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A Big Data-Enabled Aspect-Based Sentiment Analysis Framework for Airline Twitter Analytics: A Systematic Literature Review

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Abstract— *Masses of unplanned, real time textual information have been generated due to the rampant growth of social media platforms, particularly relating to the customer base such as the airlines industry. The conventional sentiment analysis methods generally achieve document-level polarity and could not store detailed opinions on particular features of the service. To circumvent these limitations, this paper proposes an Aspect-Based Sentiment Analysis (ABSA) system with Big Data capabilities, which can be utilized to perform airline Twitter analytics. The proposed solution uses supervised machine learning models together with scalable big data solutions such as Apache Spark to analyze noisy fast moving tweets in real time. To result in meaningful information of specific airline services, including timeliness, baggage handling, crew demeanor, and in-flight service, the system tweets collection, preprocessing, negation-sensitive feature engineering, aspect, and sentiment classification. The proposed approach will assist airlines to track the customer satisfaction levels, identify service gaps, and facilitate the use of data-based decision making to enhance the overall level of service quality and customer experience through aspect-based sentiment data (in action).*
Keywords— *ABSA, Airline reviews, Twitter data, Big data, Hadoop, Spark, ML, DL, Weak learning,*

I. INTRODUCTION

The social media sites are emerging as one of the most effective methods through which consumers can express their thoughts, experiences, and expectations in the present digital age. Platforms such as Twitter generate a continuous stream of short, unstructured, and real-time textual information on the opinion of the people on goods and services. This data is a valuable source of information to customer-oriented companies such as airlines in understanding their operating weaknesses, passenger satisfaction and quality of services. Nevertheless, such a large number, volume, and diversity of social media data make manual analysis impossible and inefficient.

Sentiment analysis (SA), also known as opinion mining, is a natural language processing technique that automatically determines the emotional polarity of text material as neutral, negative, or positive. The traditional sentiment analysis methods are mainly focused on sentence-level or document-level classification. In spite of the fact that these techniques provide a sentiment score in general, they often are not sufficient to reflect consumer attitudes. One tweet can be loaded with different views on points that look at different elements of the service. An example is that a traveler can praise the attitude of the cabin crew and at the same time complain about delays of flights. Such opposing opinions cannot be sufficiently demonstrated with rough-grained sentiment analysis techniques.

Aspect-Based Sentiment Analysis (ABSA) is one of the advanced and elaborate strategies of tackling this limitation. ABSA identifies specific features or characteristics that are mentioned in the text and evaluates the sentiment that is related to each of the features individually. Some of the elements in the airline industry include punctuality, baggage handling, comfortable seating, customer service and in-flight facilities just to mention but a few. By assessing attitudes in detail, airlines are able to pinpoint certain areas in which they require improvement and gain a better insight into their customer expectations.

Even though machine learning and deep learning models have achieved vast progress in ABSA, several barriers still have to be resolved. Social media text is often short, outspoken, unprofessional, and replete with language asides such as emoticons, negations, sarcasm, and abbreviations. In addition, there is a need to have scalable and efficient processing mechanisms because of the constant and swift generation of tweets. These large, real-time data streams are too large to utilize single-machine sentiment analysis algorithms.

Apache Hadoop and Apache Spark Big Data technologies have become more popular in the research of sentiment analysis as a solution to these problems. These systems are a solution to the problem of how to handle large volumes of social media data because they have distributed storage and parallel processing facilities. ABSA algorithmic methods that are based on machine learning can significantly enhance the scalability, processing speed, and accuracy of analytics when used with Big Data platforms.

This paper introduces an Aspect-Based Sentiment Analysis system of airline Twitter analytics, which is facilitated by Big Data. The proposed solution leverages a scalable Spark environment, which integrates supervised machine learning-based sentiment categorization, aspect abstraction, distributed preprocessing, and data collection of Twitter. This study will aim at providing airlines with useful and detailed sentiment information that will support proactive decision-making, service optimization and maximized customer satisfaction.

II. RELATED WORK

Over the past few years, much attention has been paid to the development of automated systems of sentiment analysis and extraction. In order to improve the accuracy of sentiment classification, scholars have considered different lexicon-based, machine learning, deep learning, and hybrid methods. In the case of airline-specific social media streams there are no in-depth evaluations incorporating Aspect-Based Sentiment Analysis (ABSA) with Big Data systems.

