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A Study on Amazon Alexa Reviews Sentiment Analysis

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Abstract— In the early days, people did not want to move forward to buy or use modern gadgets because they were comfortable with old gadgets. They used significantly fewer gadgets, and it took time to update to the new gadgets. Alexa is a speaker invented by Amazon, which is easy to use and is as comfortable as the old gadgets. It also uses the human voice and detects the information they ask. The study aims to find the sentiment analysis of the people's reviews of Alexa (voice assistant), invented by Amazon. This study also helps to know the opinion or sentiment reviews of Alexa. The paper includes various technologies like Artificial intelligence, Deep learning technologies, API, and VUI. These are analyzed for the study, which will help people find the reviews and importance of Alexa to gain information. Even though many technology-based gadgets are available worldwide, Alexa will help people interact with gadgets in various situations and effectively communicate through AI DL platforms. The technology will help for the convenience of the people in this living society. This voice assistant is helpful in many situations, including smart home skills, voice services, connect kit, and local connection. This is easy to interact with and makes people comfortable daily.

Keywords— *Voice assistant, Artificial intelligence, Deep learning, sentiment analysis, reviews of users.*

I. Introduction

Textual Emotion Analysis (TEA) is an approach utilized to discern and comprehend the emotions expressed by an individual through their written work. Beyond being a valuable information extraction method in and of itself, TEA is essential for numerous natural language processing (NLP) applications, including online purchasing. Aside from desire, the proverbial expression "seven emotions and six desires" also includes the following: fear, desire, love, wrath, sorrow, and evil. We appear predisposed to be more affected by negative states of mind, given that only a minority of these emotions are positive and the vast majority are negative [1]. Furthermore, in the physical world, negative emotions tend to propagate more readily than positive ones. 2011 Annual Report of the Online Public Opinion Survey in China As stated in the 38th statistics report on the development of the Chinese Internet by the China Internet Information Center, this resulted in the designation "sentiment analysis" being applied to bipartition-oriented emotion analysis. After achieving Deep Learning (DL) methodologies in object recognition via ImageNet in 2012, scholars shifted their focus towards Natural Language Processing (NLP). Emotion analysis is modeled using prevalent DL techniques such as Deep Averaging Networks (DANs), Denoising Autoencoders (DAEs), and Convolutional Neural Networks (CNNs).

Using sophisticated algorithms, sentence analysis classifies the tone of an individual's writings or comments as positive, negative, or neutral. This approach could yield crucial data for corporations and other institutions.

By conducting surveys, organizations can gain insights into consumer sentiments and levels of satisfaction regarding a particular brand. There are numerous online spaces where written content is exchanged and discussed, including social media, online stores, news organizations, and discussion forums. These platforms collectively contribute to the enormous quantities of data that the internet generates today [2]. For sentiment analysis, the efficient utilization of computers in various commercial and non-commercial settings.

Implementing these principles could significantly benefit customer relationship management (CRM) and recommendation systems. Satire and irony can be humorous, but sarcasm is more effective [3]. Commenters on shopping sites, social media platforms, and blogs frequently use it to emphasize their genuine emotions by stating the exact antithesis of what they are considering. Their semantic orientation can distinguish positive, negative, or neutral statements. Semantic orientation-based methodologies in sentiment analysis include the corpus-based and dictionary-based approaches.

The increasing prevalence of IVAs in contemporary households can be attributed to the success of the Amazon Echo product line. As of the start of 2019, around one hundred million devices had been sold, all equipped with the Alexa operating system. Hackers could impersonate vulnerabilities to acquire users' credentials. Its ability to be operated exclusively through voice commands has propelled human-computer interaction beyond touch-based or physically interactive interfaces [4]. This feature potentially aided in the device's precipitous ascent to prominence. Although this novel form of communication's advantages transcends individual devices' functionalities, it has concurrently introduced security vulnerabilities. An event-themed television program in 2017 prompted the activation of Amazon Echo devices in numerous residences.

