وكانت ممرات الدخان، والمصاعد القذرة، والأثاث في اللوبي موضوع عارية. الموظفين كانت مفيدة جدا. كانت الغرفة كبيرة، سرير مريح ولكن كانت الغرفة حتى عسلي والدخان القديم لينغريد. إذا كان لديك أي حساسية لا تبقى هنا!	This hotel had a great location, but you can do much better for the money. The smoky hallways, dirty elevators, and furniture in the lobby were bare. The staff were very helpful. The room was large, comfortable bed but the room was so hazel and old smoke lingered. If you have any allergies do not stay here!

Table 2: Examples of arabic and english comments.

2.4 Models

2.4.1 Deep Neural Network model

A Deep Neural Network (DNN) is a type of artificial neural network (ANN) that consists of multiple layers of nodes (neurons) between the input and output layers. Each layer in a DNN comprises numerous neurons, and the neurons in each layer are connected to neurons in the subsequent layer through weighted edges. These

weights are adjusted during the training process, allowing the network to learn from data by minimizing the error between predicted and actual outputs. DNNs are capable of modeling complex patterns and representations in data, making them highly effective for tasks such as image and speech recognition, natural language processing, and more.

Key Components:

1. **Input Layer**: Receives the raw data input.
2. **Hidden Layers**: Intermediate layers that process inputs from the previous layer and pass the transformed data to the next layer. These layers enable the network to learn hierarchical features.
3. **Output Layer**: Produces the final output of the network, typically involving an activation function suited to the specific task (e.g., softmax for classification tasks).

Training Process:

1. **Forward Pass**: Data is propagated through the network, layer by layer, to generate an output.
2. **Loss Calculation**: The difference between the predicted output and the actual target is computed using a loss function.
3. **Backward Pass**: The gradients of the loss function with respect to each weight are calculated using backpropagation.
4. **Weight Update**: Optimization algorithms (e.g., Adam) update the weights to minimize the loss.

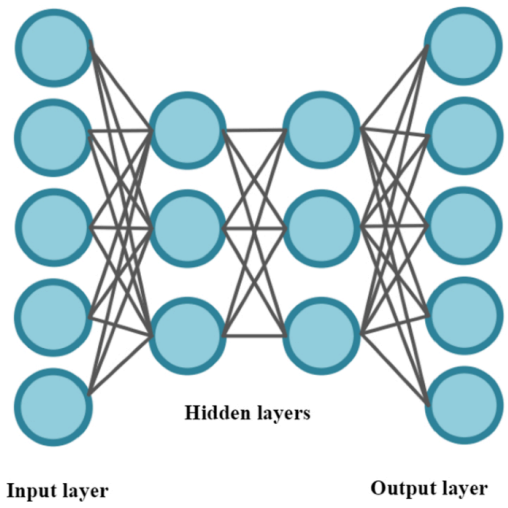

Figure 4 : DNN model

2.4.2 Recurrent Neural Network (RNN) model

A Recurrent Neural Network (RNN) is a type of artificial neural network designed for processing sequences of data by maintaining a 'memory' of previous inputs through internal states. Unlike traditional feedforward neural networks, RNNs have connections that form directed cycles, enabling them to exhibit temporal dynamic behavior. This capability makes RNNs particularly well-suited for tasks where the order of the inputs is crucial, such as time series prediction, natural language processing, and speech recognition.

Key Components:

1. **Input Layer**: Receives the sequence data.
2. **Hidden Layers (Recurrent Layers)**: Each layer contains neurons that have connections feeding back into themselves, allowing the network to maintain information from previous steps. The hidden state hth_tht at time step ttt is computed based on the input xtx_txt and the previous hidden state ht−1h_{t-1}ht−1.
3. **Output Layer**: Produces the final output at each time step, which can be used in various applications such as sequence classification, sequence generation, or sequence prediction.

Training Process:

1. **Forward Pass**: The input sequence is passed through the network, and at each time step, the current input and the previous hidden state are used to compute the current hidden state and output.
2. **Loss Calculation**: The difference between the predicted output and the actual target sequence is computed using a loss function appropriate for the task.
3. **Backward Pass (Backpropagation Through Time, BPTT)**: Gradients of the loss function with respect to each weight are calculated, considering the temporal dependencies of the sequence data.
4. **Weight Update**: Optimization algorithms (e.g., Adam, SGD) update the weights to minimize the loss over the entire sequence.

2.4.3 Long Short-Term Memory (Lstm) model

Long Short-Term Memory **(LSTM)** is a type of recurrent neural network **(RNN)** architecture designed to capture and process sequential data while addressing the vanishing gradient problem commonly encountered in traditional **RNN**s. **LSTM** networks consist of memory cells that can maintain information over extended time intervals, allowing them to effectively model and learn from sequences with long-range dependencies [24].

The **LSTM** architecture includes three main components: the input gate, the forget gate, and the output gate. These gates regulate the flow of information into and out of the memory cell, enabling the network to selectively update its state based on the input data and its current internal state. This mechanism enables

LSTMs to learn and retain relevant information over multiple time steps, making them well-suited for tasks involving sequential data processing, such as natural language processing, time series prediction, and speech recognition [24].

Key Components:

1. **Cell State (CtC_tCt)**: Acts as a memory that carries information across different time steps.
2. **Hidden State (hth_tht)**: Represents the output of the LSTM at a given time step, contributing to the next step's calculations.
3. **Gates**: Control the flow of information into and out of the cell state:
    - **Forget Gate**: Decides what information to discard from the cell state.
    - **Input Gate**: Determines which new information to add to the cell state.
    - **Output Gate**: Controls the output and what part of the cell state to pass to the next hidden state.

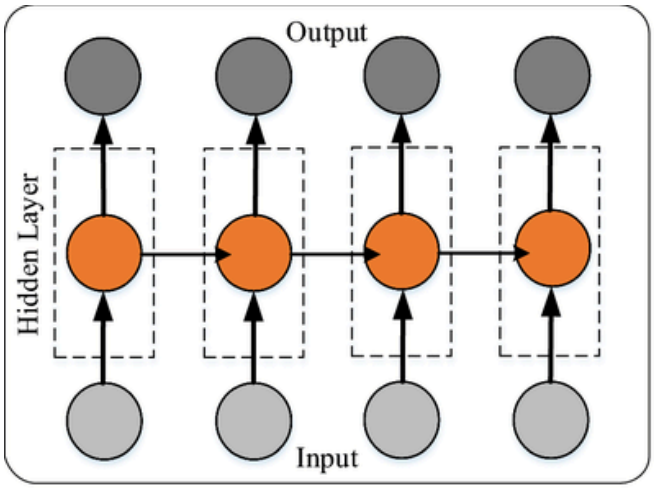

Figure 5 : LSTM architecture

2.4.4 Bidirectional Long Short Term Memory (Bi-LSTM) Model

Bidirectional Long Short-Term Memory (BI-LSTM) enhances the traditional LSTM architecture by processing input sequences in both forward and backward directions. This dual processing allows BI-LSTM to capture context from both past and future, which is crucial for many natural language processing (NLP) tasks. By combining the outputs from both directions, BI-LSTM provides a richer and more comprehensive representation of the input sequence [25].

The BI-LSTM architecture includes two LSTM layers: one that processes the sequence from the beginning to the end (forward direction) and another that processes it from the end to the beginning (backward direction). The outputs from these layers are concatenated, allowing the network to utilize information from both directions to understand the context better. This bidirectional approach helps in capturing long-range dependencies more effectively than a unidirectional LSTM, enhancing the model's performance in various applications [25][26].

Key Components:

1. **Forward LSTM**: Processes the input sequence from start to end.
2. **Backward LSTM**: Processes the input sequence from end to start.
3. **Concatenation Layer**: Combines the outputs from both forward and backward LSTMs, providing a richer representation.

Training Process:

1. **Forward and Backward Passes**: Process the input sequence in both directions.
2. **Concatenation and Loss Calculation**: Concatenate the hidden states and compute the loss based on the final concatenated outputs.
3. **BPTT and Weight Update**: Perform backpropagation through time for both forward and backward LSTMs and update weights using optimization algorithms.

