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Cross Platform Reputation Generation System Based on Aspect-Based Sentiment Analysis

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ABSTRACT

The active growth of Internet-based applications such as social networks and e-commerce websites leads people to generate a tremendous amount of opinions and reviews about products and services,Thus, it becomes very crucial to automatically process them. Over the last ten years, many systems have beenproposed to generate and visualize reputation by mining textual and numerical reviews. However, they have neglected the fact that online reviews could be posted by malicious users that intend to affect the reputation of the target product. Besides, these systems provide an overall reputation value toward the entity and disregard generating reputation scores toward each aspect of the product. Therefore, we developed a system that incorporates spam _ltering, review popularity, review posting time, and aspect-based sentiment analysis to generate accurate and reliable reputation values. The proposed model computes numerical reputation value for an entity and its aspects based on opinions collected from various platforms. Our proposed system alsooffers an advanced visualization tool that displays detailed information about its output. Experiment results conducted on multiple datasets collected from various platforms (Twitter, Face book, Amazon . . .) show theef_cacy of the proposed system compared with state-of-the-art reputation generation systems

INDEX TERMS Aspect-based sentiment analysis, decision-making, reputation generation, e-commerce.

I. INTRODUCTION

More and more individuals are engaging with companies and goods online because of how simple it is to access the web. Whether it's a real product or an online service, individuals are quick to express their thoughts and evaluations on the Internet. Whether a customer's experience is good or bad, a recent study1 found that customers are more likely to write a review if it makes them feel something. Customers may learn a lot about the product's quality by reading these reviews, so it's a good idea for them to do so before purchasing the item in question. Recognition as a subfield of natural language processing (NLP) has emerged in recent years.

The field of generation has long attracted researchers' attention.

Mining client evaluations and numerical ratings is the major emphasis of reputation generation systems, which aim to create an entity's numerical value. The review and publication of this paper were coordinated by Jad Nasreddine, the associate editor. 1-Reviews at https://business.trustpilot.com/. In order to create and display the reputation of online goods and services by combining and mining numerical and textual evaluations, several reputation creation methods have been suggested in the last ten years [1]_[8]. These systems, however, have not yet considered the following: (1) gathering and analyzing reviews from different sources; (2) identifying and removing reviews created by possible spammers; (3) assigning a numerical reputation value to each facet of the product in question; and (4) offering a sophisticated reputation visualization tool to aid in enhanced decision-making. In order to reliably calculate and display an entity's reputation (be it a product, movie, hotel, restaurant, or service), we devised and implemented an improved reputation generation model that addresses the drawbacks of the earlier methods.

The suggested method is able to gather and analyze information from social media and online stores. After that, we use a spam filtering mechanism to get rid of any spam reviews. Then, we clean up the output and make it ready for aspect-based sentiment analysis (ABSA). This is where we use the review polarity to extract aspects of the target object. Afterwards, we take use of the reviews' popularity and time characteristics, in addition to By using mathematical methods, the ASBA is able to determine the overall reputation value and the reputation values of each feature of the target entity. In addition, the system suggests a dashboard for analytical purposes, which would provide detailed information on the target entity's reputation. This study seeks to answer the following research question: can the suggested reputation model outperform state-of-the-art (SOTA) systems in terms of reputation generation and visualization while taking review popularity, review time, spam filtering, and ABSA into account? The structure of this article is as follows. In Section 2, we cover the relevant work that pertains to the ABSA models and past reputation generating methods. The essentials are laid forth in Section 3. Our suggestion is detailed in Section 4. Detailed in Section 5 are the experiments. The topic is presented in Section 6. Finally, this study is concluded in Section 7.

2. RELATED WORk

This section provides a summary of the research on ABSA and NLP-based reputation management systems. An Analysis of Attributed Sentiment One of the most active fields of study in recent years [9] that seeks to extract an entity's polarity is Sentiment Analysis (SA), often known as opinion mining. The three most common levels at which SA may manifest are the document level [10], the phrase level [11], and the aspect level [12]. Because ABSA is used in this work, it will be the emphasis of this section. ABSA finds the parts of the provided textual evaluation about the product or service and assigns them to the appropriate emotion class. Two major processing steps, aspect extraction (AE) and aspect polarity classification (APC), allow ABSA to be classified. Aspects, whether they be aspect words [13], explicit aspects [14], or implicit aspects [15], are extracted in the first step. The second step involves emotionally categorizing the previously determined characteristics as either good, negative, or neutral. The authors were the first to provide a suite of natural language processing (NLP) methods for mining and summarizing product reviews in [16]. Providing a feature-based overview of several web product evaluations was their primary goal. Using the association rule mining technique, they began by mining product attributes that buyers had indicated [17]. The next step was to find the opinion sentences in each review and then identify their polarity. Lastly, they compiled all of the findings into a summary. Moreover, the first deep learning method for the AE problem in opinion mining was described by Poria et al. in [18]. By using a 7-layer deep convolutional neural network, the writers were able to classify every word in the textual opinions as either representing an aspect or not. When compared to earlier SOTA approaches, the authors' suggested collection of heuristic language patterns and integration with the deep learning classifier resulted in a significant improvement in accuracy. Regarding aspect-level sentiment classification, the authors suggested an attention-based long short-term memory (LSTM) [20] in [19]. The goal is to train aspect embeddings and include aspects in attention weight computation. To improve their chances of winning at aspect-level classification, the suggested model may shift their attention to other portions of a phrase depending on the provided aspects. The suggested model outperformed the baseline LSTM on the SemEval 2014 Task 4 dataset [21]. Using convolutional neural networks [23] and a model based on gating mechanisms (GCAE), which has been shown to be more accurate and efficient, Wei and Toi enhanced the de_ciencies of the earlier LSTM techniques in [22]. New Gated Tanh-ReLU Units may generate emotion traits selectively based on the given entity or aspect.

