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A Survey of Surveys (SoS) on Sentiment Analysis using Machine Learning

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Abstract— This paper presents a comprehensive Survey of Surveys (SoS) on sentiment analysis using machine and deep techniques. Although several survey studies have been conducted in this domain, the absence of a centralized and structured synthesis makes it difficult for researchers to identify trends challenges, and research opportunities. To address this gap, this study systematically reviewed 70 papers categorizing them based on application domain such as fake news detection, hate speech detection, sarcasm analysis, context based, and content-based sentiment analysis. Unlike other surveys, the work provides a meta level analysis by comparing existing surveys, identifying methodological patterns, and highlighting their limitation. We present a structured taxonomy of sentiment analysis approaches, alongside an examination of the evolution from classical machine learning to deep learning techniques. In addition, recent advances such as transformer-based architecture and large language models are discussed to provide updated context. In addition, this study identifies key challenges, including data imbalance, domain adoption, multimodal complexity, and lack of standardized evaluation frameworks. The SoS serves as a comprehensive reference for researchers by consolidating existing knowledge, identifying research gaps and suggesting future research directions.

Keywords— Natural Language Processing, Machine Learning, Deep Learning, Sentiment Analysis, Multimodal, and Multi-task learning.

I. INTRODUCTION

The rapid growth of digital communication platforms has led to an unprecedented increase in user generated textual data. This development has intensified the importance of Natural language processing (NLP) as a key area within artificial intelligence for extracting meaningful insights from unstructured data ([1], [3]-[13]). Among the various application of NLP, sentiment analysis has emerged as a critical technique for identifying and interpreting opinions, emotions, and attitudes expressed in both textual and visual content [6]. Sentiment analysis, also refers as opinion mining plays a vital role in numerous domain such as business intelligence, social media analytics, political forecasting, and customer relationship management [11]. It enables organization and researchers to analyze user feedback, predict trends, and support decision making processes [15]. Over the years, machine learning, deep learning, and transformer-based techniques have significantly enhanced the performance of sentiment analysis systems, enabling more accurate and scalable solutions.

Due to the rapid advancement of this field, a substantial number of survey and review papers have been published each focusing on a specific aspects such as algorithms, applications, or data set. While these surveys provide valuable insights, the increasing volume of review studies has created a new challenge: the difficulty of identifying, comparing, and synthesizing survey contributions. Despite the availability of numerous surveys on sentiment analysis, there is currently a lack of a comprehensive meta-level study that systematically analyses and compares these surveys papers. Existing works primarily focus on the individual techniques or domain, without providing a unified perspective on the overall research landscape. This create a gap for a higher-level synthesis that can consolidate findings, identify trends, and highlight open challenges.

To address this gap, this paper presents a Survey of Surveys (SoS) on sentiment analysis using machine learning, unlike traditional surveys, this study focuses on reviewing and analysing existing survey papers and structured overview of prior survey efforts, enabling researchers better to understand the evolution, strength, and limitation of the field. The main contribution of this paper is as follows: I. A systematic collection and analysis of survey of surveys on sentiment analysis using machine learning, II. A structured taxonomy of sentiment analysis approaches based on application domain methodologies, III. A comparative analysis highlighting trends, strengths, and limitations of existing surveys and IV. Identification of key research challenges, and future directions, including emerging approaches such as transformer- based models and large language models. Recent advancement in large language models as GPT-4 [97] and LLaMA [27] have significantly transformed sentiment analysis research, enabling improved contextual understanding and performance across various NLP task.

The remainder of the papers is organized as follows: Section 2 describes the research methodology adopted in this study. Section 3 presents machine learning techniques used in sentiment analysis. Section 4 discusses open challenges and future directions. Finally, section 5 concludes the paper. Due to the rapid advancement in this field, a substantial number of surveys on sentiment analysis, there is currently a lack of a comprehensive meta-level study.

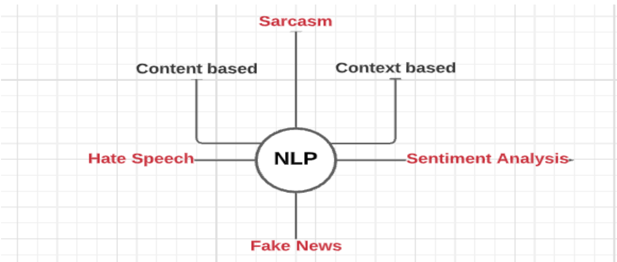

Fig. 1 Conceptual framework for NLP

Figure 1 presents the conceptual framework of natural language processing and its related components, including sentiment analysis, hate speech detection, sarcasm detection, and fake news identification. The figure highlights the interconnected nature of these domains, demonstrating how sentiment analysis operates as a central task within NLP ecosystem.

This framework provides a foundational understanding of how different analytical tasks contribute to extracting meaningful insights from textual data, thereby justifying the scope of this study. Unlike traditional survey compilations that primarily list and categorize prior studies, this work goes beyond descriptive summarization by providing a comparative and analytical synthesis of existing survey papers.
Specifically, the study evaluates methodological trends, identifies common limitations, and highlights research gaps across different survey contributions. This analytical perspective distinguishes the present work as comprehensive Survey of Surveys rather than a simple aggregation of prior studies

II. Research Methodology

This study adopts a structured review methodology to systematically identify, analyse, and synthesize existing survey papers on sentiment analysis using machine learning. The approach is inspired by established systematic literature review guidelines, including PRISMA principles, to ensure transparency, reproducibility, and minimization of bias. The review process consists of four main stages: (1) Search strategy, (2) study selection, (3) data extraction, and (4) analysis and synthesis. A comprehensive set of survey papers was systematically identified and analysed based on predefined inclusion and exclusion criteria. The survey adopted the procedures given by [81] for systematic literature review and surveys in computing, and [84] to serve as the research guide.