On the basis of more than 29,000 tweets collected with the hashtag #Article370, Singh et al. [2] executed an empirical study of machine learning technique, either(supervised and unsupervised) or aspect-based sentiment analysis. In the case of supervised learning, they applied KNN, SVM, Random Forest, and Naive Bayes; unsupervised classification, they applied lexicon-based methods such as TextBlob, AFINN and Vader. As per their results, supervised classifiers yielded more accurate results; however, the framework was not extensible to real-time Big Data applications.

Haddad et al. proposed an intelligent sentiment prediction system that used deep learning with batch and streaming analytics of Big Data [3]. Their method showed the usefulness of combining semantics and deep learning to short text sentiment prediction by using convolutional and recurrent neural networks to process massive amounts of Twitter data.

To analyze and visualize Twitter real-time data to determine a disaster, Demirbaga introduced HTwitt, a Hadoop platform. Naive Bayes classification and MapReduce preprocessing were employed in the study that demonstrated how Big Data systems can handle high-speed social media streams.

For aspect-level sentiment analysis, Wang et al.[5]suggested a gradual machine learning paradigm that allows for automatic labeling without requiring a lot of manual labor. Several unsupervised baselines were outperformed by their framework, which included scalable progressive inference.

Jelodar et al.[8] used topic modeling and LSTM-based deep learning for sentiment analysis pertaining to COVID-19. In order to extract valuable insights from extensive user chats, their work highlighted the significance of coupling NLP with deep learning.

Al-Guribi et al.[9] introduced a hybrid ABSA method for large-scale unlabeled datasets that merged syntactic relation-based and frequency-based approaches. Their approach, which uses domain-specific lexicons, performed better on datasets from Yelp and Amazon.

More recent research has investigated transformer-based ABSA models , CNN-LSTM architectures, explainable machine learning for online reviews , and sentiment models based on graph neural networks . These studies show how huge language models and deep learning are becoming more prevalent. The primary driving force behind this research is the dearth of studies that incorporate these methods into scalable Big Data frameworks for real-time airline Twitter analytics.

III. RESEARCH PROCEDURE

This study aims to collect valuable information based on the most relevant research articles on opinion mining and sentiment analysis published in the last five years.Systematic literature review, as per, examines gaps between two or more studies that have been conducted in the course of a specific time period. A research protocol refers to a guideline that outlines many steps, which must be undertaken in a specific sequence. To select the most applicable research papers of high quality, this research uses an extensive process with a certain structure and limit lines. The most current review publications in the field of software engineering provided guidelines in this systematic literature review.

The following steps make up the research protocol or methodology for this study. (Fig. 1):

- Finding the research topic
- Choosing the query's string keywords
- Determining the search space
- Describe the selection criteria
- Extract literature using selection criteria
- Evaluate the extracted literature's quality
- Data synthesis and extraction
- Results presentation

Fig. 1. Steps of SLR

A. Research Questions

The aims of SLR are reflected in the research questions, which must be addressed throughout the critical evaluation of the most pertinent retrieved articles. The following lists the research questions for this SLR.

RQ1 What ABSA techniques have been applied to social media sentiment analysis?

RQ2 Which Big Data platforms are used for large-scale Twitter sentiment processing?

RQ3 What machine learning and deep learning models are used for ABSA?

RQ4 What are the major challenges and limitations in existing ABSA studies?

B. String Query and Search Space

A query string is a collection of chosen keywords that are used to get research articles from relevant libraries. The following list of keywords was taken from research question :
ABSA, Airline reviews, Twitter data, Big data, Hadoop, Spark, ML, DL, Weak learning,

The aforementioned key words complete the search query that follows.
("aspect-based sentiment analysis" OR ABSA) AND ("airline reviews" OR "airline customer feedback" OR "flight service sentiment") AND ("Twitter data" OR "social media") AND ("big data" OR Hadoop OR Spark) AND ("machine learning" OR "deep learning" OR transformer)
Searching the query multiple times with different keyword combinations was crucial. Results of search query along with some significant parameters can be seen in Table I.