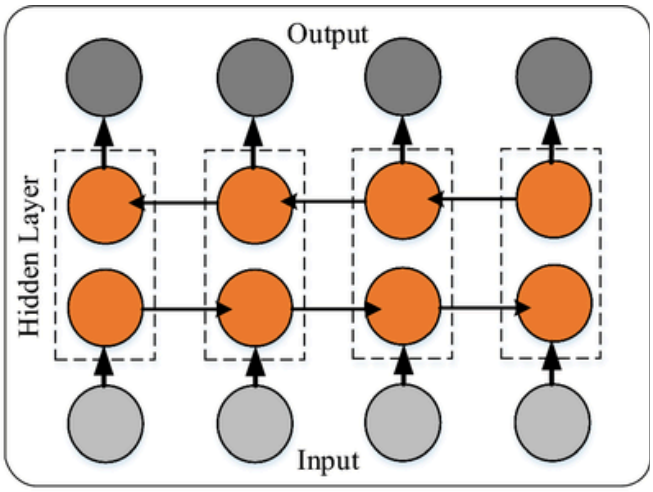

Figure 6 : Bi-LSTM Architecture

3. Conclusion

In my research, I trained several different **RNN** models to compare their performance in detecting Arabic spam using the same dataset. By employing a variety of models, I aimed to evaluate their effectiveness in accurately identifying deceptive content while maintaining consistency across the experimental setup.

CHAPTER 03: Implementation and Results and

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1. Software

Python

Python is a high-level, interpreted programming language that emphasizes code readability and simplicity. Created by Guido van Rossum and first released in 1991, Python's design philosophy focuses on code readability with its notable use of significant whitespace. Its syntax allows programmers to express concepts in fewer lines of code compared to languages such as C++ or Java. Python supports multiple programming paradigms, including procedural, object-oriented, and functional programming. It has a dynamic type system and automatic memory management, making it a versatile choice for a wide range of applications from web development to scientific computing, artificial intelligence, and data analysis. Python's extensive standard library, along with a vibrant ecosystem of third-party packages, enables developers to quickly implement complex functionalities. [27]

Google Colab

Google Colab, short for Colaboratory, is a free, cloud-based Jupyter notebook environment that allows users to write and execute Python code in a web browser. Colab provides free access to computing resources, including GPUs and TPUs, making it an excellent platform for machine learning, data analysis, and educational purposes. It supports the entire Python data science ecosystem, including libraries such as NumPy, pandas, TensorFlow, Keras, and PyTorch. Users can also save and share their work via Google Drive integration, enabling easy collaboration. Colab is particularly popular among researchers and practitioners in machine learning and deep learning due to its ease of use and powerful hardware support. [28]

2. Deep Learning Libraries

Keras

Keras is an open-source, high-level neural networks API developed by François Chollet. Written in Python, it is capable of running on top of TensorFlow, Microsoft Cognitive Toolkit, Theano, or PlaidML. Keras is designed to enable fast experimentation with deep neural networks, making it simple and efficient to build and train models. Its user-friendly, modular, and extensible architecture simplifies the process of developing complex neural network models. Keras provides a range of pre-built layers, activation functions, optimizers,

and loss functions, facilitating the rapid development and testing of machine learning models. It is widely used in industry and academia for tasks such as image recognition, natural language processing, and recommendation systems.[29]

TensorFlow

TensorFlow is an open-source machine learning framework developed by the Google Brain team. It is designed for large-scale machine learning and numerical computation, offering flexible and comprehensive tools for building, training, and deploying machine learning models. TensorFlow supports a range of tasks, from deep learning and traditional machine learning to production deployment and scalable computation. Its architecture allows deployment of computation across a variety of platforms, including CPUs, GPUs, and TPUs. TensorFlow's ecosystem includes TensorFlow.js for machine learning in JavaScript, TensorFlow Lite for mobile and embedded devices, and TensorFlow Extended (TFX) for end-to-end machine learning pipelines. TensorFlow's popularity and extensive community support make it a preferred choice for both researchers and practitioners. [30]

NLTK (Natural Language Toolkit)

NLTK, the Natural Language Toolkit, is a suite of libraries and programs for symbolic and statistical natural language processing (NLP) in Python. Developed by Steven Bird and Edward Loper, NLTK provides easy-to-use interfaces to over 50 corpora and lexical resources, along with a suite of text processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning. It also includes wrappers for industrial-strength NLP libraries. NLTK is widely used for research and teaching in computational linguistics and text analytics. Its comprehensive documentation and active community make it an invaluable resource for anyone working in NLP. [31]

Farasa

Farasa is a suite of Arabic language processing tools designed to address the unique challenges of Arabic text analysis. Developed by the Arabic Language Technologies (ALT) Group at the Qatar Computing Research Institute (QCRI), Farasa provides functionalities such as tokenization, part-of-speech tagging, named entity recognition, morphological analysis, and diacritization. These tools are essential for performing advanced NLP tasks on Arabic text, which is characterized by its rich morphology, complex script, and use of diacritics. Farasa is widely used in academic research and commercial applications to enhance the processing and understanding of Arabic language data.[32]

3. Adam Optimization Algorithm

Adam (short for Adaptive Moment Estimation) is an optimization algorithm used to update network weights iteratively based on training data. It combines the advantages of two other extensions of stochastic gradient descent: AdaGrad and RMSProp.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) \left[\frac{\delta L}{\delta w_t} \right]$$
$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) \left[\frac{\delta L}{\delta w_t} \right]^2$$

4. Activation Functions

ReLU (Rectified Linear Unit)

ReLU (Rectified Linear Unit) is an activation function commonly used in neural networks. It is defined as the positive part of its argument: f(x)=max(0,x)f(x)=max(0,x). ReLU introduces non-linearity to the model while maintaining computational efficiency. One of its main advantages is that it mitigates the vanishing gradient problem, which is a common issue with traditional activation functions like the sigmoid and tanh functions. By allowing only positive values to pass and setting all negative values to zero, ReLU accelerates the convergence of stochastic gradient descent and is therefore widely used in convolutional and feedforward neural networks.[33]

Sigmoid Activation

The Sigmoid activation function is an S-shaped curve that maps any real-valued number into the range (0, 1). It is defined by the formula σ(x)=11+e−xσ(x)=1+e−x1. The sigmoid function is used in neural networks to introduce non-linearity and is particularly useful for binary classification tasks, as it can output a probability value. However, it has some drawbacks, such as the vanishing gradient problem and the fact that it is computationally expensive due to the exponential function. Despite these limitations, the sigmoid function remains a fundamental component of logistic regression and some neural network architectures. [34]

5. Experiments

4.1 Models and results :

In this section, we will discuss and compare the results obtained from several models developed for our project. Each model is named according to its layer types. We will analyze each model individually, presenting

the results, including accuracy, loss, validation accuracy, and validation loss, and provide a detailed discussion of the findings. Finally, we will summarize the results in a table to provide a comprehensive overview of the performance of each model.

Accuracy: a measure of how many predictions the model got right (number of correct predictions)

Loss: a measure of the error of the model's predictions (usually measured as a difference between predicted and actual values)

Validation Accuracy: the accuracy of the model's predictions on a validation dataset (a subset of the dataset that was not used during training, used to evaluate the model's performance on unseen data)

Validation Loss: the loss of the model's predictions on the validation dataset / the number of epochs (complete passes through the dataset) that the model was trained for.