In contrast to earlier models, which made use of an attention layer, the suggested model's design is far more straightforward.

Performance on SemEval datasets is higher than that of LSTM-based models, according to the trials. A multi-task learning network (IMN) was suggested by the authors of [24] that can learn many related tasks at the token-level and the document-level concurrently. In order to make greater use of the correlation, the IMN implements a message transmission system that permits informative interactions across jobs. Results from experiments conducted on three benchmark datasets derived from SemEval 2014 and SemEval 2015 [25] demonstrate that IMN significantly surpasses the other baselines. The authors of [26] suggested a hierarchical attention-based position-aware network (HAPN) to learn position-aware sentence representations and generate target-specific contextual word representations, since most current methods do not take aspect position information into account when encoding the sentence. HAPN uses position

embeddings to accomplish this. When tested against earlier approaches on the SemEval 2014 dataset, HAPN attained SOTA performance. Review reading comprehension (RRC) was introduced by Xu et al. [27]. They used BERT [28] as their foundational model and suggested a combined post-training and netuning method for ATE, APC. The suggested post-training method works quite well, according to the experimental data.
To use adversarial training for AE and APC, the authors later suggested a new architecture in [29] called BERT Adversarial Training (BAT). This design generates artificial data and is executed in the embedding space. When it comes to AE and APC tasks, the suggested model is superior to both the regular BERT and the in-domain post-trained BERT. The authors of [30] use supervised task-specific tuning and domain-specific BERT language model _netuning to create a new SOTA performance on the SemEval 2014 Task 4 restaurants dataset. Additionally, the authors demonstrated that compared to strong baseline models like XLNet-base [31] and vanilla BERT-base, the cross-domain adapted BERT model outperforms both. For the ABSA challenge, the authors of [32] contrasted the induced trees on several popular models with the dependency parsing trees on pre-trained models. In comparison to the parser-provided tree, they discovered that FT-RoBERTa, an induced tree from _netuned RoBERTa [33], performed better. The results demonstrate that the RoBERTa-based model can achieve better results than or on par with the prior SOTA performances on six datasets in four languages, including task 4 from SemEval 2014. A multi-task learning model called LCF-ATEPC for ABSA was recently suggested by authors in [34] using the processes of multi-head self-attention and local context focus (LCF) [35]. Suitable for use with the SemEval-2014 task4 and other standard English review SA tasks, the suggested model is multilingual. Automatic aspect extraction and sentiment polarity determination are also capabilities of the suggested model. The LCF-ATEPC model was chosen for this work because it presently reaches SOTA performance on AE and APC tasks.
B. Building a Reputation
Reputation is defined as "the opinion that people have about what someone or something is like, based on what has happened in the past" according to the Oxford Learner's Dictionaries.
To calculate a satisfaction score for a wide range of internet objects, such as movies, TV programs, hotels, and products, several reputation systems have been suggested in the 21st century [36]_[42]. Until 2012, when Abdel-Hafez et al. [1] developed a reputation model that incorporates opinion orientation and opinion strength (opinion mining) to calculate a realistic reputation value for each product feature and the product itself, these systems relied solely on numerical reviews (ratings) for reputation computation and ignored the use of textual reviews. However, no evidence has been presented to support the efficacy of their product reputation system. To create and display reputation for Amazon's goods, Yan et al. [3] presented the first method that merges opinion fusion with semantic analysis. An updated version of this system including a binary sentiment classification step prior to opinion fusion and grouping is available in [4]. A reputation model that takes review duration, review usefulness, and review sentiment intensity into account when calculating and visualizing reputation was developed and implemented by Benlahbib and Nfaoui [6]. Using a SA model, Elmurngi and Gherbi [5] suggested a method for calculating reputation ratings from user input. When we divide the amount of good reviews by the total number of reviews for a product, we get its reputation score. The concepts presented in [43] and [44] are identical. The writers introduced a reputation system for television and film in [45]. To get an accurate reputation value from user evaluations, the model combines _ne-grained opinion mining (Multinomial Naïve Bayes classifier trained on the SST-5 dataset [46]) with semantic analysis (Embeddings from Language Models (ELMo) [47]). Based on user-generated data posted on Twitter microblogging, Boumhidi and Nfaoui [8] developed the first system to assign a reputation value to different entities, such as movies, goods, hotels, and restaurants.website's repute (https://www.oxfordlearnersdictionaries.com/de_nition/american_english/reputation). In order to determine the tone of the tweets, the system used a classifier called Bidirectional Encoder Representations from Transformers (BERT). The next step is to use the positive tweets to get the sentiment intensity score. At last, the suggested approach combined the above findings with a popularity score derived from the extracted Twitter attributes (follower count, account legitimacy, likes, and retweets) to provide a single numerical reputation value ranging from 0 to 10. Both our reputation system and the ones that came before it relied on opinion mining methods for both reputation creation and display, as seen in TABLE.
Defining the Issue
A specific entity's reputation and its constituent parts' reputations will be quantified via this study. Assuming the target is a phone product, the objective is to generate a reputation value for the phone as a whole, say "7/10," from textual reviews collected from different platforms. Individual features of the phone, like "camera: 5/10," "design: 9/10," etc., should also be generated. This is the compiled