TABLE I. SEARCH SPACE

Sr#	Digital Library	Search Scheme	Date Searched	Total Results
1	IEEE Xplore DL	Query Search	2025-06-05	80
2	ACM library	Query Search	2025-06-05	70
2	Elsevier	Query Search	2025-06-06	50
3	Springer	Query Search	2025-06-05	50

C. Selection Criteria

Utilizing specific selection criteria, the most pertinent literature is chosen for this section. IC (inclusion criteria) and EC (exclusion criteria) make up the selection criteria as well.

1) Inclusion Criteria (IC)

Inclusion criteria is formed with the following rules:

IC1: Papers published from year 2020 till 2024.
IC2: publications utilized in sentiment analysis.

IC3: papers that applied sentiment analysis to huge data.

IC4: papers that analyzed sentiment using different machine learning algorithms.

2) Exclusion Criteria (EC)
Exclusion criteria is formed with the following rules:
EC1: Papers which are not in English.
EC2: Papers published before 2020 or after 2024.
EC4: Papers that do not target sentiment/opinion/polarity analysis of textual data.
EC6: Papers that do not contain any results.

The shortlist only includes papers that are more relevant to the study subjects.Ninety of the most pertinent studies are located after using IC and EC. According to EC's definition, all other studies were eliminated.

D. Quality Assessment

Effective outcomes require adherence to quality evaluation criteria. To preserve the quality of this SLR, the following factors are taken into account.

- To locate pertinent study material, the best scientific libraries are choosen.
- To determine the highest quality , the most recent research articles were choosen.
- Selection procedure is impartial
- All Every SLR step—discussed above—is carried out in its purest form.

E. Data Extraction and Syntesis

Eight of the most pertinent research publications were shortlisted after using the search procedure (Fig. 2), as shown in Table II, where CP stands for Conference Paper.

TABLE II. MOST RELEVENT RESEARCH LITERATURE

Sr#	Digital Library	Type	Selected Papers	No. of Researchers
1	IEEE	J / C.P	[5], [6], [7], [8]	4
2	Elsevier	J	[4]	1
3	Springer	J	[2], [3]	2
4	De Gruyter	J	[1]	1

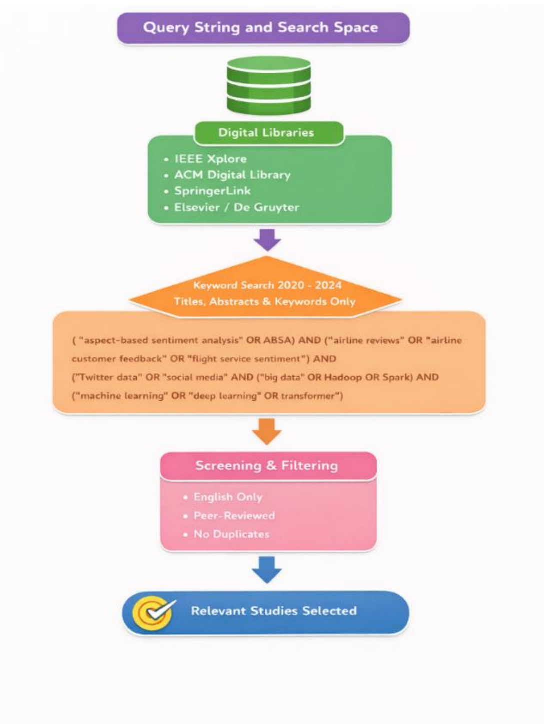

Fig.2. Search space

IV. LITERATURE ANALYSIS

A. Aspect-Level Sentiment Analysis based on Gradual Machine Learning

The work is based on an extension of the Gradual Machine Learning (GML) paradigm to introduce a new unsupervised framework of Aspect-Level Sentiment Analysis (ALSA) without the use of manually labeled training data. The system operates in two phases:The lexicon-based algorithms use evidentiary confidence on labeled samples to guide the learning process, which labels hard instances as the system grows by the use of inference on factor graphs. GML is also applied in Aspect-Term Sentiment Analysis (ATSA) and Aspect-Category Sentiment Analysis (ACSA) projects and extensive experiments using benchmark datasets like LAP16, RES16, and LAP15 all demonstrate that GML outperforms old-fashioned approaches, like LEX-SYN and VADER, by a 7-10 percent margin. It is also equally or more effective than several of the supervised deep learning models, such as RAM, AT-LSTM and IAN.