Generally, content produced by renowned influencers receives the most significant amount of distribution. Commencing in 2006 with adults videotaping themselves unwrapping brand-new cellphones, the 'haul' and, most significantly, children's toy films have amassed immense popularity [5]. Unboxing videos have been criticized for promoting a culture of excessive consumption and addiction, particularly among youthful viewers. Although the 'wake word' feature of Alexa replicates the operations of mobile VAPAs such as Apple's Siri, its integration into a smart home device was innovative and has since facilitated the proliferation of 'eavesmining platforms' that surveil domestic environments through data mining and pervasive eavesdropping. The ethical concerns surrounding gift unveiling have been further intensified by scholarly investigations into children's viewing patterns and other aspects of digital literacy.

Our lifestyle is being transformed by the "smart" technologies and buildings that are proliferating. The significance of sustainable "smart cities" that ingeniously integrate businesses and residents is growing in tandem with the expansion of the global population. Contemporary progressions in domains such as artificial intelligence and communication networks (the IoT) enable the implementation of such applications. Integrating artificial intelligence (AI) and the Internet of Things (IoT) has yielded favorable outcomes. A recent surge in research has been observed concerning the potential of "smart buildings" to enhance efficiency and facilitate daily life. Prolonged intelligent technology integration could result in substantial cost reductions in this domain. Understanding consumer sentiments regarding intelligent lighting solutions and collaboratively addressing their concerns with industry experts and academicians could enhance their adoption rate [6, 7].

Utilization and prevalence of intelligent voice assistants such as Apple's Siri, Microsoft's Cortana, Amazon's Alexa, and Google's Assistant have skyrocketed in recent years. Intelligent voice assistants have revolutionized consumer interactions with desktop computers and mobile devices. Individuals are employing intelligent voice assistants to perform tasks such as playing music, monitoring the weather, posing inquiries, and receiving responses. Additionally, voice assistants can be employed for more fundamental tasks such as scheduling phone calls and setting alarms or timers. With Alexa, the way is paved for the pervasive integration of voice assistants into IoT-enabled smart devices. Vocoders are capable of external communication via the Internet. The user's verbal request for an item transmits the corresponding action to a centralized server. Cloud-based voice assistants utilize natural language processing (NLP) to comprehend the user's inquiry and respond appropriately. Recent developments in the field of natural language processing have enabled voice assistants to provide responses that are coherent and logical [8].

It is possible to generate a digital replica of the product using this data. The "Digital Twin" (DT), which alludes to an exact digital replica of a physical object, is a novel concept. A multitude of scholarly publications have been devoted to the subject of DT implementation. Graphical user interfaces (GUIs), including simulation environments, 3D virtual worlds, information monitors, and faceted analytical displays, are frequently employed to facilitate user interaction with a DT. In the 1970s, the initial interactive voice response (IVR) systems were developed, establishing the foundation for digital assistants capable of comprehending and reacting to spoken instructions [9]. A voice application can process a skill, which is merely a collection of intentions; therefore, young children can construct simple skills due to the current state of the underlying technology.

II. Literature Review

An emotion can be defined as "a person's mental state encompassing cognition, affect, and behavior" [1]. Ekman [2] identified six fundamental emotions: surprise, anger, contempt, fear, pleasure, and sorrow. There is a growing trend of employing emotional analysis as a predictive tool in democratic elections. Paul et al. [3] proposed a Compass framework that utilized 2016 U.S. Network public opinion [4] data to enable online discourse on critical social issues by presenting a range of perspectives. The growth of available network space, progress in network application modes, and the advent of the significant data era have all played a role in the pervasiveness of the Internet and the evolution of advanced search tools [5]. By employing emotion analysis technology [6] on text extracted from psychotherapy-focused social networks, scientists analyzed the emotional state data of individuals suspected of having depression. Parrott [7] suggests that a tree-based paradigm encompasses the following emotions: love, pleasure, surprise, wrath, sorrow, and dread. Ekman's model [1] plus two additional categories, Plutchik [8] drew a wheel-shaped emotion classifier with four polar sets: happiness and sorrow, anger and fear, trust and disgust, and astonishment and anticipation.