4.1.1 Experiment 1 : With DNN Model

Model architecture :

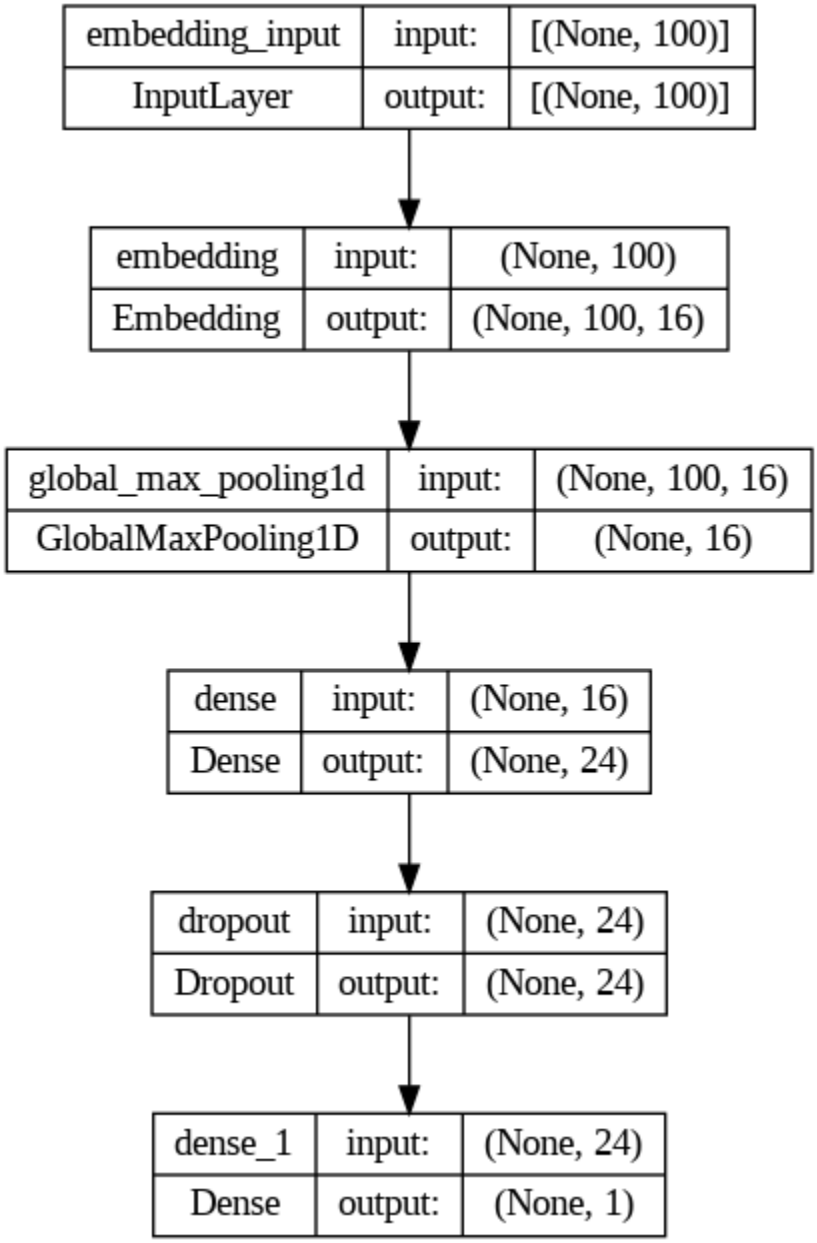

Figure 7 : DNN model architecture

```
Epoch 1/10
32/32 [==============================] - 1s 11ms/step - loss: 0.6924 - accuracy: 0.5127 - val_loss: 0.6902 - val_accuracy: 0.5312
Epoch 2/10
32/32 [==============================] - 0s 4ms/step - loss: 0.6857 - accuracy: 0.6465 - val_loss: 0.6852 - val_accuracy: 0.6055
Epoch 3/10
32/32 [==============================] - 0s 4ms/step - loss: 0.6756 - accuracy: 0.7441 - val_loss: 0.6753 - val_accuracy: 0.7695
Epoch 4/10
32/32 [==============================] - 0s 5ms/step - loss: 0.6564 - accuracy: 0.7852 - val_loss: 0.6607 - val_accuracy: 0.7188
Epoch 5/10
32/32 [==============================] - 0s 4ms/step - loss: 0.6265 - accuracy: 0.8320 - val_loss: 0.6387 - val_accuracy: 0.7695
Epoch 6/10
32/32 [==============================] - 0s 4ms/step - loss: 0.5856 - accuracy: 0.8340 - val_loss: 0.6078 - val_accuracy: 0.7539
Epoch 7/10
32/32 [==============================] - 0s 4ms/step - loss: 0.5265 - accuracy: 0.8506 - val_loss: 0.5722 - val_accuracy: 0.7617
Epoch 8/10
32/32 [==============================] - 0s 4ms/step - loss: 0.4667 - accuracy: 0.8750 - val_loss: 0.5436 - val_accuracy: 0.7656
Epoch 9/10
32/32 [==============================] - 0s 6ms/step - loss: 0.4048 - accuracy: 0.8896 - val_loss: 0.5242 - val_accuracy: 0.7656
Epoch 10/10
32/32 [==============================] - 0s 4ms/step - loss: 0.3584 - accuracy: 0.8926 - val_loss: 0.5111 - val_accuracy: 0.7656
```

Figure 8 : training & validation loss values for dnn model

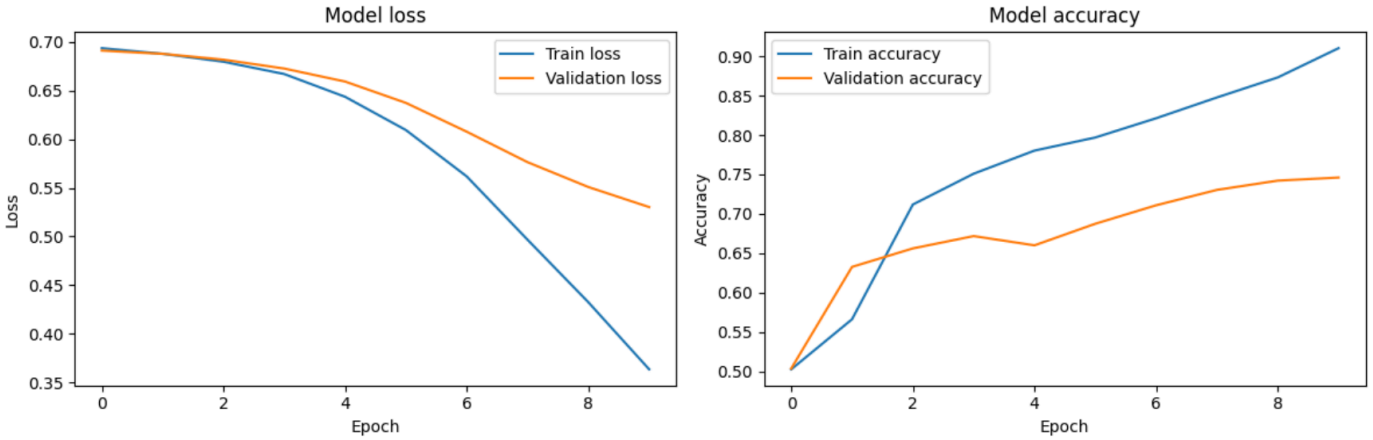

Figure 9 : charts of the dnn model loss and accuracy

- **Model Loss**

▪ *Training Loss*

- Starts at a higher value and consistently decreases with the number of epochs.

- This indicates that the model is effectively learning and reducing its error on the training dataset over time.

- *Validation Loss*

- Starts close to the training loss but decreases at a slower rate.

- While it shows a general downward trend, it does not decrease as sharply as the training loss and starts to plateau towards the end.

- This could suggest that while the model is learning, it might not generalize as well to unseen data, hinting at potential overfitting or the need for more training data or regularization.

- **Model Accuracy**
- *Training Accuracy*

- Shows a steady increase, indicating that the model is progressively getting better at correctly predicting the training data.

- The accuracy improves significantly over the epochs and continues to rise, reflecting the decreasing training loss.

- *Validation Accuracy*

- Initially increases, suggesting that the model is generalizing well to the validation set early on.

- However, it starts to plateau after a few epochs and does not increase as steeply as the training accuracy.

- This disparity between training and validation accuracy could again suggest overfitting, where the model performs well on the training data but not as well on the validation data.