The scalability analysis further demonstrates that GML is suitable in all large real-life scale applications since its run time increases in a more or less linear fashion with the size of the task. The authors conclude that the GML is a helpful and effective method of sentiment analysis on an aspect level when labeled data is difficult to obtain or not available at all.

B. Unsupervised Semantic Approach of ABSA for large scale user reviews.

An unsupervised semantic technique for Aspect-Based Sentiment Analysis (ABSA) is presented in this research. It is intended tohandle large-scale and unbalanced user reviews from Yelp and Amazon datasets. To extract domain-relevant elements and their key phrases, the suggested approach combines frequency-based word-level extraction with syntactic-relation analysis and semantic similarity using Word2Vec. A modified TF-IDF weighting technique is used to calculate aspect importance, a domain-specific lexicon is used to assess sentiment polarity, and the weighted sum of aspect sentiments is used to get the overall review score. Four test cases with five-fold cross validation are used to assess the model's accuracy, coverage, and F-measure. Results demonstrate that the proposed SEAE-Domain approach outperforms fixed aspects and existing extracted-aspect baselines, achieving around **7% higher accuracy and 4.5% higher F-measure** than general lexicon-based systems. The study concludes that combining syntactic, semantic, and frequency-based techniques with a domain-specific lexicon significantly enhances aspect extraction and sentiment scoring performance for large-scale real-world datasets.

C. Semi-Supervised Deep Learning Framework for Aspect Based Sentiment Analysis(SEML)

This study introduces a Semi-supervised Multi-view Learning (SEML) framework of Aspect-Based Sentiment Analysis that is trained on both labeled and unlabeled data to simultaneously perform Aspect Sentiment Classification (ASC) and Aspect Extraction (AM) utilizing a stacked Bi-directional Multi-layer Gated Recurrent Unit (BiMAGRU) network with three hidden layers. In an effort to deal with the short-age of annotated information, the framework presents four auxiliary prediction modules; past, forward, backward, and future that use limited perspectives of unmarked sentences. These modules cause consistency in predictions by training multi-view and regularization where the model utilizes both directions of a word context without extra labeling input. The main prediction modules are trained using a small set of labeled data, and auxiliary modules produce soft signals of supervision using unlabeled data, thus the system is immensely data-efficient. Experimental results show that SEML performs much better than conventional supervised Bi-LSTM and CNN baselines on normalized ABSA datasets in both AM and ASC subtasks especially when using low resources. The findings demonstrate that the F1-scores are higher, and the convergence remains stable even with the decreased volume of labeled data by over half, which demonstrates the strength of the framework. The authors conclude that SEML is one of the most effective applications of unlabeled corpora using multi-view consistency learning and deep contextual modeling to provide an economical and practical solution to the aspect-based sentiment analysis problem in reality when manual annotation is too expensive or impossible.

D. Weakly Supervised Framework for Aspect-Based Sentiment Analysis on Students' Reviews of MOOCs

This paper tackles the primary problem of the unlabeled educational data manually by providing a weakly supervised deep learning model to perform aspect-based sentiment analysis (ABSA) upon large volumes of student comments collected on MOOCs.

The method produces weak supervision cues with few or a small number of seed keywords or a few labeled reviews per aspect category. The signals are further measured using CNN and LSTM structures that are pre-trained with domain and general-purpose word embedding. The method will categorize the sentiment of each of the identified factors by initially establishing vital MOOC-related concepts like the content of the courses, instructor skills, evaluation, and design. The approach is tested using two real-world datasets 105,000 Coursera reviews and 5,989 typical classroom feedback entries. The proposed weakly supervised method, according to experimental results, is better than fully supervised baselines, which require manual annotation that is expensive. The CNN and LSTM models trained using weak supervision demonstrate great stability and generalization capability, which validates the claim that domain-specific embeddings improve the classification accuracy greatly. The authors conclude that their framework provides an applicable and scalable approach to automatically investigate large amounts of feedback provided by students with the least amount of human involvement and can allow educators and course designers to obtain actionable information about the course effectiveness and enhance the overall teaching-learning experience in large-scale online education settings.