A. *Search Keywords*

The most keywords used for search benchmarks in this paper are (“Machine Learning”), (“Deep Learning”), (“Natural Language Processing”), (“Deep Learning” AND “Sentiment Analysis”), ((“Machine Learning”) AND (“Natural Language Processing”) AND (“Sentiment analysis” OR “Opinion Mining” OR “Sarcasm”)), ((“Fake news” OR “Hate speech” OR “Context based” OR “Content” AND “Natural Language processing”)). Many key words were initially generated to get insight about the research and were later concentrated in order to achieve the main purpose of the entire research.

B. *Search article results*

During the search era journal articles, edited books, and conference proceeding were search using the key words from the previous section 2.1, the initial search was conducted from 3rd July to 30th July 2021, the second search was conducted between October to November 2021, and the final search has been conducted in November 10, 2021. The nominated papers were scrutinized and also studied to (1) Define NLP and SA with regard to their types and distinction, (2) Identify and give details of NLP taxonomy, (3) presents the challenges of SA and recommend the alternative future direction.

C. *Academic databases*

The emphasis was on papers from reputable publishers such as IEEE, Elsevier, MDPI, Nature, ACM, and Springer. We have reviewed article journals on various SA, ML, NLP, and DL topics. The papers were engendered based on the keywords in the above section of 2.1; the goal of this review is to retrieve papers from reputable and reliable conference proceedings, journals, and edited book chapters indexed within reputable data bases. Table 1 shows the listed the academic data bases visited to source and retrieve articles.

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TABLE I
THE SOURCES AND DATABASE LINKS FOR PAPERS EXTRACTED FOR THIS STUDY

Database	Database link
IEEEXplore	http://ieeexplore.ieee.org/
ACM Digital Library	http://dl.acm.org/
Springer	http://www.link.springer.com/
ISI Web of Science	https://apps.webofknowledge.com/
Scopus	https://www.scopus.com/
Science Direct	http://www.sciencedirect.com/
DBLP	http://dblp.uni-trier.de/
Wiley Online Library	http://onlinelibrary.wiley.com/

D. *Inclusion and exclusion measures*

In order to have the rightful and eligible articles from this data bases, a certain criterion was set and observed (see Table 2).

Initial search of 1026 papers were retrieved, firstly we removed duplicate from the initial search generated from the academic bases to have the new total as 867, secondly abstract and conclusion were considered to remove and eliminate articles to directly related to the research. And finally, a total number of 74 references have succeeded in becoming eligible for the survey. Figure 2 represents and identified the process adopted in this literature for article selection

TABLE III
THE INCLUSION AND EXCLUSION MEASURES

Inclusion	Exclusion
We only consider papers written in English language.	We do not consider articles that are not written in English language
We considered papers published in reputable peer review journals, conferences and edited books.	Articles published as thesis, editorials, keynote speeches, abstract, and text book were not considered
We considered articles with the application of NLP to machine learning	NLP applications in other domains were not considered
The review focus on the survey papers in NLP	Any paper that does not cover NLP was eliminated

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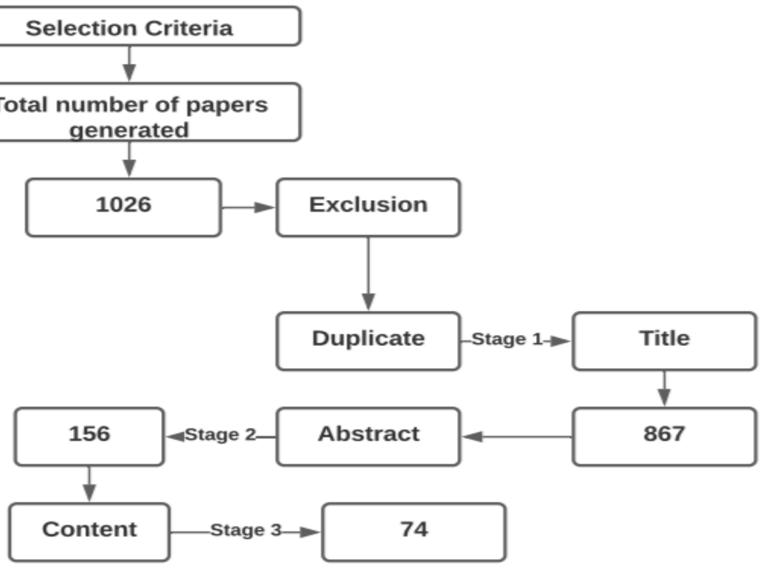

Fig. 2 Article exclusion procedures

III. MACHINE LEARNING ALGORITHMS

Machine learning plays a central role in sentiment analysis by enabling the automatic classification of textual data in to sentiment categories. Existing approaches can broadly be categorized in to shallow learning and deep learning techniques. While Shallow learning methods rely on handcrafted features, deep learning approaches automatically learn feature representations from data.

Over time, sentiment analysis has evolved from traditional machine learning models to deep learning and, and more recently large language models which offer improved contextual understanding and performance ([21]-[55]). This section provides a concise overview of these techniques, focusing on their relevance and application in sentiment analysis.