Observations

The divergence between training and validation metrics (especially noticeable towards the end) suggests overfitting. The model is likely memorizing the training data rather than learning general patterns that apply to new, unseen data.

4.1.3 Experiment 2: LSTM Model

Model architecture :

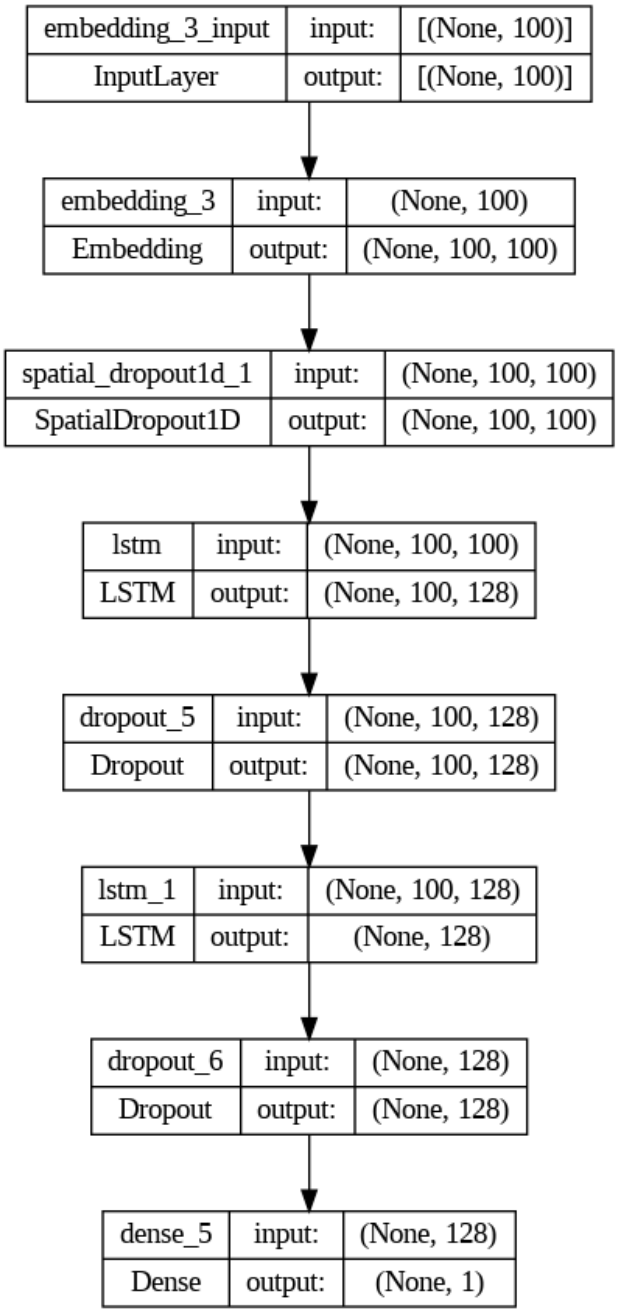

Figure 10 : lstm model architecture

```
Epoch 1/30
32/32 - 27s - loss: 0.6968 - accuracy: 0.4854 - val_loss: 0.6932 - val_accuracy: 0.5039 - 27s/epoch - 842ms/step
Epoch 2/30
32/32 - 21s - loss: 0.6933 - accuracy: 0.5049 - val_loss: 0.6940 - val_accuracy: 0.4961 - 21s/epoch - 653ms/step
Epoch 3/30
32/32 - 10s - loss: 0.6937 - accuracy: 0.5020 - val_loss: 0.6931 - val_accuracy: 0.5078 - 10s/epoch - 306ms/step
Epoch 4/30
32/32 - 11s - loss: 0.6939 - accuracy: 0.5000 - val_loss: 0.6931 - val_accuracy: 0.5039 - 11s/epoch - 349ms/step
Epoch 5/30
32/32 - 12s - loss: 0.6943 - accuracy: 0.4766 - val_loss: 0.6933 - val_accuracy: 0.4961 - 12s/epoch - 370ms/step
Epoch 6/30
32/32 - 13s - loss: 0.6937 - accuracy: 0.4834 - val_loss: 0.6932 - val_accuracy: 0.4922 - 13s/epoch - 397ms/step
Epoch 7/30
32/32 - 9s - loss: 0.6932 - accuracy: 0.5068 - val_loss: 0.6933 - val_accuracy: 0.5039 - 9s/epoch - 285ms/step
Epoch 8/30
32/32 - 12s - loss: 0.6918 - accuracy: 0.4922 - val_loss: 0.6934 - val_accuracy: 0.4961 - 12s/epoch - 388ms/step
Epoch 9/30
32/32 - 12s - loss: 0.6922 - accuracy: 0.5068 - val_loss: 0.6934 - val_accuracy: 0.4844 - 12s/epoch - 388ms/step
Epoch 10/30
32/32 - 15s - loss: 0.6934 - accuracy: 0.4834 - val_loss: 0.6937 - val_accuracy: 0.4883 - 15s/epoch - 480ms/step
Epoch 11/30
32/32 - 10s - loss: 0.7018 - accuracy: 0.5059 - val_loss: 0.6933 - val_accuracy: 0.4922 - 10s/epoch - 307ms/step
Epoch 12/30
32/32 - 11s - loss: 0.6930 - accuracy: 0.5020 - val_loss: 0.6932 - val_accuracy: 0.5039 - 11s/epoch - 357ms/step
Epoch 13/30
32/32 - 14s - loss: 0.6905 - accuracy: 0.4873 - val_loss: 0.6934 - val_accuracy: 0.4961 - 14s/epoch - 430ms/step
Epoch 14/30
32/32 - 12s - loss: 0.6913 - accuracy: 0.5156 - val_loss: 0.6940 - val_accuracy: 0.4961 - 12s/epoch - 385ms/step
Epoch 15/30
32/32 - 12s - loss: 0.6913 - accuracy: 0.4922 - val_loss: 0.6955 - val_accuracy: 0.4961 - 12s/epoch - 372ms/step
Epoch 16/30
32/32 - 15s - loss: 0.6892 - accuracy: 0.5078 - val_loss: 0.6944 - val_accuracy: 0.4883 - 15s/epoch - 467ms/step

Epoch 17/30
32/32 - 21s - loss: 0.6882 - accuracy: 0.4766 - val_loss: 0.6938 - val_accuracy: 0.4883 - 21s/epoch - 659ms/step
Epoch 18/30
32/32 - 15s - loss: 0.6878 - accuracy: 0.4893 - val_loss: 0.7214 - val_accuracy: 0.5156 - 15s/epoch - 457ms/step
Epoch 19/30
32/32 - 11s - loss: 0.6907 - accuracy: 0.5088 - val_loss: 0.6934 - val_accuracy: 0.4961 - 11s/epoch - 339ms/step
Epoch 20/30
32/32 - 12s - loss: 0.6896 - accuracy: 0.4883 - val_loss: 0.6936 - val_accuracy: 0.4961 - 12s/epoch - 383ms/step
Epoch 21/30
32/32 - 13s - loss: 0.6899 - accuracy: 0.5020 - val_loss: 0.6951 - val_accuracy: 0.4961 - 13s/epoch - 411ms/step
Epoch 22/30
32/32 - 16s - loss: 0.6878 - accuracy: 0.5107 - val_loss: 0.6942 - val_accuracy: 0.4883 - 16s/epoch - 485ms/step
Epoch 23/30
32/32 - 13s - loss: 0.7043 - accuracy: 0.5049 - val_loss: 0.7192 - val_accuracy: 0.5039 - 13s/epoch - 403ms/step
Epoch 24/30
32/32 - 12s - loss: 0.7083 - accuracy: 0.5156 - val_loss: 0.7011 - val_accuracy: 0.4961 - 12s/epoch - 377ms/step
Epoch 25/30
32/32 - 13s - loss: 0.6972 - accuracy: 0.4961 - val_loss: 0.6936 - val_accuracy: 0.5039 - 13s/epoch - 417ms/step
Epoch 26/30
32/32 - 11s - loss: 0.6878 - accuracy: 0.5303 - val_loss: 0.6948 - val_accuracy: 0.5039 - 11s/epoch - 354ms/step
Epoch 27/30
32/32 - 12s - loss: 0.6896 - accuracy: 0.4971 - val_loss: 0.6933 - val_accuracy: 0.4961 - 12s/epoch - 386ms/step
Epoch 28/30
32/32 - 12s - loss: 0.6931 - accuracy: 0.4844 - val_loss: 0.6936 - val_accuracy: 0.4961 - 12s/epoch - 371ms/step
Epoch 29/30
32/32 - 13s - loss: 0.6964 - accuracy: 0.5098 - val_loss: 0.6994 - val_accuracy: 0.4961 - 13s/epoch - 409ms/step
Epoch 30/30
32/32 - 10s - loss: 0.6921 - accuracy: 0.5029 - val_loss: 0.6933 - val_accuracy: 0.5039 - 10s/epoch - 318ms/step
```