E. Financial Sentiment Analysis: Techniques and Applications

The survey paper offers an in-depth overview of Financial Sentiment Analysis (FSA) both in terms of technical methodologies and downstream finance applications, but in the process, redefines the connections between financial textual sentiment, investor sentiment, and market sentiment. The authors divide the FSA research into technique-based and aspect-based and targeted sentiment detection with lexicon-based, machine learning, deep learning, and pre-trained language models, and application-based research, where the sentiment that is extracted can be used to make financial predictions, hypothesis tests, and market predictions. The paper discusses popular benchmark datasets including PhraseBank, SemEval Task 5, FiQA and StockTwits, where the tendencies towards fine-grained and target-aware sentiment annotation are observed. It also describes the difference between the financial and general texts in terms of specific terminology, metaphorical phrases, brevity, and the combination of qualitative and quantitative data, which requires the use of special FSA methods. The survey also addresses the role of financial sentiment as a proxy measure of investor psychology and a driver of market behavior connecting sentiment analysis and behavioral finance and the Efficient Market Hypothesis. The authors provide an overview of the current developments, current issues that may arise like the domain dependency, annotation inconsistency, and direction-sensitive sentiment as well as offer prospects in future research such as multimodal sentiment modeling and the combination of the sentiment with reinforcement learning to manage a portfolio. As a conclusion to the paper, it is concluded that the connection between FSA techniques and real-world financial processes is key to solid market prediction and decision-support systems, making FSA one of the foundations of modern computational finance.

F. Twitter Data Analysis for Live Streaming by Using Flume Technology

The article introduces a real-time analysis platform of Twitter data using the Hadoop ecosystem to provide support to live streaming applications. The system uses Apache Flume to keep on retrieving tweets which are stored under the Hadoop Distributed File System (HDFS). Data transformation is done under Hive thus plotting structured query processing via HQL. The architecture incorporates MapReduce to process in large volumes and Word Cloud visualization to display trending topics with the frequency of a word being represented in big fonts. The suggested architecture can process large social media streams, and these streams can be missed, which is useful when the organization needs to track the opinions of masses. The experimental implementation shows that FlumeHadoopHive pipeline is capable of processing large streams of tweets efficiently and deriving significant patterns to make effective decisions. The authors find that the system provides a viable solution to real-time social media analytics, which is a low-cost and scalable platform through which businesses can understand user behavior and market trends.

G. Sentiment Analysis of Danmaku Videos Based on Naïve Bayes and Sentiment Dictionary

The paper suggests a hybrid sentiment analysis system that is suitable in case of danmaku videos where real-time viewer comments are displayed as the video runs. The traditional sentiment models do not work well, as the text of danmaku is very short, informal and symbolic. The authors create a rich danmaku sentiment dictionary based on the DUT Chinese emotional ontology, a catchword dictionary, and a recently designed emoticon set that consists of 161 high-frequency symbols. The sentiment dictionary is used to extract features and a Naive Bayes model is used to classify the features. The framework further brings on board the degree adverbs and negation words to calculate the polarity of sentiment weighted over seven emotion categories. Large Tencent Video experiments also show that the hybrid dictionary -NB model can provide impressive improvement in the accuracy of sentiment scores and polarity recognition. This paper finds that combining lexical knowledge and probabilistic learning is a beneficial technique to capture dynamic emotional patterns in danmaku videos and offers useful information to assess the video content and predict its popularity.

H. Deep Sentiment Classification and Topic Discovery on COVID-19 Online Discussions Using LSTM

In this paper, the author suggests a combined NLP and deep learning system that is used to examine the problem of COVID-19 discussions on Reddit with the emphasis on topic discovery and sentiment classification. Ten subreddits gathered more than 563,000 comments, which were preprocessed with removing noise and stop-words. Latent Dirichlet Allocation (LDA) and Gibbs sampling are employed to reveal the latent semantic topics with respect to the public issues, including infection, symptoms, testing, and government policies. In case of sentiment analysis a deep LSTM recursion neural network is used with GloVe embeddings to represent long time contextual dependencies in text. The LSTM model is compared with a number of conventional machine learning classifiers and it scores an accuracy of 81.15% which is better than the competing approaches. The findings underscore that deep learning models are very useful in sentiment classification of health-related social media data. The authors draw a conclusion that mining the society opinion with the help of LDA and LSTM can be really helpful to comprehend the community reactions in the situation of the pandemic and can exhibit the adequate means of making health decisions.