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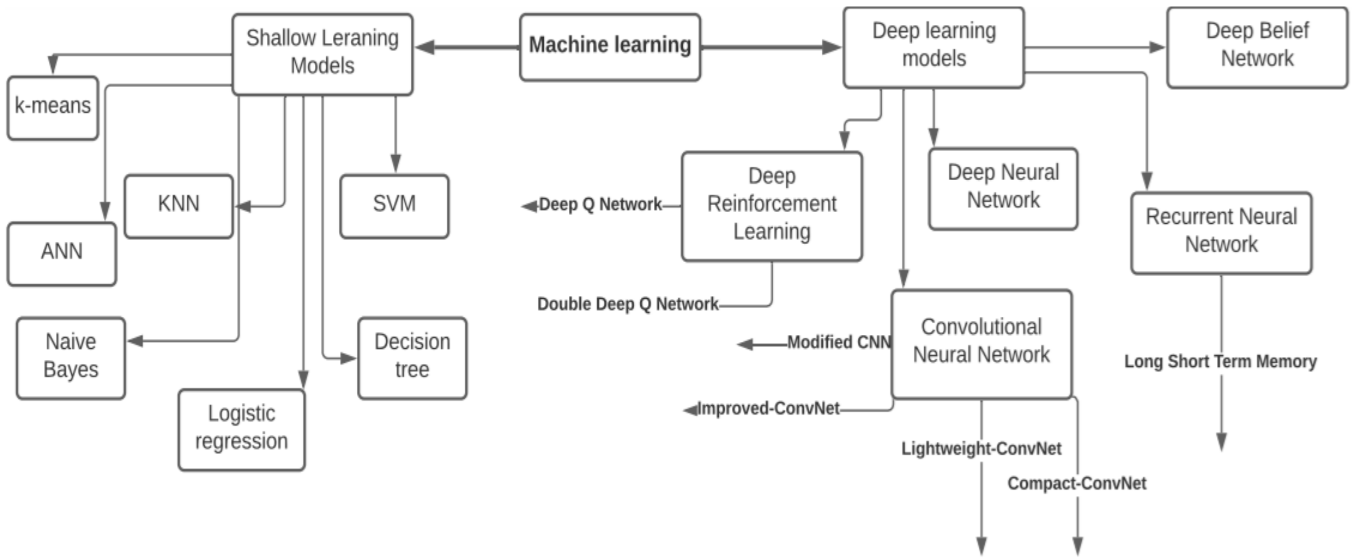

Fig. 3 Taxonomy of Machine learning architecture

Figure 3 illustrate the taxonomy of machine learning techniques in sentiment analysis, categorizing them in to shallow and deep learning approaches. This classification is significant as it highlights the evolution from traditional models such as Support Vector Machines and Naïve Bayes to more advanced deep learning architectures. The figure also emphasizes the increasing complexity and capability of models in handling large scale and unstructured data. A key insight from the figure 3 is the key insight is the increasing shift toward deep learning techniques, which offer improved performance due to their ability to capture contextual and semantic information. These trends reflect the growing demands for more robust and scalable sentiment analysis solutions

A. Shallow learning

Shallow learning methods were among the earliest approaches used in sentiment analysis and remain relevant due to their simplicity and computational efficiency. Common techniques include

K-nearest neighbour (KNN), neural network (ANN), support vector machine (SVM), logistic regression (LR), decision tree, clustering, naïve Bayes and joined hybridize approaches. Most of these approaches were considered some decades ago and their method is established [51]. These models rely heavily on feature engineering techniques such as n-gram, term frequency-inverse document frequency (TF-ID), and lexical features. Despite their limited effectiveness in structured environments, their performance is often limited handling large scale and context dependent data. Nevertheless, recent studies show that shallow models are still useful in low resources and domain specific application where computational constrains exist [42].

Artificial Neural Network (ANN) is an example of shallow learning algorithms and the intention is to reflect the way human being brain is working. ANN is made up several layers both input and output respectively. There is full connection between links at adjacent layers containing large amount of data that can tentatively estimate arbitrary meanings. Whenever it comes to nonlinear functions ANN poses resilient fitting capability. Out of the complexity in ANN structure, it ingests a lot of time while training data. It is worth noting that ANN model is being trained with back propagation there by making it impossible to be used in training deep networks algorithms.

K-Nearest Neighbour (KNN) is an easy and simple supervised shallow learning algorithm aimed at solving regression and classification related problems, the main focus of KNN is based on the multiple theory and hypothesis. The major problem of KNN is that it's very slow and insignificant with large amount data. Also, to note, that the easier and simpler the method is the infective and inefficient the fitting capability will be.

Support Vector Machine (SVM) is another example of supervised shallow learning algorithm used for the purpose of regression, classification and outliers' discovery. SVM memory is proficient in achieving acceptable results even with small amount of training sets. This is because splitting hyper plane can be determined by small amount of support vectors. It's worth noting that SVM can be used in solving nonlinear difficulties effectively

K-Mean clustering is a process of vector estimation, initially from indication process, that target to divide n observations into k clusters.

Decision Tree is to classify data using sequence of regulations, the technique is similar to a tree procession, and these make it to be understandable. The algorithm is

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capable of eliminating redundant and inappropriate features. Feature selection, tree generation, and tree snipping are amongst the learning process, appropriate features are selected independently before generating subsequent child nodes.

Naïve Bayes is an artless technique mainly used for classifiers construction. Naïve Bayes models is used to allocate class labels to difficult occurrences, characterized as vectors of feature principles, the Naïve Bayes classifier computes the provisional possibilities for dissimilar classes.