collection of user-posted reviews for an entity Ej: R0 j D fr1jk1 ; r2jk2 ; : : : ; rmjkp g. After going through review spam filtering, the inputs (Uj D fujk1 ; ujk2 ; : : : ; ujkp g) are returned with a set of reviews that are free of spam. Each review in the Rj set will have its entity aspects and sentiment orientations extracted using an ABSA model called LCF-ATEPC. The inputs for this model are Rj D fr1jk1 ; r2jk2 ; : : : ; rnjko g(n _ m).

Next, we group similar characteristics with their polarities. Then, we use mathematical formulae to combine the prior findings with a set of review time ratings that we computed.
A set of review popularity ratings, TSRj D, ftsr1j, tsr2j, : : : ; tsrnjg PSRj D fpsr1j; psr2j; : : : ; psrnjg in order to provide trustworthy and dependable reputation values. The set of review likes is used to calculate the set of review popularity scores, abbreviated as PSRj. The set of review shares and Lj D fl1j, l2j, : : : ; lnjg
All right. Here are the variables: fs1j, s2j, : : : ; snjg.
There are eight parts to this section that Part IV: The Suggested Method explain

Part IV: The Suggested Method
Sections 1–8 detail the proposed system's architecture, data gathering and processing, opinion spam detection, aspect extraction and classification, popularity score calculation, time score calculation, reputation generation, and finally, reputation visualization.

Section A: Overview of the Retired System
The goal of this system is to calculate a satisfaction score for each part of online entities (e.g., movies, hotels, restaurants, etc.) and to generate a reputation value for such entities.
Section A: Overview of the Retired System
The goal of this system is to compute a satisfaction score for each feature of a target entity (e.g., a movie, hotel, restaurant, service, etc.) and to generate a reputation value for the target entity based on textual and data in numerical form gathered from several services. You may see its design in FIGURE 1. The first step is to collect reviews from consumers social media sites, online retailers, video sharing websites, etc.
The next step is to use a spam filtering system that is automated to

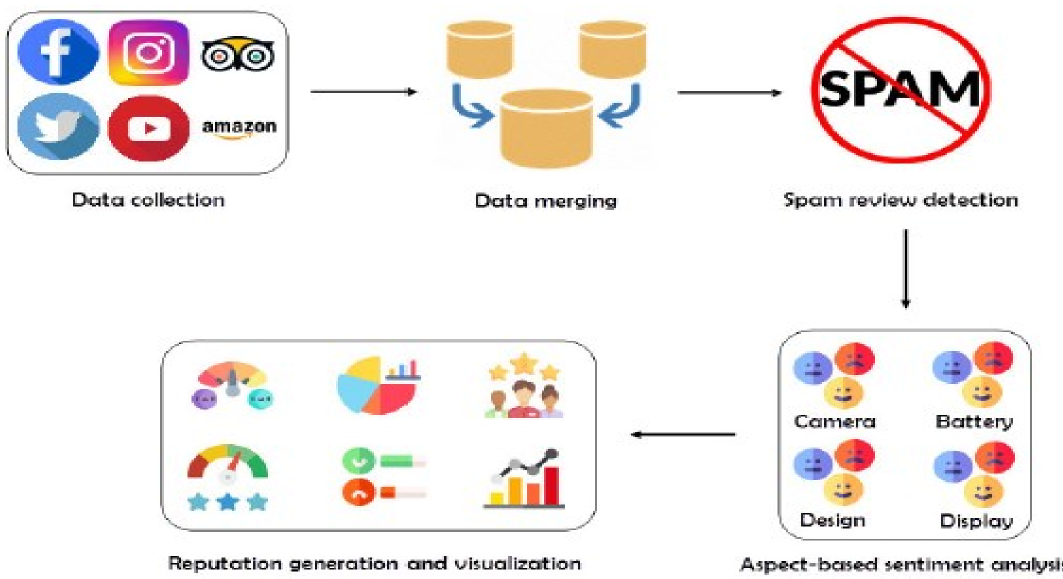
Work	Language	Domain	Semantic Analysis	Document-Level Sentiment Analysis	Aspect-Based Sentiment Analysis
Abdel-Hafez et al. (2012) [1]	N/A	N/A	N/A	N/A	N/A
Farooq et al. (2016) [2]	English	Products	N/A	N/A	• Association rule mining • SentiWordNet [48], [49]
Yan et al. (2017) [3]	• English • Chinese	Products	Latent Semantic Analysis (LSA)	N/A	N/A
Benlahbib and Nfaoui (2019) [50]	English	Movies	Latent Semantic Analysis (LSA)	N/A	N/A
Benlahbib et al. (2019) [51]	English	Movies	Latent Semantic Analysis (LSA)	Logistic Regression	N/A
Benlahbib and Nfaoui (2020) [4]	English	Movies	Latent Semantic Analysis (LSA)	• Naive Bayes • Linear Support Vector Machine	N/A
Elmurngi and Gherbi (2020) [5]	English	Products	N/A	Logistic Regression	N/A
Benlahbib and Nfaoui (2020) [6]	English	• Products • Movies & TV Shows • Hotels	N/A	Bidirectional Encoder Representations from Transformers (BERT)	N/A
Benlahbib and Nfaoui (2020) [52]	English	Products	N/A	Bidirectional Gated Recurrent Unit (Bi-GRU)	N/A
Boumhidi and Nfaoui (2020) [43]	English	• Movies • Restaurants	N/A	Bidirectional Gated Recurrent Unit (Bi-GRU)	N/A
Gupta et al. (2020) [7]	English	• Movies • Books	N/A	• Bidirectional Encoder Representations from Transformers (BERT) • Naive Bayes • Support Vector Machine	N/A
Boumhidi et al. (2021) [44]	English	Movies	N/A	Bidirectional Long Short-Term Memory (BI-LSTM)	N/A
Benlahbib and Nfaoui (2021) [45]	English	Movies & TV Shows	Embeddings from Language Models (ELMo)	Multinomial Naive Bayes	N/A
Boumhidi and Nfaoui (2021) [8]	English	• Products • Services • Hotels • Movies	N/A	Bidirectional Encoder Representations from Transformers (BERT)	N/A
This study	English	• Products • Services • Hotels	N/A	N/A	LCF-ATEPC