Figure 11: training & validation loss values for lstm model

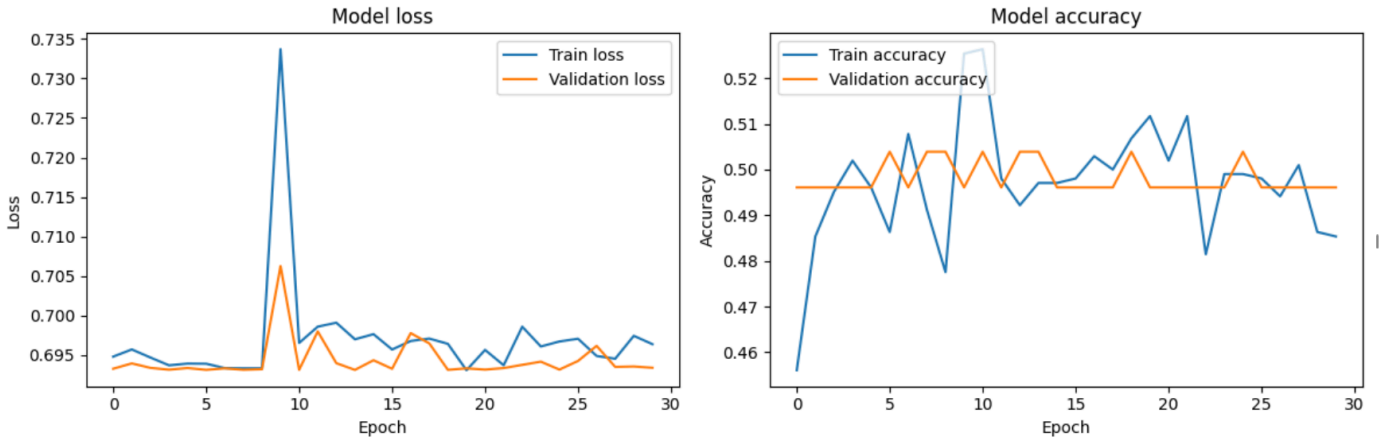

Figure 12 : Charts of the lSTM model loss and accuracy

- **Model Loss**

  - *Training Loss*

- The training loss shows erratic behavior, with a significant spike around epoch 10. After the spike, it generally fluctuates but stays within a lower range.

- This kind of fluctuation suggests instability during training, possibly due to a high learning rate or poor initialization of weights. The significant spike may indicate a drastic change in the learning rate or some irregularities in the training data at that epoch.

  - *Validation Loss*

- The validation loss also shows fluctuations but remains more stable compared to the training loss. It gradually decreases over time.

- The relatively stable validation loss compared to the erratic training loss might suggest that the model generalizes reasonably well, but the training process itself is unstable.

- **Model Accuracy**

  - *Training Accuracy*

- The training accuracy is highly volatile, with noticeable peaks and drops, especially around the same epoch where the loss spikes.

- This volatility indicates that the model's performance on the training set is inconsistent, which again suggests instability in the learning process.

- *Validation Accuracy*

- The validation accuracy is more stable compared to the training accuracy, though it does not show significant improvement over epochs.

- The flat and slightly higher validation accuracy suggests that the model's generalization capability is not improving substantially over time.

Observations

The validation loss and accuracy are relatively stable compared to their training counterparts, suggesting that the model's performance on unseen data is not changing dramatically. This might indicate that while the model is struggling during training, its ability to generalize is less affected by the fluctuations in training.

4.1.4 Experiment 3: Bi-LSTM Model

Model architecture:

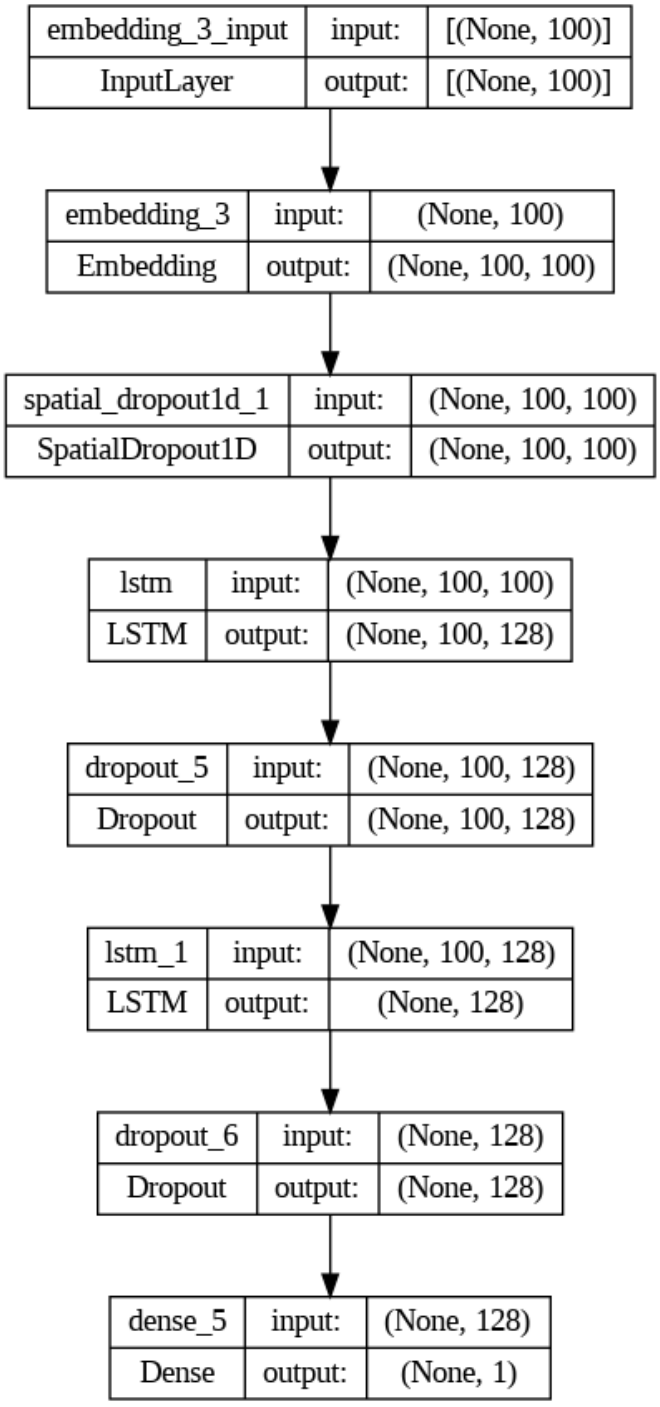

Figure 13 : Bi- lstm model architecture

```
Epoch 1/30
32/32 - 60s - loss: 0.6796 - accuracy: 0.5547 - val_loss: 0.5700 - val_accuracy: 0.7578 - 60s/epoch - 2s/step
Epoch 2/30
32/32 - 25s - loss: 0.4587 - accuracy: 0.8027 - val_loss: 0.4418 - val_accuracy: 0.8125 - 25s/epoch - 789ms/step
Epoch 3/30
32/32 - 26s - loss: 0.3002 - accuracy: 0.8867 - val_loss: 0.4829 - val_accuracy: 0.7773 - 26s/epoch - 827ms/step
Epoch 4/30
32/32 - 28s - loss: 0.1856 - accuracy: 0.9258 - val_loss: 0.6751 - val_accuracy: 0.7500 - 28s/epoch - 885ms/step
Epoch 5/30
32/32 - 26s - loss: 0.1090 - accuracy: 0.9668 - val_loss: 0.8851 - val_accuracy: 0.7227 - 26s/epoch - 824ms/step
Epoch 6/30
32/32 - 28s - loss: 0.0845 - accuracy: 0.9717 - val_loss: 0.9533 - val_accuracy: 0.7461 - 28s/epoch - 866ms/step
Epoch 7/30
32/32 - 27s - loss: 0.0846 - accuracy: 0.9775 - val_loss: 0.8277 - val_accuracy: 0.7539 - 27s/epoch - 830ms/step
Epoch 8/30
32/32 - 23s - loss: 0.0779 - accuracy: 0.9775 - val_loss: 0.9198 - val_accuracy: 0.7148 - 23s/epoch - 729ms/step
Epoch 9/30
32/32 - 27s - loss: 0.0551 - accuracy: 0.9834 - val_loss: 1.1398 - val_accuracy: 0.7148 - 27s/epoch - 853ms/step
Epoch 10/30
32/32 - 24s - loss: 0.0726 - accuracy: 0.9746 - val_loss: 1.1658 - val_accuracy: 0.7266 - 24s/epoch - 749ms/step
Epoch 11/30
32/32 - 26s - loss: 0.0462 - accuracy: 0.9863 - val_loss: 1.1812 - val_accuracy: 0.7227 - 26s/epoch - 799ms/step
Epoch 12/30
32/32 - 29s - loss: 0.0165 - accuracy: 0.9941 - val_loss: 1.2898 - val_accuracy: 0.7305 - 29s/epoch - 909ms/step
Epoch 13/30
32/32 - 22s - loss: 0.0147 - accuracy: 0.9922 - val_loss: 1.5231 - val_accuracy: 0.7305 - 22s/epoch - 701ms/step
Epoch 14/30
32/32 - 25s - loss: 0.0037 - accuracy: 0.9990 - val_loss: 1.7620 - val_accuracy: 0.7539 - 25s/epoch - 779ms/step
Epoch 15/30
32/32 - 24s - loss: 0.0028 - accuracy: 0.9990 - val_loss: 1.9030 - val_accuracy: 0.7578 - 24s/epoch - 738ms/step
Epoch 16/30
32/32 - 26s - loss: 0.0159 - accuracy: 0.9961 - val_loss: 1.8847 - val_accuracy: 0.7188 - 26s/epoch - 799ms/step

Epoch 18/30
32/32 - 28s - loss: 0.0061 - accuracy: 0.9980 - val_loss: 1.5843 - val_accuracy: 0.7422 - 28s/epoch - 873ms/step
Epoch 19/30
32/32 - 23s - loss: 0.0114 - accuracy: 0.9961 - val_loss: 1.2060 - val_accuracy: 0.7422 - 23s/epoch - 718ms/step
Epoch 20/30
32/32 - 25s - loss: 0.0394 - accuracy: 0.9834 - val_loss: 1.3236 - val_accuracy: 0.7148 - 25s/epoch - 794ms/step
Epoch 21/30
32/32 - 25s - loss: 0.0112 - accuracy: 0.9941 - val_loss: 1.6066 - val_accuracy: 0.7383 - 25s/epoch - 771ms/step
Epoch 22/30
32/32 - 24s - loss: 0.0108 - accuracy: 0.9971 - val_loss: 1.7962 - val_accuracy: 0.7227 - 24s/epoch - 738ms/step
Epoch 23/30
32/32 - 26s - loss: 0.0089 - accuracy: 0.9971 - val_loss: 1.8637 - val_accuracy: 0.7148 - 26s/epoch - 806ms/step
Epoch 24/30
32/32 - 22s - loss: 0.0027 - accuracy: 1.0000 - val_loss: 1.8529 - val_accuracy: 0.7305 - 22s/epoch - 694ms/step
Epoch 25/30
32/32 - 29s - loss: 0.0041 - accuracy: 0.9990 - val_loss: 1.8963 - val_accuracy: 0.7227 - 29s/epoch - 897ms/step
Epoch 26/30
32/32 - 26s - loss: 0.0021 - accuracy: 1.0000 - val_loss: 1.9170 - val_accuracy: 0.7422 - 26s/epoch - 821ms/step
Epoch 27/30
32/32 - 24s - loss: 7.9819e-04 - accuracy: 1.0000 - val_loss: 2.1291 - val_accuracy: 0.7383 - 24s/epoch - 740ms/step
Epoch 28/30
32/32 - 24s - loss: 2.3859e-04 - accuracy: 1.0000 - val_loss: 2.1954 - val_accuracy: 0.7305 - 24s/epoch - 758ms/step
Epoch 29/30
32/32 - 24s - loss: 0.0024 - accuracy: 0.9990 - val_loss: 2.1324 - val_accuracy: 0.7227 - 24s/epoch - 755ms/step
Epoch 30/30
32/32 - 24s - loss: 4.0400e-04 - accuracy: 1.0000 - val_loss: 2.2405 - val_accuracy: 0.7148 - 24s/epoch - 765ms/step
```

Figure 14 : training & validation loss values for bi-lstm model

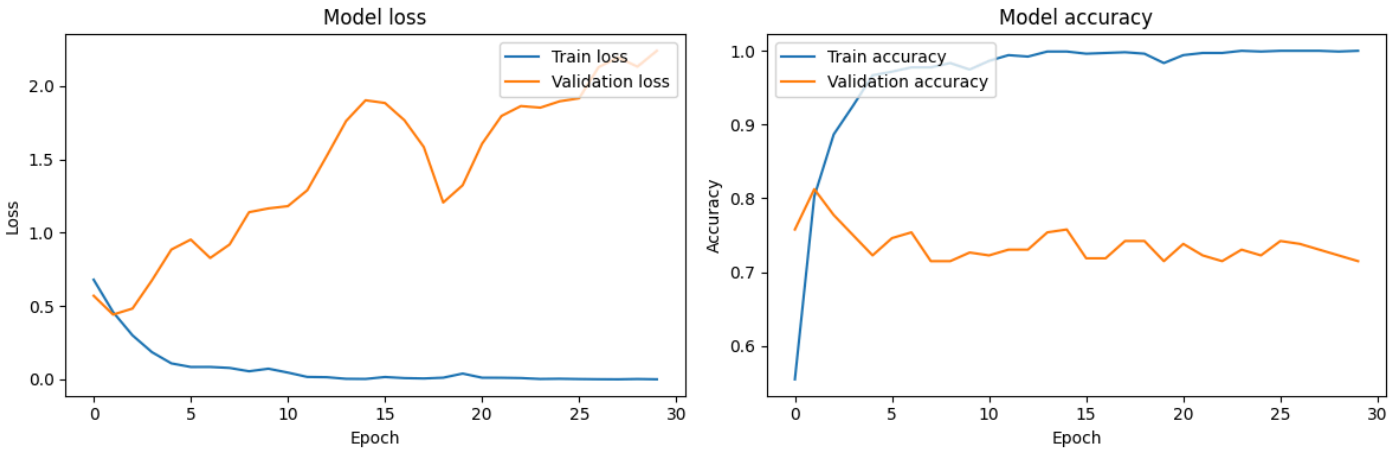

Figure 15 : Charts of the Bi-LSTM model loss and accuracy

- **Model Loss**

  - Training Loss

- The training loss starts at a very low value and remains close to zero throughout the epochs.

- The extremely low training loss indicates that the model fits the training data very well, suggesting almost perfect performance on the training set. However, this can be a red flag for overfitting, as the model may not generalize well to unseen data.