Logistic Regression the LR is another type of logarithm type of shallow algorithms with linear model. The LR algorithm calculates the chances of diverse classes via parametric logistic dissemination.

B. *Deep learning*

Deep learning approaches have significantly improved sentiment analysis by enabling automatic feature extraction from large and unstructured datasets. Prominent architectures include Convolutional Neutral Networks (CNN), Recurrent Neural Network (RNN), and Deep Neural Networks (DNN) (see Table 3).

TABLE III
COMPARISON BETWEEN SEVERAL DEEP LEARNING TECHNIQUES

Algorithms	**Function**	**Supervised/ Unsupervised**	**Data types**
CNN	Feature Classification and Extraction	Supervised	Feature vectors, Raw data and Matrices
DNN	Feature Classification and Extraction	Supervised	Feature vectors
RNN	Feature Classification and Extraction	Supervised	Feature vectors, Sequence data and Raw data
DBN	Feature Classification and Extraction	Supervised	Feature vectors
DRL	Feature classification and augmentation	Supervised	Feature vectors

Unlike shallow learning methods, deep learning models capture contextual and semantic relationships within text making them more effective for complex sentiment analysis task such as sarcasm detection and multimodal analysis. These approaches have demonstrated superior performance across various benchmark datasets ([41], [55] - [96]). However, deep learning models require large annotated datasets and substantial computational resources, which may limit their applicability in low resource settings. The evolution from shallow learning to deep learning techniques highlights the increasing capability of sentiment analysis models. Deep learning is agreed to have gained an ideal reputation because of the innovation in computational capability, with the advent of graphics processing unit (GPU), it reduces the amount spent in hardware and has enhanced and upgraded network connectivity with robustness in result.

C. *Transformer-Based Models in Sentiment analysis*

Recent advances in NLP have been significantly influenced by the introduction of the Transformer architecture, which enables efficient modelling of contextual relationships in textual and visual data. Transformer based models heavily rely on self-attention mechanisms to capture long range dependencies, making them highly effective for sentiment analysis task. Pre trained languages such as BERT have achieved state of the art performance across various NLP applications, including sentiment classification. These models leverage large-scale training data and transfer learning technique techniques to improve generalization and accuracy. The emergence of transformer-based approaches represents a significant shift in sentiment analysis research. Therefore, these models are highlighted as an important direction for future research and extension of existing survey of surveys. Recent studies demonstrate that large language models outperform traditional deep learning models in sentiment classification task providing improved contextual representation and generalization capabilities. This revision incorporates recent studies published between 2023 and 2025 to ensure the timeliness and relevance of the review.

Convolutional Neural Network (CNN) is among deep learning techniques examples developed for processing visual data such as videos and images among others. It is capable of handling visual data, audio data and text data respectively no matter the amount data [41]. CNN executes well whenever used in processing images more specific to image detection, classification recognition, and computer vision. In CNN input data must be transformed in to matrices for detection of attacks as CNN only works with two-dimensional data. Deep Neural Network (DNN) is a deep learning architecture generally adopted in dealing with classification and regression related problems. It is formed in hierarchical layers each layer having number of neurons [41].

Subsequent layers gradually learn any composite patterns from the received input in preceding layers. Every unit in DNN requires current and previous state in order to obtain contextual information, supervised and unsupervised learning techniques can be used to train data in DNN. Supervised learning methods uses labelled data to train DNN in order to learn for accurate prediction. While the unsupervised learning, method do not require labelled data to train DNN and are commonly used for clustering and future selection.

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Recurrent Neural Network (RNN) is powerful algorithms ordinarily adopted and used in NLP for dealing with sequential and serial data problem that are normally characterized as contextual [85]. The sentence level representation can be used to create concluding classification for a particular input sentence. The vector of node "very interesting" is composed from the vectors of the node "very" and the node "interesting." Similarly, the node "is very interesting" is composed from the phrase node "very interesting" and the word node "is". The edifice of an RNN is depicted in

Deep Belief Network (DBN) is a multiplicative algorithm with quite a lot of layers. Every layer considers conspicuous units as an input and considers hidden units as an output. Each layer is coupled and connected to one another. Therefore, the detectible units are totally associated with the unseen units without any interconnection between the two [41]. In most cases upper layers have subsidiary contacts between them, however subordinate layers require straight and top-down assembly with the upper layers [6]. In general, there is direct connection between additional layers with the flow directing to the layer that is closer to the input. As a result, the connections between the two leading layers remain undirected.

Deep Reinforcement Learning (DRL) is a semi supervised algorithm that uses unlabelled data for input in order for the algorithm to study and acquire feature demonstration of the data. Cultured features will be later used in supervised learning task. The need for regulatory dataset is not required. For example, an agent will study and learn to finish a task through testing and getting errors. Thus, DRL uses examination and manipulation to take decision. In manipulation, action is taken based on recent best policy. Examination deals with taking action purposely to gain additional training data. The major challenge in DRL is trade-off has to be made between exploitation and exploration.

IV. Sentiment Analysis Epitome: Conception and Taxonomy

The rapid development of smart devices with the introduction of web 2.0 has led to the advent of social media network, forums, and blogs and has enabled users to take part in sharing their opinions explicitly over these platforms [29]. In consequence, the messages posted by users can reach to a giant spectator in a segment of minutes [72]. Sentiment analysis sometimes refers as Opinion mining is deliberated as an effective method or approach for categorizing and organizing user assessments into positive and negative polarities. However, sentiment analysis can be further classified into lexicon-based methods, machine learning methods and hybrid approaches. Furthermore, the main data source in sentiment analysis is from online social media, it generates considerable amount of data. Moreover, this kind of information must be considered and carefully measured using immense data approach in order to achieve effective and efficient data access, processing and storage for a better result.