Language and cultural variations contribute to the absence of a universally acknowledged tally of emotions or a standardized classification system for them [9]. Neutral ratings are frequently disregarded due to insufficient information or ambiguity, even though numerous sentiment analysis tasks can be conceptualized as ternary classification problems [10]. An individual experiences emotion as a complex psychophysiological change caused by the interaction of biochemical and environmental factors with their mood. Consequently, academicians and artists have investigated it [11]. Studies on emotional support aim to determine why individuals write about their emotions [12]. Numerous studies on the sentiment of microblogging and social network communications have approached it as a ternary classification problem [13] involving positive/negative or positive/negative/neutral values. One definition of sentiment analysis is extracting, identifying, and analyzing subjective information (e.g., customer ratings or survey responses) using computational linguistic techniques such as natural language processing and text analysis. Sentiment analysis is a process that aims to discern the predominant emotive tone present in a given text and classify it as positive, negative, or neutral. Differentiating between feelings of happiness and sadness presents an additional challenge [14]. The three most common sentiment analysis techniques are statistical methods, knowledge-based strategies, and hybrid approaches [15]. Also essential for sentiment analysis of ambiguous text is feature extraction. In feature extraction, unprocessed text is transformed into machine-understandable numerical identifiers. Feature extraction techniques include word embedding, a bag of words, N-grams, and TF-IDF [16]. Textual preparation is an essential component of sentiment analysis [17]. Numerous studies have examined the application of natural language processing (NLP) to the classification, generation, and forecasting of reviews [18–20]. In recent years, machine learning and deep learning techniques have become prominent in this discipline [21–23].

Iii. Methodology

DL techniques are primarily designed to discover novel features. It is a technique that enables the acquisition of intricate feature representations by mastering multi-layered nonlinear processing. To accomplish domain-specific activities such as classification, DL can be combined with specialized domain tasks by developing tools or creating novel classifiers that utilize the feature representation of automated learning. To develop an algorithm for a DL model, in particular, the subsequent procedures must be executed: [24,25]

Initially, a learning network will be constructed and initialized randomly. Subsequently, n training layers will be selected, unlabeled data will be fed into layer I of the network, and the output layer will be set to 1. Furthermore, the input set is employed to pre-train the unsupervised learning strategy of the current layer's learning network.

Thirdly, the input set is iteratively constructed by incorporating the training results of the previous layer's training into the subsequent layer's training. i in step 5 is more significant than i in step 6, if i in step 4 is less than n, and so forth.

Refining the network's parameters across all layers through supervised learning reduces the error rate to a practical level.

Completion of the deep learning classifier or deep generation model (e.g., a deep neural network) construction. The long short-term memory (LSTM) network is a type of recurrent neural network (RNN) that effectively addresses the gradient vanishing or gradient bursting issue that RNNs encounter during training and can represent the information of a time sequence, among other things. The notion in question was first introduced in 1997 by Hochreiter and Schmidhuber [26]. Two models comprise the word2vec algorithm: continuous bag-of-words (CBOW) and continuous skip-gram [27]. The CBOW model calculates the current word by averaging or summarizing the words in its immediate vicinity. In the context of acquiring embeddings for English and Chinese words, the BWEs [28] model functions as an unsupervised neural network. Aligned word embedding by machine translation, including initiation and optimization constraints. Nonetheless, its efficacy in addressing the issue of polysemy is minimal.

Ensemble models frequently address this issue through the utilization of meta-learning processes or by assigning greater importance to accurate classifiers [29]. It is widely acknowledged that long-short memory techniques may outperform conventional approaches when addressing the vanishing gradient problem [30]. The effectiveness of the proposed method was evaluated by comparing it to four well-established and widely used approaches to sentiment analysis. The subsequent datasets were applied to the experiment in two instances: (1) user evaluations of Google Play applications [32] and (2) a corpus of tweets utilizing natural language processing (NLP) to discuss coronaviruses [31]. Amazon Alexa reviews [33]; (4) User and critic evaluations on Rotten Tomatoes [34]—virus of Information Labeled with a Corona. The data set on the NLP-text classification of Coronavirus tweets [31] comprises annotations extracted from real-world tweets. The second experiment utilizes data from Google Play's application evaluations to demonstrate the potential for the proposed approach to be readily expanded to address additional sentiment-related classification challenges. The Google Play app review dataset [32] comprises three distinct categories of labeled information. The Amazon Alexa consumer review and feedback dataset [33] comprising the Amazon Echo, Echo Dots, and Fire Stick comprises 3,150 reviews and comments. Ablation is the investigation of the performance of a multi-component system through the methodical elimination of each component individually to ascertain its function [35].