  - Validation Loss

- The validation loss starts at a higher value and shows significant fluctuations, especially between epochs 10 and 20, before slightly stabilizing.

- The validation loss remains relatively high compared to the training loss and shows an overall increasing trend with some volatility, indicating that the model struggles to generalize to the validation set.

- **Model Accuracy**

  - Training Accuracy

- The training accuracy is nearly 1.0 (100%) from the beginning and remains consistently high throughout the epochs.

- This extremely high training accuracy further supports the notion of overfitting, as the model appears to be memorizing the training data rather than learning generalizable patterns.

  - Validation Accuracy

- The validation accuracy starts at a lower value and exhibits fluctuations, indicating inconsistency in model performance on the validation set.

- Despite the high training accuracy, the validation accuracy does not show significant improvement over the epochs and remains relatively flat, suggesting poor generalization.

Observations

The stark contrast between the very low training loss and the high validation loss, coupled with the perfect training accuracy and the fluctuating validation accuracy, is a clear indication of overfitting. The model has learned to fit the training data perfectly but fails to generalize to new, unseen data.

4.1.6 Experiment 4: CNN Model

Model architecture:

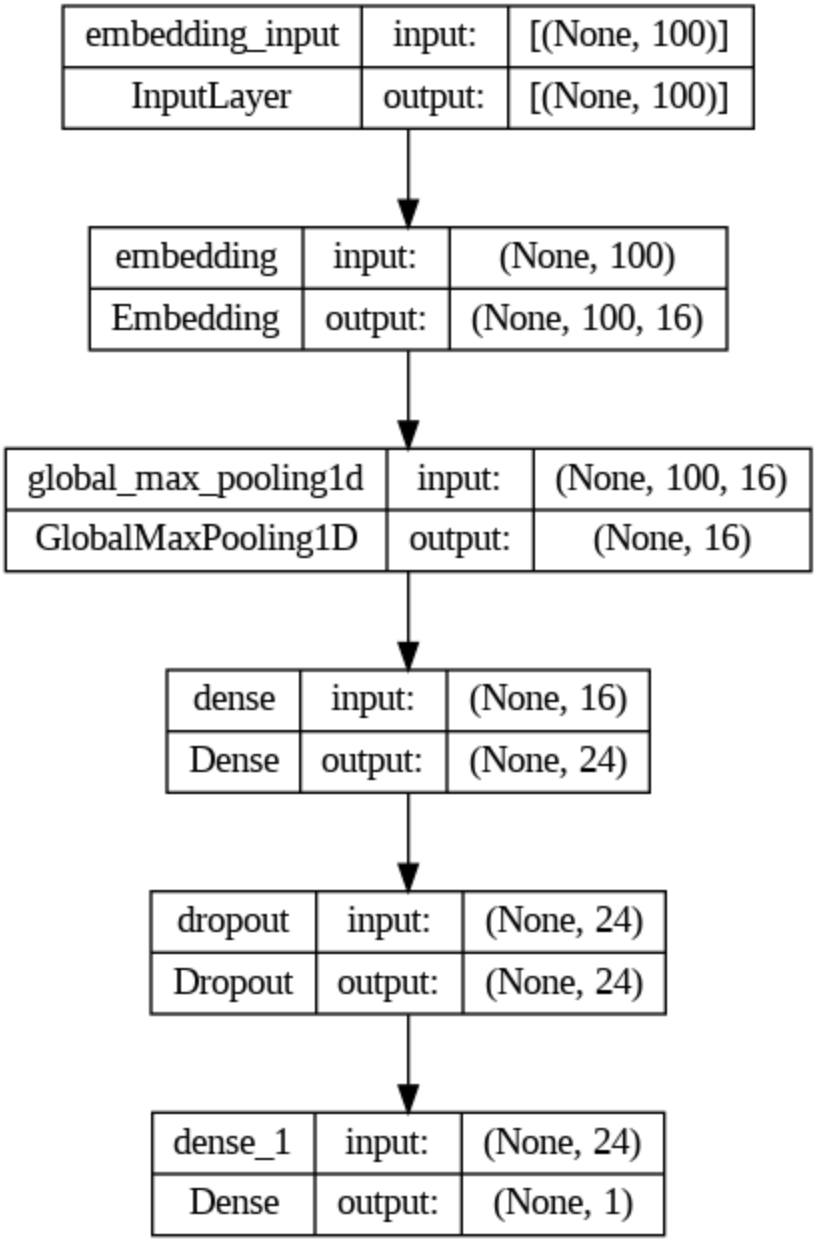

Figure 16 : Cnn model architecture

```
Epoch 1/30
32/32 - 3s - loss: 0.6942 - accuracy: 0.4873 - val_loss: 0.6910 - val_accuracy: 0.5469 - 3s/epoch - 104ms/step
Epoch 2/30
32/32 - 2s - loss: 0.6876 - accuracy: 0.6064 - val_loss: 0.6884 - val_accuracy: 0.6172 - 2s/epoch - 54ms/step
Epoch 3/30
32/32 - 1s - loss: 0.6789 - accuracy: 0.7148 - val_loss: 0.6827 - val_accuracy: 0.6328 - 1s/epoch - 43ms/step
Epoch 4/30
32/32 - 1s - loss: 0.6647 - accuracy: 0.7617 - val_loss: 0.6706 - val_accuracy: 0.7109 - 1s/epoch - 34ms/step
Epoch 5/30
32/32 - 1s - loss: 0.6393 - accuracy: 0.8018 - val_loss: 0.6479 - val_accuracy: 0.7148 - 1s/epoch - 34ms/step
Epoch 6/30
32/32 - 1s - loss: 0.5955 - accuracy: 0.8447 - val_loss: 0.6125 - val_accuracy: 0.7422 - 1s/epoch - 34ms/step
Epoch 7/30
32/32 - 1s - loss: 0.5373 - accuracy: 0.8408 - val_loss: 0.5708 - val_accuracy: 0.7461 - 1s/epoch - 34ms/step
Epoch 8/30
32/32 - 1s - loss: 0.4654 - accuracy: 0.8682 - val_loss: 0.5291 - val_accuracy: 0.7656 - 1s/epoch - 31ms/step
Epoch 9/30
32/32 - 1s - loss: 0.3850 - accuracy: 0.9062 - val_loss: 0.4957 - val_accuracy: 0.7734 - 1s/epoch - 33ms/step
Epoch 10/30
32/32 - 1s - loss: 0.3151 - accuracy: 0.9248 - val_loss: 0.4788 - val_accuracy: 0.7734 - 1s/epoch - 32ms/step
Epoch 11/30
32/32 - 1s - loss: 0.2378 - accuracy: 0.9609 - val_loss: 0.4658 - val_accuracy: 0.7617 - 1s/epoch - 34ms/step
Epoch 12/30
32/32 - 1s - loss: 0.1845 - accuracy: 0.9707 - val_loss: 0.4518 - val_accuracy: 0.7773 - 1s/epoch - 38ms/step
Epoch 13/30
32/32 - 2s - loss: 0.1451 - accuracy: 0.9746 - val_loss: 0.4532 - val_accuracy: 0.7500 - 2s/epoch - 53ms/step
Epoch 14/30
32/32 - 2s - loss: 0.1150 - accuracy: 0.9824 - val_loss: 0.4579 - val_accuracy: 0.7578 - 2s/epoch - 54ms/step
Epoch 15/30
32/32 - 2s - loss: 0.0841 - accuracy: 0.9902 - val_loss: 0.4713 - val_accuracy: 0.7617 - 2s/epoch - 56ms/step
Epoch 16/30
32/32 - 1s - loss: 0.0647 - accuracy: 0.9922 - val_loss: 0.4745 - val_accuracy: 0.7617 - 1s/epoch - 34ms/step
Epoch 17/30
Epoch 17/30
32/32 - 1s - loss: 0.0503 - accuracy: 0.9961 - val_loss: 0.4841 - val_accuracy: 0.7539 - 1s/epoch - 32ms/step
Epoch 18/30
32/32 - 1s - loss: 0.0438 - accuracy: 0.9951 - val_loss: 0.4948 - val_accuracy: 0.7656 - 1s/epoch - 34ms/step
Epoch 19/30
32/32 - 1s - loss: 0.0336 - accuracy: 0.9990 - val_loss: 0.5065 - val_accuracy: 0.7656 - 1s/epoch - 34ms/step
Epoch 20/30
32/32 - 1s - loss: 0.0285 - accuracy: 0.9980 - val_loss: 0.5127 - val_accuracy: 0.7617 - 1s/epoch - 32ms/step
Epoch 21/30
32/32 - 1s - loss: 0.0232 - accuracy: 0.9990 - val_loss: 0.5315 - val_accuracy: 0.7578 - 1s/epoch - 34ms/step
Epoch 22/30
32/32 - 1s - loss: 0.0195 - accuracy: 0.9990 - val_loss: 0.5389 - val_accuracy: 0.7539 - 1s/epoch - 32ms/step
Epoch 23/30
32/32 - 1s - loss: 0.0169 - accuracy: 0.9990 - val_loss: 0.5570 - val_accuracy: 0.7734 - 1s/epoch - 32ms/step
Epoch 24/30
32/32 - 1s - loss: 0.0171 - accuracy: 0.9980 - val_loss: 0.5608 - val_accuracy: 0.7578 - 1s/epoch - 34ms/step
Epoch 25/30
32/32 - 2s - loss: 0.0121 - accuracy: 0.9990 - val_loss: 0.5753 - val_accuracy: 0.7656 - 2s/epoch - 48ms/step
Epoch 26/30
32/32 - 2s - loss: 0.0120 - accuracy: 0.9990 - val_loss: 0.5823 - val_accuracy: 0.7617 - 2s/epoch - 53ms/step
Epoch 27/30
32/32 - 2s - loss: 0.0101 - accuracy: 0.9990 - val_loss: 0.5920 - val_accuracy: 0.7617 - 2s/epoch - 55ms/step
Epoch 28/30
32/32 - 1s - loss: 0.0096 - accuracy: 0.9990 - val_loss: 0.6019 - val_accuracy: 0.7617 - 1s/epoch - 40ms/step
Epoch 29/30
32/32 - 1s - loss: 0.0083 - accuracy: 0.9990 - val_loss: 0.6107 - val_accuracy: 0.7617 - 1s/epoch - 32ms/step
Epoch 30/30
32/32 - 1s - loss: 0.0069 - accuracy: 0.9990 - val_loss: 0.6166 - val_accuracy: 0.7695 - 1s/epoch - 32ms/step
```