A. *Taxonomy of sentiment analysis architecture*

The taxonomy of the sentiment analysis architectures has three architectures: Lexicon based, Machine Learning based, and Hybrid based approach. Several architectures have been proposed for the Sentiment analysis and the trending structures f will be discussed as follows:

Lexicon based is the first approach to be used in sentiment analysis, the approach is classified in two distinct categories namely corpus based and dictionary based that uses arithmetic or semantic procedures to discover sentiment polarity [60]. Formerly, sentiment classification is done through dictionary such as WordNet and SentiWordNet [29].

Machine learning based approach depends on the prominent ML algorithms in order to solve sentiment analysis as an ordinary text organization with difficulty using phonological features [85].

Hybrid based approach is the combination of the two approaches and demonstrates to corporate with sentiment lexicons playing a key role in the majority of methods. Therefore, [45] reports the hybridize experiment carried on Lithuanian data set using machine learning (Naïve Bayes Multinomial, Support Vector Machine) and deep learning (Long Short-Term Memory, Convolutional Neural Network) approaches. Similarly, the ordinary machine learning techniques were applied to feature based lexical, morphological, and character information and the deep learning approaches were applied to the word embedding (Vord2Vec continuous bag-of-words with negative sampling and FastText).

The taxonomy of sentiment analysis approaches, includes lexicon based, machine learning based, and hybrid methods. The taxonomy is important as it enables a comparative understanding of different methodological approaches and their respective strengths and limitations. The taxonomy also reveals a growing trend toward hybrid and data driven models, indicating a shift away from purely rule-based systems. This insight supports the need for more robust and integrated approaches in the future research.

1) *Aspect based sentiment analysis*

Aspect based sentiment analysis usually refers to feature based or entity-based sentiment analysis. It involves aspect identification in a given sentence for classifying its features to either negative or positive and will be later categorized in to diverse polarities ([4], [94]-[95]). Aspect-level SA is to categorize the sentiment with esteem to the precise aspects of entities. The first stage is to detect the entities with their

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respective aspects. Moreover, aspect level classification is one of the areas that needs attention as far as NLP is concern ([16], [47], [94]-[95]). Thus, aspect level sentiment analysis is cantered on a short text semantic richness and has been reflected to be one of the most promising research directions in the future ([66], [69], [70]-[78]). However, abundant machine learning frame work has been developed to solve aspect-based problem but deep learning techniques could also be employed in order to have more accurate results ([48]-[75]).

Similarly, Deep learning has achieved quite number of success in the field of aspect based and have proved productivity in application fields such as economics, products, biomedicine, and in policy making by both private and public agencies ([40],[94]–[95]). Consequently, RNN achieved the highest result as compared to other techniques, therefore the performance of deep learning-based models on the aspect level sentiment classification is quite a challenge that needed much more efforts to be solved [54]. Whereas LSTM is one of the most commonly used tools for aspect based sentiment analysis [85], employing deep learning in aspect based sentiment analysis is still in the early stage.

Therefore, a better performance could be achieved by joining extraction and classification of aspect with classification and sentiment. Common approaches used in aspect sentiment analysis include CNN, LSTM, and GRU [31]. Finally, applying deep learning approaches in aspect based will provide a better result in getting the most comprehensive research in sentiment analysis [23]. The central objective of aspect-based classification is to discover the sentence and assume sentiment conveyed in each aspect

2) Sentence based sentiment analysis

Sentence based sentiment aims at classifying user's opinion conveyed in each and every sentence. The first stage is to identify if the sentence is subjective or objective. If the sentence happens to be subjective, therefore sentence based will determine if the sentence expresses positive or negative opinion ([58]-[85]). For example, *"I have a beautiful wallet"* indicates positive polarity on wallet and is measured as subjective statement and so can be categorized in to several polarities.

Therefore, genuine statements are considered as objectives, for example *"The laptop is silver in colour"* presents reality with no sentiment and is classified as objective statement. Furthermore, several approaches were proposed to solve sentence-based problem, thus the realization of these approaches depending on their applications and primary domain in which they were employed makes it very difficult to standardize and evaluate the methods in order to understand the best among them [67].

3) Document based sentiment analysis

Document-level SA organize an opinion in a document by expressing a positive or negative opinion polarities. Document level ruminates the entire document as a simple information unit. Therefore, it becomes difficult and tasking to extract different sentiment about dissimilar entities independently [85]. Several applications such as Recurrent Neural Network, Convolutional Neural Network and Hybrid Neural Network are widely used to solve the document sentence-based sentiment classification, and have performed well with document level sentence [54].

Hausa WordNet (HWN), a lexical resource for Hausa language was developed, which extracts knowledge from a conservative Hausa dictionary and accepts the structure of Hindi and English WordNet as it groups words based on different categories [2].Traditional approaches are insufficient and inadequate to solve the persistent problems of opinion mining, therefore, for effectiveness a proposed model has been proposed for contextual feature incorporated with n-gram graph and many process for enhancing efficiency [19].