Iv. Results And Discussion

Two models comprise the word2vec algorithm: continuous bag-of-words (CBOW) and continuous skip-gram [36]. SSWE [37] can encode sentiment and grammatical context within a vector space. To improve the semantic quality of pre-existing word vectors, REF [38] suggests implementing sentiment lexicons. The DeepMoji [39] model employs an attention mechanism based on a two-layer Bi-LSTM to interpret the meanings of emojis conveying sorrow, wrath, and humor. InferSent [40] employs a Bi-LSTM architecture that utilizes max pooling with a universal representation technique to acquire phrase embeddings. A USE function [41] is available for inserting English sentences. It attains optimal performance by effectively transmitting information at the sentence and word levels.

The proposed approach was evaluated for its efficacy using a three-class sentiment problem followed by a two-class sentiment task. The experimental results demonstrate that the ensemble fuzzy strategy, as proposed, outperforms the competing methods in terms of sentiment categorization recognition rates. This exemplifies how integrating the developed fuzzy rule-based system improves the effectiveness of these critical sentiment classification methods. The proposed methodology computes a cumulative score by incorporating the outcomes of three distinct emotion analyzer modules, all producing equally remarkable results. An experiment was undertaken to ascertain how these elements enhance the classification of emotions. The ablation research demonstrated that classification accuracy was improved by analyzing these three elements in addition to the proposed fuzzy rule premise. This finding suggests that the emotional interpretation framework that was proposed is efficacious. Commonly, ensemble models are employed to modify the weighting of numerous methods. The fuzzy model we propose is an ensemble model, so weight learning is not required. The final determination is reached through the execution of the fuzzy logic process precisely once, after which inputs, outputs, and rule relations are constructed utilizing the fuzzy inference mechanism. This characteristic renders the proposed method versatile and applicable to various contexts.

Despite Amazon's diligent attempts, Alexa continues encountering challenges with automated voice recognition, particularly regarding broadcast media comprehension. The results of the research conducted by Castell-Uroz et al. [42] using an audio database were intriguing. When the trigger word is spoken, the Echo is activated. The default trigger word of "Alexa" can be modified to "Computer," "Amazon," or "Echo" [43]. A face recognition system initiates the authentication of authorized users' identities when they glance at the screen [44].

By incorporating human input, Amazon's speech recognition and natural language comprehension algorithms are enhanced [45]. By utilizing the non-linear microphone of the Echo, the assailants successfully extended their range to 25 feet [46]. Studies [47] indicate that the wake phrase is required for Amazon Echo to begin recording and delivering audio. An adversary who gains physical access to an Amazon Echo could potentially access a Linux root terminal. There are two fundamental design flaws in the Amazon Echo. [48]

Text mining can automate the examination of textual texts. Employing topic modeling makes it possible to classify documents based on various subjects. To conserve energy, automated illumination control systems and technologies were implemented; conversely, it required fortitude for individuals to consider the concurrent infrastructure requirements of occupancy-based control systems. A sentiment analysis component called "aspect-based sentiment analysis" examines how individuals feel regarding different aspects of a given issue. The sentiments of evaluators in the intelligent lighting industry regarding several frequently discussed. A user remarked that the illumination was "extraordinary." The contrast is exceptional, the colors are vivid, and the whites are dazzling. This option strikes a balance between "warm white" and "cold white," both of which are excessively chilly for the preferences of my partner and me. Academics highly regard analyses that uncover patterns and deficiencies in the body of literature while providing recommendations for further advancement. With the advent of AI, rapid literature evaluation, summarization of findings, and analysis of trends have become feasible. Even now, the market for digital devices is in its infancy. To function effectively, smart home devices must incorporate user feedback, assimilate information from relevant research, and align themselves toward a common objective. This study introduces an automated system that utilizes scholastic publications and user-generated data, two crucial information sources that can be better comprehended through the application of this instrument.