find spam reviews and remove them. Afterwards, we utilize a SOTA ABSA model to analyze user evaluations and derive a score according to the sentiment orientation of the retrieved characteristics.

Also, using the statistical data retrieved from the textual evaluations, we determine a time score and a popularity score. We conclude by calculating a reputation value using the scores that were previously

computed, and we suggest a new visualization interface that is easy for users to understand and use, which provides detailed information on the target entity's reputation.
Chapter B: Information Gathering and Preprocessing
Data collection and processing capabilities across several platforms are key components of the proposed system.

Ancestral reputation generating systems would collect relevant data from social networking sites like Facebook and Twitter or e-commerce platforms like Amazon and TripAdvisor. The goal of this work was to create a unified dataset by standardizing the features of all platforms. We did this by categorizing online platforms into two groups: the first group includes sites like Amazon and YouTube, where users can easily access reviews along with the number of likes they've received. The second kind allows users to get the review's content along with its likes and shares on social media platforms like Twitter and Facebook.
The following fields have been added to the combined dataset: "user name," "review text," "review time," "review likes," "review shares," and "review host." This data has been retrieved from both kinds of platforms using web scraping tools. The number of "review shares" that have been awarded is zero for reviews that are



taken from _rst type platforms since all they provide is the amount of likes.
Natural language processing methods (such as text normalization, lower-casing, noise reduction, etc.) are used to sanitize the textual reviews.
C. Identifying Opinion-Based Spam
The fact that everyone, regardless of location, may publish evaluations about any service or product is one of the biggest problems with opinion-sharing sites. Opinion spammers try to mislead consumers by boosting or lowering the target's reputation in order to influence their views [53]. Our reputation system relies on filtered and removed spam reviews to provide a trustworthy and dependable reputation value, which helps consumers make safe decisions.
There has been tremendous advancement in the detection of spam reviews on commercial review hosting sites like Yelp and Amazon [54]. Nevertheless, we choose to identify spam reviews by using two normalized spammer behavioral traits [55] due to the fact that we are gathering people's opinions from several sites. In Table 2 you can see all of the notations that are used in this part. 1) CS Author Content .Since it is a common practice for spammers to publish reviews that are similar to or even the same as their earlier evaluations,
1) Identifying Similar Author Content (CS)
Since it takes effort to compose a fresh spam review every time, spammers often publish reviews that are similar to or even the same as their prior evaluations. To find spammers, we apply a cosine similarity calculation to each pair of reviews in the combination set CP(R0 jk). This involves finding a pair-combination of reviews from the set of reviews R0 jk posted by author k without repetition, converting them into vectors using a pre-trained BERT model