4) Multimodal sentiment analysis

Multimodal this is one of the evolving research directions in sentiment analysis where sentiment from videos, text, images, audio data are mined using verbal and non-verbal manners. There are quite number of customary datasets for multimodal sentiment analysis such a, YouTube, ICT-MMMO, MOUD and CMU-MOSI. "Ref. [39]" performed a review on computational methods in multimodal sentiment analysis to outline a number of researches in the field and prove how multimodal approach (textual, visual, and audio data) behaves and performs better than the traditional unimodal approaches., Similarly, together with textual review, facial and vocal expressions of multimodal approach can assist in identifying sarcastic review. DAM approach was developed for forming feature level tasks with attention device for multi-domain classification, the model was made up of two distinct segments namely; sentiment section and domain section [85].

DAM model proves to perform well for multimodal sentiment analysis when compared to machine learning approaches. Box office prediction, Stock Market prediction, Business Analytics, TV Program and News summarization, Recommender systems, politically trend prediction are all among the different application of multimodal sentiment analysis. With the rapid development in technology, individuals are geared towards audio, images, videos to indicate their opinions [8]. Therefore, several researchers

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define and express opinions or sentiment in different customs. Formerly, the text has been measured as the major key to express view which is referred as unimodal. However, multimodal sentiment analysis is the process of adopting and using multiple techniques to detect the sentiment or opinion. Henceforward, researchers are therefore concentrating on this new direction for cultivating the sentiment analysis procedure.

5) Multi-domain sentiment analysis

Multi-domain sentiment analysis focuses on a set of different documents that can be related to a particular topic, the main aim of multi-domain is to transfer information from one domain to another domain. The model will be first trained in the initial or basic domain and will later be transferred to a different domain [85]. Several researches have been conducted on multi-domain sentiment analysis where [58] provided a report on sentiment analysis related fields such as emotion detection, building resources and transfer learning. "Ref. [78]" also performed a multi-class sentiment analysis with deep learning techniques (DAM) on amazon product review data. However, DAM was proposed for forming the feature-level tasks by means of attention device for multi-domain sentiment classification [85]. Finally, Transfer learning is a process of extracting information from secondary domain to increase the learning procedure of a targeted domain [58].

B. Sentiment datasets

Researches that employ sentiment analysis can either generate data by i. generating a virgin data that fits the problem formulation and ii. using available standard data set. The main problem is extracting a label data set which is a daunting and challenging as far as sentiment analysis is concern. Therefore, researchers need to judiciously choose data set that will be accepted by research community, data set that is accessible and available. This is a publication requirement in some journal act and regulation. It is worth noting that there is insufficient amount of benchmark data set to be used in the meadow of sentiment classification [58]. Example of some standard and frequently datasets used are SemEval 2014, SemEval 2015, SemEval 2016, Twitter, Sentihood, Mitchell [94].

Fig. 4: Machine learning techniques used

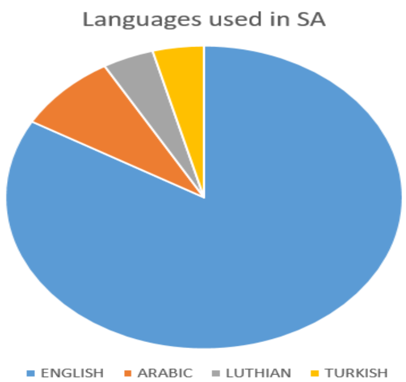

Fig 5: Language used

The Figure 4 above depicts the algorithms used and adopted in the survey paper reviewed, and Figure 5 depicts language representation of the survey conducted in this research. As such it is worth mentioning that most of the researches conducted is in English language, therefore it is important for researchers to consider other languages in order to have the best and exact sentiments of different personalities.

C. . Natural Language Processing Taxonomy

Question: What are researches conducted using machine learning to solve problem in NLP? We presented the different categories of NLP that employ machine learning algorithms to solve NLP problem. Figure:6 depicts the

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taxonomy of the natural language processing in machine language. The taxonomy presents NLP and it is categorization with respect to machine learning algorithm. The proceeding Figure 6 depicts the NLP taxonomy with several sub categories within the NLP family.