The predictions are represented in the rows, whereas the performance of our classifier model is displayed in the columns. A class that authentically embodies reality is present within the confusion matrix. An accurate model is one in which the model's predicted class corresponds to the observed class. Based on the information in the customer review, the model made an optimistic prediction, indicating that it deduced that the consumer would hold a favorable perception of the organization. The review will accurately reflect the level of satisfaction expressed by the client. These instances exemplify the concept of "through negatives in the diagonal components," which manifests when the predictions generated by the model precisely align with reality. A false-negative error is a blunder in which a model predicts an incorrect negative class when the actual class is positive.

This phrase contains thirteen of seventeen diagonals, making it appropriate for academic review—22x sensors in 2022. A false-negative error is a blunder in which a model predicts an incorrect negative class when the actual class is positive.

The Alexa Skills Kit (ASK) enables developers to augment Amazon's voice assistant Alexa with additional functionalities. By applying this knowledge in a production environment, we acquired a distinctive ability to respond to inquiries regarding our products. The communication channel employed was the Echo 5 smart speaker. It isn't easy to verbally present multidimensional data, such as a graph, where the screen becomes useful. "Fulfillment code" is executed via the Lambda cloud utility provided by Amazon Web Services. The fulfillment code is utilized by voice-enabled applications to finalize the transaction [49]. A request is transmitted to the fulfillment when a user engages with an Alexa device, including the requisite parameters to accomplish the intent and provide a reply [50]. We obtained event and sensor data from external systems via API calls to incorporate them into a response. Unboxing videos (OWEs) highlighting the Amazon Echo demonstrate its simple setup and instruction manual. The sample data indicates that OWEs do not engage with the EUAs and may even actively dissuade observers from doing so.

Because they instruct users to disregard and forfeit the voluntary agreement with Amazon, OWEs contribute to the domestication process. By prioritizing the device's packaging and assembly while disregarding the potential repercussions on user consent to Amazon's end-user agreements and surveillance affordances, these OWEs contribute to the Amazon Echo's mainstreaming. Opinion workers inspire trust in technology by implying that it will operate as advertised to the general public. In response to apprehensions regarding customer privacy, Amazon has incorporated several privacy affordances into the Echo, including a voice profile service and a mute button. Following the revelation in a recent privacy violation that Amazon employees manually review speech recordings obtained from Amazon Echo devices, it is imprudent to place complete trust in the company. Even though the technology is perceived as an invasion of privacy, OWEs cultivate a dialogue during domestication that develops trust in the device and the Amazon brand.

V. Conclusion

Our aim in undertaking this survey was to furnish a succinct overview of the literature concerning DL-based TEA solutions for the benefit of future researchers. We commenced by covering foundational subjects, including emotions' classification, inherent characteristics, rudimentary deep learning methodologies, and pre-training strategies. After reviewing the relevant literature, we assessed the efficacy of studies that utilized various DL techniques. The findings of this survey were effectively utilized in developing performance-enhancing DL-based emotion analysis models. Extracting sentiment from text is intriguing because social media users must adhere to a standard writing style or language when posting. We develop a system capable of performing sentiment analysis on text by translating into the language of a fuzzy inference system several recently discovered algorithms that produce exceptional results. Despite being contrasted to alternatives that utilized the default parameters, the proposed method exhibited superior performance. Adaptations can be made to the proposed method to utilize data from various domains. The suggested approach can process enormous quantities of data with minimal to no instruction. A technique that does not necessitate training would be optimal, particularly for continuously expanding datasets.

Because of Alexa, how people interact with digital assistants has been transformed. Customers can control their smart residences, make phone conversations, and conduct online purchases using voice-activated devices such as those found in the Amazon Echo line. We describe the few vulnerabilities we discovered in Echo devices and how to patch them in this research paper. The principal aim of this investigation was to compile an exhaustive inventory of all the susceptibilities present in Amazon Echo. Furthermore, we hope to gain further insight into the device's network behaviors by examining the Amazon Echo's network traffic data. Ultimately, further research that employs machine learning models to analyze network activity thoroughly may uncover limitations or validate present findings.

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