Figure 17: training & validation loss values for bi-lstm model

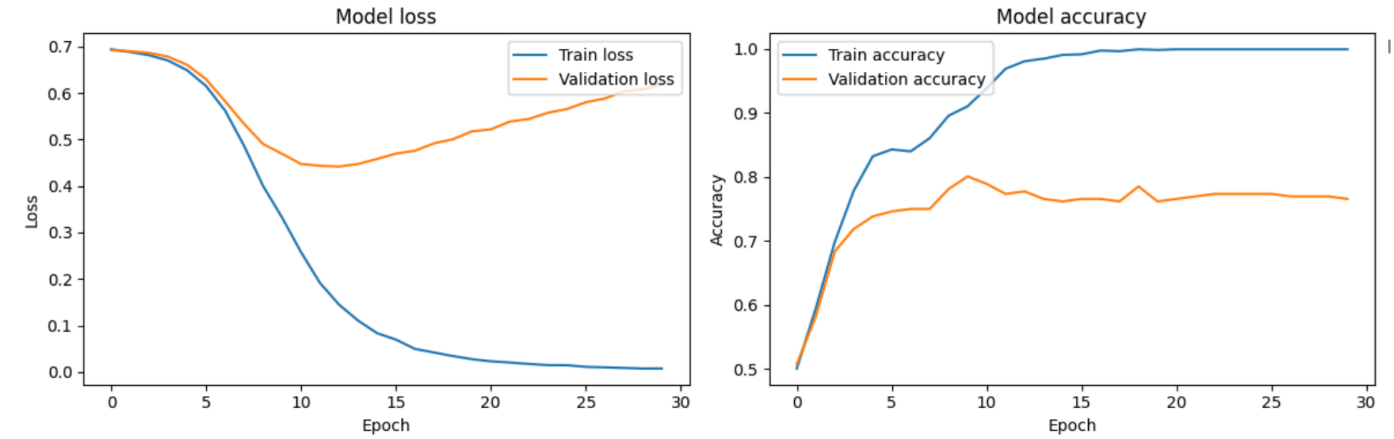

Figure 18 : Charts of the CNN model loss and accuracy

- **Model Loss**

  - *Training Loss*

The training loss consistently decreases and approaches zero as the number of epochs increases. This indicates that the model is learning and fitting well to the training data.

  - *Validation Loss*

The validation loss initially decreases, indicating that the model is learning from the data. However, after about 5 epochs, the validation loss starts to increase. This is a sign of overfitting, where the model is performing well on the training data but not as well on the validation data.

- **Model Accuracy**

  - *Training Accuracy*

The training accuracy rapidly increases and approaches 100% as the number of epochs increases, showing that the model is very good at predicting the training data.

  - *Validation Accuracy*

The validation accuracy also increases initially but then starts to plateau and even slightly decreases after around 5 epochs, indicating that the model's performance on the validation data is not improving further and is likely overfitting.

Observations

The divergence between training and validation metrics after around 5 epochs suggests overfitting. The model learns the training data very well but fails to generalize to unseen data. Early stopping could be used to prevent overfitting by stopping the training process around the point where the validation loss starts increasing (around 5 epochs).

4.2 Comparative study

The table below encapsulates the performance metrics of our models alongside those from other notable works, providing a holistic view of the comparative performance landscape. This comparative analysis not only serves to validate our experimental outcomes but also underscores the advancements and current trends in the field of deep learning for natural language processing.

Model	Validation Accuracy	Validation Loss	Source of Comparison
Dnn model	0.7656	0.5110	This Study
Lstm model	0.5039	0.6932	This Study
Bi-lstm	0.7148	2.2405	This Study
Cnn model	0.7695	0.6165	This Study
Caractéristiques Statistiques	0.8981	//	[Ott 2011]
Caractéristiques sémantiques et statistiques proposées	0.8910	//	[Ziani 2016]

Table3 : The performance metrics of the models

Conclusion general

In this study, we undertook an extensive examination of various neural network architectures to develop an effective spam detection model. The models evaluated included Long Short-Term Memory (LSTM), Deep Neural Network (DNN), Bidirectional LSTM (Bi-LSTM), and Convolutional Neural Network (CNN). Our aim was to compare their performance in identifying spam emails and to determine the most suitable model for this task.

The DNN and Bi-LSTM models emerged as the top performers, demonstrating superior accuracy and robustness in our experiments. The DNN model, with its deep layered structure, was adept at capturing complex patterns within the data, leading to highly accurate predictions. Similarly, the Bi-LSTM model excelled by processing input sequences in both forward and backward directions, thereby enhancing its contextual understanding and improving its detection capabilities. However, it is important to note that the state and quality of the data played a crucial role in the performance of these models. The models' ability to generalize and perform well on unseen data heavily depended on the comprehensiveness and representativeness of the training data. Any inconsistencies or biases in the dataset could significantly impact the models' performance, highlighting the importance of thorough data preprocessing and augmentation.

Overall, while the LSTM and CNN models also contributed valuable insights and exhibited competitive performance, the DNN and Bi-LSTM models were particularly notable for their effectiveness in spam detection. This study underscores the critical importance of selecting appropriate neural network architectures and ensuring high-quality data to develop reliable and efficient spam detection systems. Future research can build on these findings by exploring more sophisticated models and leveraging larger and more diverse datasets to further enhance spam detection accuracy.

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