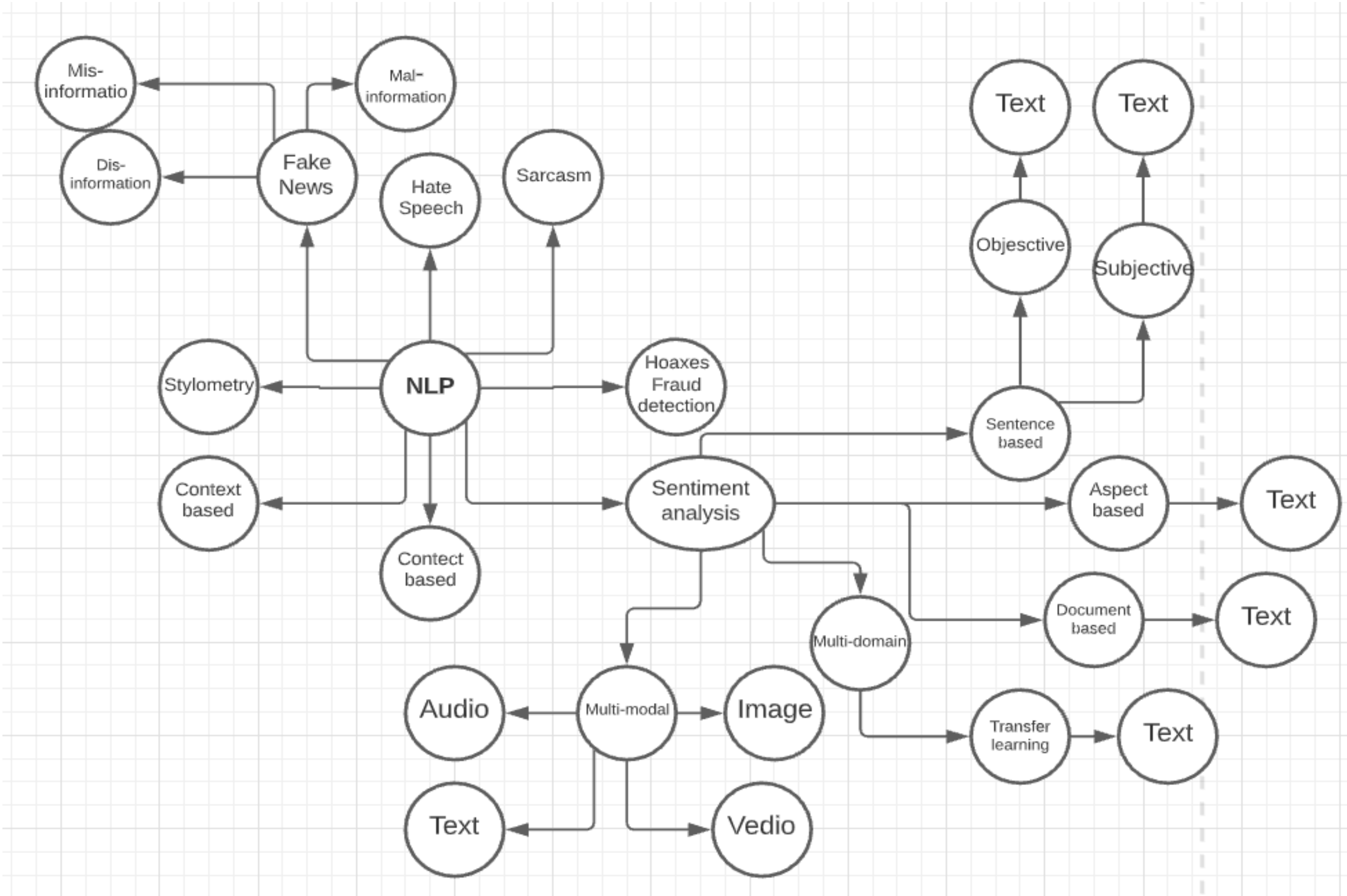

Fig 6: Taxonomy of the natural language processing in machine language

Figure 6 summarizes the relationships and trends observed across the reviewed survey papers. It provides a comparative overview of the focus areas, methodologies, and application domains addressed in existing studies. This figure supports the identification of research gaps and reinforces the need for a comprehensive Survey of Surveys. To ensure clarity and consistency throughout this study, standardized terminology is adopted for sentiment analysis categories. Specifically, “Content-based sentiment analysis” refers to approaches that analyze the textual content itself without external context. “Context-based sentiment analysis” considers surrounding contextual information such as behaviour or situation factors. “Multi-domain sentiment analysis” refers to models trained and evaluated across multiple application domain to improve generalization. This standardization ensures consistency in interpretation and improves the clarity of the taxonomy presented in this study.

1) Hate Speech

Online Hate speech is a communal way of expressing prejudice and aggression which is categorized in to three levels namely; religious, racist and gendered hate speech, in most cases tribe and racist have their own interpretation on cyber bullying, therefore each community is expected to work accordingly for intervention to eliminate such acts [9]. Also, a survey was conducted to presents a holistic view on the all the approaches, containing methods and basic algorithms used, the study also analyses the complication of conception in hate speech that has been define in several context and platforms, and offers cleaving definition [34]. Thus, social network platforms spend considerable amount of Euro to stop this act, but are still being condemn for not doing sufficient [93]. Additionally, corpus was introduced to be used for training and testing sentiment analysis systems, the researcher’s with effort from academia and industries are needed be applied in order to achieve this goal, the current contribution in the recent researches is mainly in designing whereas trying a novel schema for hate speech will be of great advantage [65]. Following the increasingly growing body of social media content the amount of online hate speech is growing on daily basis, this study is on NLP approaches focusing on feature extraction in particular in order to provide a holistic view to researchers that are new in the field of hate speech detection and want to have body knowledge in the state of the art in the trending and upcoming field [73]. Thus, most of the techniques are completely intended for common languages such as English, French, and Spanish and this serve as the major drawback of NLP nowadays, therefore, other language such as African languages and Arabic has a major challenge in using the available tools because of their peculiarities [9].

Furthermore, online hate speech is a common way of expressing prejudice and aggression among people [9]. Similarly, cyber hate is growing on a daily basis following the increasingly rising body of social media content [73]. Its growth has forced social media platforms to spend considerable amount of money to end the act, however their efforts are still being condemn as insufficient [93]. Also, survey conducted by [34] has concluded on the lack of studies and publication in automatic hate speech detection from a computing domain. Additionally, recent studies have looked into automatic hate speech detection and found out that: Deep Neural Network (DNN) structures are very effective feature extractors for detecting specific types of hate speech [93]. Finally, automatic cyber hate detection is challenging probably due to the fact that different tribe and racist have their own interpretation and characteristics of cyber hate [9].