from Huggingface, and finally, we apply this calculation to identify spammers. Using Equation (1), we averaged the results from each pair's cosine function and arrived at a single numerical score ranging from 0 to 10. Later on in this section, a spammer behavior score will be calculated using this score.
This is the formula: F1(ujk) D P Cosine(CP(R0 jk)) Njk _ 10.Second, the frequency of user reviews (UNRF)
Real reviewers don't often post many reviews about the same entity. Only 5-8% of spammers had a lower ratio of submitting reviews in a single day, according to a recent research [56]. We suggested Equation (2) to determine the frequency of the number of reviews submitted by user k toward the target object j, as our gathered dataset could also include reviews from other users.Equation 2(ujk) = D * Njk * Nj _ 10 (2) Equation (3) is used to determine the spammer score, which is based on the two previously proposed behavioral aspects of spammers. A specified threshold outlined in section 5 is used to compare the spammer score with, and then each author is given a label from the set L D{normal, spammer}. Reviewers who often submit their work are labeled as "normal," whereas those who often submit their work as "spammer" are labelled as such. Each user is labeled using Equation (4).
Total score (ujk)
The output will be either spam if the score of ujk is more than _ or normal if the score of ujk is less than _, depending on the function F1(ujk) and the coefficients C and F2(ujk).
If a person is found to be a spammer, all of their reviews will be removed from the database. The suggested reputation system may now go on to the next level using the freshly cleaned dataset, which is devoid of spammers.
D. ASR Score Based on Attributes of Sentiment
This section's objective is to anticipate the sentiment polarity of the evaluations by extracting their components. With the following product review as an example: "The camera on this phone is good but the design is bad." In order for the ABSA model to function properly, it must first extract the elements "camera" and "design" and then accurately calculate the polarity of these two factors. The reviewers have good things to say about the "camera" and bad things to say about the "design" in this product.
Hence, we used LCF-ATEPC, a multi-task learning model, for ABSA. This model can extract aspect terms and infer their polarity since it combines the APC job with the aspect term extraction task (ATE). Each input sequence is converted into a unique token and given two types of labels. The first label specifies whether the token is part of an aspect, while the second one specifies which direction the aspect's tokens face. Using the pre-trained BERT model as a foundation, the LCF-ATEPC model combines ABSA with the concepts of self-attention and local context focus (LCF). You may see the LCF-ATEPC network design in FIGURE 2. The following is a description of its primary elements:
The LCF-ATEPC model uses two separate BERT-Shared layers, BERTl for local context characteristics and BERTg for global context information.
The two BERT-Shared layers are considered to beintegrated layers, and each layer's fine-tuning is executed autonomously in accordance with the multi-task learning joint loss function.
MHSA stands for "multi-head self-attention." In order for the model to learn the words' significant information in distinct presentation subspaces, the multi-head attention mechanism is used.
Deep semantic characteristics may be extracted from context using MHSA, which is based on multiple scale-dot attention.
MHSA is able to learn the characteristics withoutingg negatively affected by the context's long-distance dependency.
One novel approach that may be modified to suit the majority of fine-grained natural language processing (NLP) jobs is local context focus. One method for establishing local context is the semantic-relative distance (SRD) measure. This measure finds the distance between a token and the aspect, which is then used to ascertain whether the context word is part of the local context of the aspect in question.
contextual characteristics To hide the BERTl layer's learnt non-local context characteristics, a Dynamic Mask (CMD) layer is used. By deploying the CDM layer, the characteristics of the less-semantic-relative context at the appropriate output position will be the only ones concealed. On the respective output places, you'll find the correlative representations of the less semantically related context terms and features.
A second Context characteristics Dynamic Weighted (CDW) layer is used to zero in on words with specific local context, in addition to the (CDM) layer.
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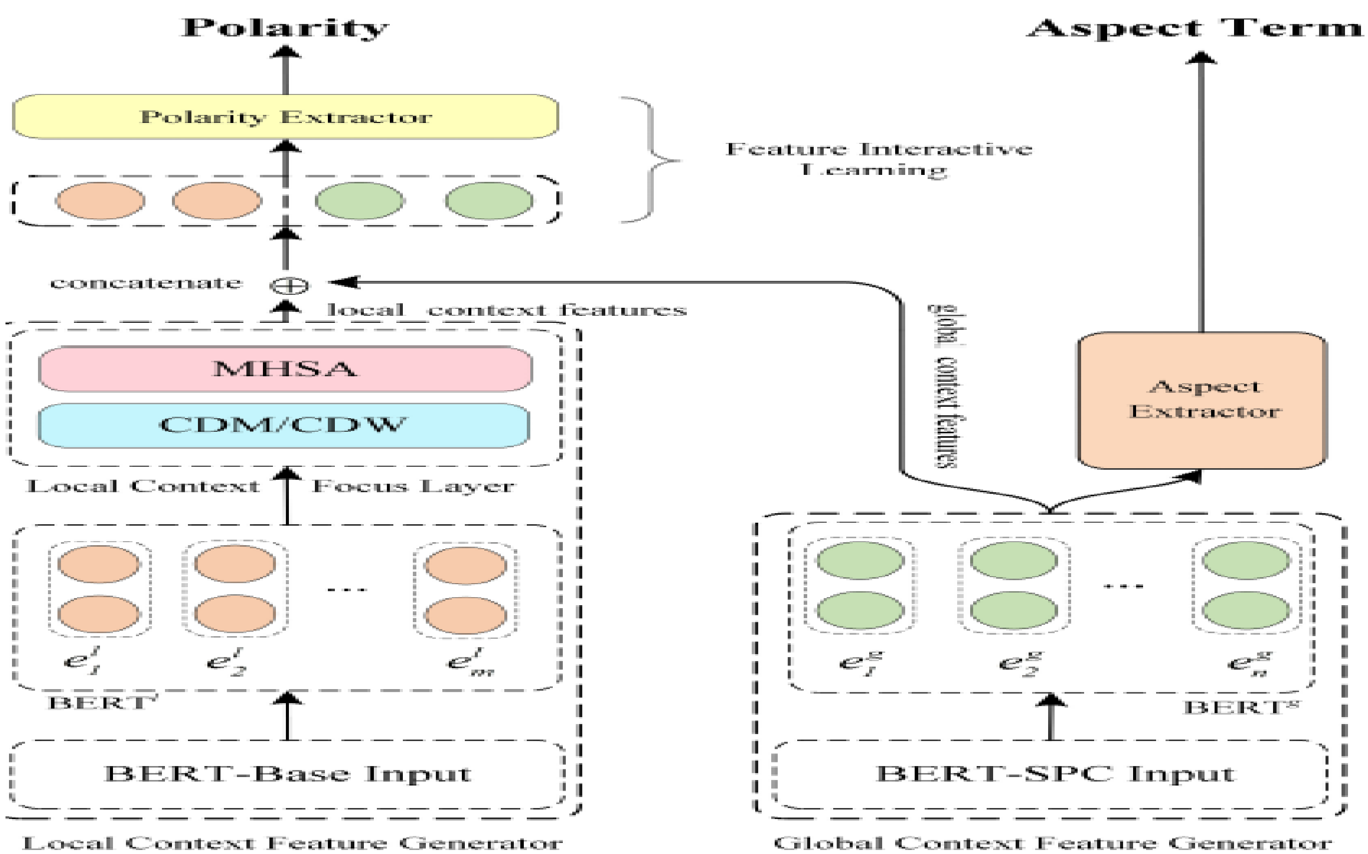
the basic token-level classi_cation for each token, which means that each token will be given a label, and a classi_cation is performed to predict the aspects in the