V. RESULTS AND DISCUSSIONS

Lastly, eight research papers are chosen utilizing the methodical methodology described in Section II. Section IV of this study has a detailed discussion of these works. After a thorough examination and analysis of the chosen articles, the following responses are found in relation to the designated Research Questions (RQs).

RQ1: What ABSA techniques have been applied to social media sentiment analysis?
Lexicon-based approaches, syntactic dependency analysis, TF-IDF weighting, unsupervised semantic models, Gradual Machine Learning, CNN, LSTM, GRU, attention-based networks, graph neural networks, and transformer models like BERT and GPT are among the ABSA techniques employed on social media. These techniques use brief, noisy texts, such as tweets and online comments, to extract fine-grained aspect feelings.

RQ2: Which Big Data platforms are used for large-scale Twitter sentiment processing?
Hadoop ecosystem features including HDFS for storage, MapReduce for batch processing, Hive for querying, and Flume for real-time tweet ingestion are mostly used for large-scale sentiment analysis on Twitter. Because of its in-memory processing and low latency, which allow for scalable, fault-tolerant analysis of large-scale social media streams, Apache Spark has gained popularity recently.

RQ3: What machine learning and deep learning models are used for ABSA?
Some of the main challenges include handling short and noisy social media communications, understanding sarcasm and denial, a lack of labeled data, model domain dependency, limited real-time interaction with Big Data platforms, and explainability. Currently, a lot of systems rely on offline processing, which makes it challenging for them to offer accurate, scalable, and dependable aspect-level sentiment insights in real-world scenarios.

RQ4: What are the major challenges and limitations in existing ABSA studies?
Handling brief and loud social media texts, comprehending denial and sarcasm, a lack of labeled data, model domain reliance, restricted real-time connection with Big Data systems, and explainability are some of the primary obstacles. Many systems currently rely on offline processing, which makes it difficult for them to provide reliable, scalable, and accurate aspect-level sentiment insights in practical settings.

Limitations of Research:
Following are the limitations of this research:
1) Instead of using real-time industrial Twitter feeds, the majority of evaluated ABSA models were tested on benchmark or domain-specific datasets, which could cause performance degradation when implemented in actual aircraft monitoring systems.
2) High-quality research carried out in other languages or local databases may be overlooked since the systematic literature review mostly concentrates on English-language publications from significant digital libraries.
3) Because the evaluated research use various datasets, measures, and experimental setups, they lack a consistent evaluation framework that limits the credibility of aggregated conclusions and makes direct performance comparison among models challenging.

VI. CONCLUSION AND FUTURE WORK

This study highlights the importance of integrating Aspect-Based Sentiment Analysis (ABSA) with Big Data technologies to effectively evaluate large volumes of social media comments.This is especially true for the airline sector, where customer opinions are extremely dynamic and complex. The literature study shows that conventional sentiment analysis techniques are inadequate for gathering detailed opinions regarding particular areas of service, like staff conduct, baggage handling, and punctuality. Despite the fact that sophisticated machine learning, deep learning, and transformer-based models greatly increase the accuracy of sentiment identification, their real-time deployment is still constrained by scalability problems and a lack of smooth interface with distributed processing platforms. Through the integration of trained and weakly supervised ABSA models with Hadoop and Apache Spark, this study offers a scalable and effective system that can handle high-velocity Twitter data and extract useful aspect-level insights. The suggested method makes it possible for airlines to keep a closer eye on customer satisfaction and take proactive measures to address issues with service.

To better understand users' feeling, we can integrate multimodal sentiment analysis (photos/videos/emojis +text) into the system in future work. Sentiment predictions made by machines will be more transparent and reliable when explainable AI methods are included. The system will also be more usable for international airline operations by deploying transformer-based solutions targeted at streaming cases and multilingual sentiment analysis.

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