2) *Fake News*

Fake news can be defined as an information that is deliberately false and has been broken down in to three distinct categories namely: mal-information, misinformation and disinformation [33]. Although, the enormous development of internet has urge for rapid spread of information of any kind, people are using this information without giving emphasis on it is credibility [22]. Globally, fake news dissemination is one of the major issues to both public and government sectors that raises incredible cause for alarm to researchers and academia, since people are using the internet space for disseminating information for one reason or the other [35].

Therefore, fake news detection is considered one of the most dangerous types of deception in recent time. The spread of fake news, fake reviews, fake advertisements, fake speech, misleading content and rumours has raised an important cause for alarm in the social media space. Since the use of social network has increased the spread of false content than mainstream media therefore, fake news identification and detection in social media platforms is among the most challenging task to be considered [71]. Thus, disseminating fake news and misinformation online is very easy and fast, the main challenge is in finding methods for identifying and detecting the difference between actual and false news online [64]. Moreover, inadequate consensual information can mislead user's opinion; therefore, machine learning and deep learning are referred as the best suited methods for handling problems of fake news, rumours, and misinformation [26].

Despite numerous prevailing computational solutions on fake news detection, however, lack of comprehensive remain a core barrier in the field [22]. However, with the recent development in technology, use of social media to gather, share and disseminate information has become a woven adore, people consume information from social media platform more than the traditional method as a result it has become an advanced repository of sharing and disseminating fake news and misinformation of any kind [74]. The effect of fake news has been extremely increasing, so often extending to the offline realm and intimidating public safety [63]. Social media platform has played a substantial role in portraying user's decisions and opinions in choosing or assessing a particular product, so often E-Comers customers' uses online review as their main source of getting insight about any product they intend to buy.

Therefore, product reviews and customers feedback are not the only ways opinion spam exist, misleading news and fake news is an additional form of opinion spam, the study proposed fake news detection approach using n-gram analysis via the lenses of possible feature extraction techniques, and examined two different feature extraction models with six diverse machine learning approaches [5]. Their model achieves its highest accuracy whenever uses linear SVM classifier and n-gram features.

Another study proposed end-to-end framework referred to as Event Adversarial Neural Networks (EANN) for fake news detection that is basically on multi-modal features and incorporate the event discriminator to predict the event auxiliary labels to training stage [83]. A new approach for fake news detection was proposed which incorporates sentiment as significant feature to improve the accurateness of existing models [22].

Rumours, misinformation, and fake news spread on various internet platforms just like pure and authenticated news, it's often difficult and tasking for online users to differentiate between real and fake news in such platforms [24]. Finally, the doubtful nature of news distributed by social networks, and the determination of judging its authenticity raises the need for developing computational tool to guide and assist in automatic identification of such news and information online [56].

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3) Others in NLP

Deep learning and machine learning approaches especially neural network models have been identified to be one of the remarkable achievements in both sentence and document modeling in natural language processing ([46], [80]- [87]). Hybridization of some machine learning algorithm have harnessed the advantages of both algorithm as shown in the study of ([91], [92] -[93]). Also, language such as African and Arabic have challenges associated with the difficulty to adapt to available tools for feature extraction due to differences in dialect and acoustics among others.

Moreover, [2] developed a lexical resource for Hausa language which can extract knowledge from a conservative Hausa Language dictionary and accepts a structure of Hindi and English WordNet. So also [1] developed a Hausa Language Words embedding model hauWE which is bigger and better than the existing model, making them more useful in NLP tasks. Subsequently, a recent SLR conducted and highlighted that quite a number of studies exist in sentiment analysis but there is potential research gap in the domain of sarcasm identification [30].

4) Open Challenges and Future Directions

Despite significant progress in sentiment analysis, several challenges remain unresolved:

1. Data Imbalance: several datasets suffer from skewed class distributions, affecting model performance.
2. Domain Adaption: Models trained in one domain often fail to generalize effectively to other domains.
3. Multimodal Complexity: Integrating text, audio, and visual data remains a challenging task and many deep learning models lack interpretability, making their decision difficult to understand.
4. Low Resource Languages: There is limited research on languages such as Hausa, and other African languages, therefore these languages are underserved by technology.
5. Lack of Standard Evaluation Frameworks: Inconsistent evaluation metrics hinder fair comparison across studies.

Therefore, future research should focus on addressing these challenges by developing robust, interpretable and scalable models

V. . Conclusion

This paper presented a comprehensive Survey of Surveys (SoS) on sentiment analysis using machine learning. By analysing existing studies, this work provides a centralized perspective on the evolution, methodologies, and research trends in the field. The study introduced a structured taxonomy and highlighted key differences among survey papers, offering valuable insights for researchers. A cross analysis reveals that most existing surveys focus on specific techniques or domains with limited efforts toward integrating multiple approaches. Furthermore, earlier surveys emphasize algorithmic performance, while recent works increasingly incorporate deep learning and transformer-based methods. However, a lack of standardized evaluation frameworks remains a consistent limitation across studies. Additionally, several open challenges were identified, emphasizing the need for improved methodologies, standardized evaluation frameworks, and inclusion of emerging techniques such as transformer-based models.

This work serves as a foundational reference for both novice and experienced researchers, facilitating better understanding and guiding research directions in sentiment analysis. This study moves beyond descriptive aggregation by providing a structured comparative analysis of existing survey works, enabling the identification of research trends, methodological gaps, and future directions in sentiment analysis.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHORS CONTRIBUTIONS

All authors contributed to the development of this manuscript

DATA AVAILABILITY

No new data were created or analyzed in this study. Data sharing is not applicable

ETHICS STATEMENT

This study does not involve humans or animal subjects

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