sentence.

Authors in [34] trained LCF-ATEPC model on commonly

used ABSA datasets, including the Laptop and Restaurant datasets of SemEval-2014 Task4, and ACL Twitter socia ldataset. However, they trained the model on those datasets separately. In this paper, we trained the model on a mixed dataset of the three previously mentioned datasets in order to allow our system to treat reviews of different domains. LCF-ATEPC model achieved SOTA performance on the



E. Building a Reputation

The public's perception of an entity changes over time due to a number of variables, including the views expressed about it on the Internet. A few examples of these criteria include the review's posting time, the user's popularity and credibility, and the review's sentiment orientation toward an entity. In order to get the final reputation value for a certain entity, this section will present all three elements and provide numerical scores for each.

1) Check the ranking of popularity

Everyone knows that there are a ton of customer evaluations of different online items on e-commerce and social media sites. The opinions of other users and the entity's reputation are both impacted by these evaluations, albeit to varying degrees. In 2017, researchers found that a whopping 93% of buyers said that reviews on websites had an impact on their purchases, with an even higher percentage saying they are more inclined to buy after reading a review from someone they trust. The quantity of interaction a review has with other users is really what makes it more influential than average. We have settled on two modes of interaction—likes and shares—because we are working with reviews gathered from several online sites. The number of likes an item receives is indicative of the user's taste.

A user's interest and approval in a review are both increased when he gives it a thumbs up. On the other hand, when people share reviews, they are effectively endorsing the material to their whole following. The objective of this part is to determine how popular each user's review is by tallying up the number of likes and shares it has gotten. This will help in categorizing the reviews. Our system pulls information from two distinct platforms, as stated earlier in the article: one gives us text and like features alone, while the other gives us text, like, and share features as well. One platform that falls under the _rst category is "TripAdvisor."

It doesn't let users share their reviews, therefore they can't be shared inside the network. When we gather data for the characteristic "review shares," it will be set to zero. In order to determine the popularity score for every review in our dataset, we devised Equation (5).In order to convert the found popularity score into a range from 0 to 1, we multiplied the like and share values by 0.5 in the formula. Referring to TABLE 3, the notations used in this subsection are catalogued.

D psrij lij = 0.5 max(Lj) C sij = 0.5 max(Sj) (5)

For each review, a numerical number between 0 and 1 is computed to reflect its popularity. An influential review will have a high popularity score.

In order to determine the target entity's reputation, those popularity ratings will be used.

2) COUNT THE TIMES

As a first step in reviewing a product, many individuals look at the review's publishing date and, more often than not, prioritize the most current evaluations. Since a company's ownership, branding, and goods and services are all subject to change, the date of the reviews is crucial in establishing credibility with prospective clients. A recent research conducted by Brightlocal7 shown that customers place much less weight on older reviews. Approximately 85% of consumers find any review, regardless of age, to be meaningless, which may affect how a product or service is regarded. Time, however, does not effect all products in all fields. There are times when an old online review of a product, like cheese, or a vintage film, may be just as pertinent as it was then. Therefore, the review's date is irrelevant here. Here we presented Equation (6) as a means of determining a review time score. According to the suggested equation, the most up-to-date reviews will have a score around 1 while older reviews would have a value closer to 0. Table 4 lists the notations used in this subsection. We have indicated that the planned reputation system would make this functionality optional.

The review time score is not used to generate reputation for specific items or services if the user chooses to ignore the time component.

3) Assess the sentiment

Applying the LCF-ATEPC model to the review dataset that does not include spam allows us to extract review characteristics together with their corresponding sentiment polarity. We then arrange the retrieved characteristics according to the emotion polarity of each review. Each review's extracted features will also be given the popularity score that was previously computed for it. The process for extracting and predicting the review's sentiment is shown in TABLE 6, and related extracted characteristics are grouped according to their popularity ratings in TABLE 7.

Based on the positive and negative sentiment orientation of each aspect, our method computes a sentiment score ssaspij using Equation 7. Aspects lacking in emotional investment are detailed in TABLE 5.

The user's emotional neutrality means that orientation will not be taken into account when determining the ssaspij.

F. Calculating Reputation

A reputation value is computed for each facet utilizing the previously determined characteristics in the proposed system.

The equation (8). To get a number between 0 and 9, we multiply the emotion score ssaspij and the

average time scores sum (Tij) mij by 9. Then, we add a tailored average of negative and positive popularity ratings, which is limited to 0 to 1. The reputation of an aspect aspij is represented by a numerical number between 0 and 10, which is the final outcome. Whenever this section makes use of notations, they are detailed here.
0
Using Equation (9), the system averages the reputation values of all aspects to create an entity's total reputation. G. Evaluation Mark
In order to find the most influential review, a value is determined by combining the popularity and time scores using Equation (10). This value is then utilized as the review score. Only when using reputation visualization may this score be used to identify the most influential posting review; it is not included in the calculation of reputation value.
(10) rsij D psrij C tsrij 2
When we say:
review score for entity i as it pertains to entity j
H. Visualizing Your Reputation
When compared to earlier reputation systems, ours offers a more sophisticated, user-friendly interface that is both efficient and well-designed. The interface shows all the information about a product's reputation, including the entity's total reputation value, the values of its characteristics, the aspects that have been evaluated the most, and the reviews that have been deemed the most influential. Given that Figure 3 shows the suggested visualization tool as an interactive user interface. When the user clicks on a certain feature, or moves the pointer over it on the screen, additional comprehensive information about that feature is shown. In order to aid customers in making informed decisions, the suggested reputation visualization tool would provide them with greater information into the targeted product or service. **V. EXPERIMENT RESULTS**

A. EXPERIMENTAL DATA COLLECTION AND

PREPROCESSING

Four experimental review datasets were collected where each dataset belongs to a different domain (product, movie, hotel, restaurant). Every dataset contains a combination of reviews from various social media and e-commerce platforms, and each review includes a textual opinion expressed by the user, user name, review posting year, number of likes, number of shares, and the platform host. We hired four human

annotators to extract and determine the polarity of each aspect in the reviews in order to manually label the four datasets.
Table 10 displays review samples from one of the datasets, whereas Table 9 presents statistical details regarding the evaluation dataset. The dataset's text evaluations are all cleaned and pre-processed, with special characters, punctuation, and URLs removed, and colloquial terms replaced with professional ones. Lastly, we tokenize and add specific tokens to the cleaned textual reviews in order to get them ready for the LCF-ATEPC model.
B. SPAM DETECTION OF OPINIONS
Owing to the dearth of spam review datasets, an assessment dataset including one thousand reviews was gathered manually from many online platforms. Based on their review posting habits, we employed annotators to manually classify each user into one of two potential types (Spammer or Normal). This process's consequence is the identification of

In our analysis, there were 682 real reviews and 318 bogus reviews.suggested a spam review detection model by adjusting the threshold value in steps of 0:01, from 0:50 to 0:68, and using accuracy, recall, and precision as assessment metrics. According to TABLE 7, the threshold value _ D 0:57 yields the greatest accuracy results.

Domain	Number of reviews	Host platfroms
Movie	713	IMDb, Twitter, Facebook
Product	1109	Twitter, Amazon, Ebay
Hotel	686	TripAdvisor, Twitter, Facebook
Restaurant	725	Yelp, TripAdvisor, Twitter

Domain	Number of reviews	Host platfroms
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Restaurant	725	Yelp, TripAdvisor, Twitter

C. ASPECT-BASED ANALYSIS OF SENTIMENT
1) HYPERPARAMETERS & TRAINING DATASETS
The laptops and restaurant datasets from SemEval-2014 Task4 and an ACL Twitter dataset were combined to generate a merged dataset that we utilized to train LCF-ATEPC [57]. This dataset is one of the most widely used ABSA datasets. Each sample was labeled with the Inside_outside_beginning (IOB) labels for ATE tasks and the polarity labels for APC tasks after the original three datasets were restructured. Every component has the potential to be good, neutral, or negative in polarity. The specifics of these datasets are shown in TABLE 12. TABLE 13 presents the global hyperparameter values of the LCF-ATEPC model that provide the best outcomes as reported by the model's original creators.
2) MODEL EXAMINATION
The LCF-ATEPC model has been compared to the following SOTA techniques:
_ AEN-BERT [58]: an attentional encoder network that uses the BERT model that has already been trained to solve the APC.
This is the original pre-trained model, BERT-BASE [28]. It was modified for aspect-based sentiment analysis to automatically identify aspects' polarity and extract aspect words from the dataset. There are two stages to the spam review detection process that use the spammer's behavioral traits: (1) figuring out the spammer score Based on the two spammer behavioral traits, CS and MNR, score (a) is calculated. (2) Assessing
A fine-tuned BERT for text pair classification, BERT-SPC [58] is modified to address the aspect-based sentiment-analysis requirement.
The primary experimental findings of LCF-ATEPC in comparison to the other ABSA-oriented models are listed in TABLE 14.
The LCF-ATEPC model achieves SOTA performance in both ATE and APC tasks, according to experimental data.
3) REUSTS OF THE LCF-ATEPC MODEL ON THE EVALUATION DATASETS
The foureach dataset was subjected to the pre-trained LCF-ATEPC model. It is evident that the model performs well when it comes to aspects extraction and sentiment orientation prediction. It's interesting to note that despite having been trained on a mixed dataset devoid of evaluations pertaining to the aforementioned domains, the model performed well on the movie and hotel datasets.
D. VISUALIZATION OF REPUTATION
A thorough depiction of an item's reputation is offered by our suggested reputation creation mechanism. The visual depiction of the output facilitates the identification of new insights about the target item. Along with other statistical information, the built dashboard displays the total reputation of the business, the most influential reviews, and the reputation value of each feature. Users are able to utilize the Dashboards to make data-driven business choices.
In contrast to other reputation generating systems [3, 4, 6,], our suggested approach provides more sophisticated information on the display of a certain entity's reputation.
The comparative results between TABLE 15 and the earlier reputation generating methods in terms of the visualization feature are shown.
E. SYSTEM APPraisAL
Earlier reputation building methods relied on the general tone of the evaluations gathered and generated the reputation from social media or e-commerce websites. In this research, we suggested a sophisticated cross-platform system that: 1) simultaneously harvests and modifies user data from many platforms, enabling it to provide a trustworthy reputation value.
2) uses a spam filtering system to exclude reviews from authors who could be spammers.
3) makes use of the aspect-based sentiment-analysis approach to identify and extract aspects pertaining to the target item. By predicting these sentiment polarities, we are able to use mathematical formulae to determine the reputation of each aspect.
4) takes into account other significant elements to improve the dependability of the created reputation value, such as the time feature and the popularity of the individuals expressing their thoughts.
evaluation datasets to evaluate ATE and APC's performance. The ATE and APC F1-scores are shown in FIGURE 4. The F1-scor

TABLE 14. Experimental results (%) of the LCF-ATEPC model. $F1_{ate}$, Acc_{apc} and $F1_{apc}$ are the macro-F1 score of aspect term extraction (ATE) subtask, accuracy and macro-F1 score of the aspect polarity subtask. The unreported experimental results are indicated by "-". The "Δ" means the F1 score of the ATE task is not available for the BERT-SPC input format. The optimal performances are in Bold.

Models	Laptop			Restaurant			Twitter			Mixed		
	$F1_{ate}$	Acc_{apc}	$F1_{apc}$	$F1_{ate}$	Acc_{apc}	$F1_{apc}$	$F1_{ate}$	Acc_{apc}	$F1_{apc}$	$F1_{ate}$	Acc_{apc}	$F1_{apc}$
AEN-BERT	–	79.93	76.31	–	83.12	73.76	–	74.71	73.13	–	80.12	71.62
BERT-BASE	82.57	79.4	75.24	88.6	82.66	74.13	95.45	76.27	74.91	84.9	81.13	75.5
BERT-SPC	Δ	79.56	75.55	Δ	**86.77**	80.52	Δ	76.27	**75.16**	Δ	76.84	74.77
LCF-ATEPC	**83.82**	**80.97**	**77.86**	**89.02**	**86.77**	**80.45**	**96.4**	**76.7**	74.54	**85.44**	**83.02**	**76.18**

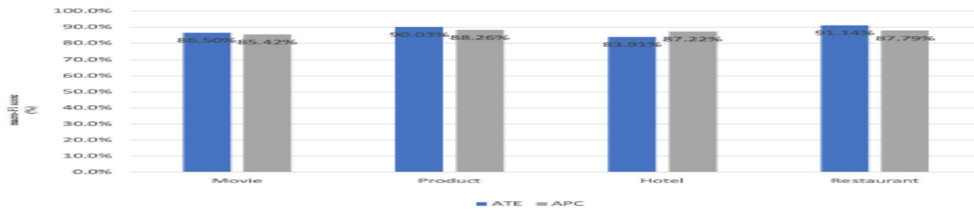

FIGURE 4. F1-score results for the ATE & APC tasks on the evaluation datasets.

TABLE 15. Comparison between the features displayed in the visualization tool among reputation generation systems.

System	Influential Reviews	Aspects reputation	Most reviewed Aspects
Yan et al.(2017) [3]	✗	✗	✗
Benlahbib and Nfaoui (2019) [4]	✗	✗	✗
Benlahbib and Nfaoui (2020) [6]	✓	✗	✗
This study	✓	✓	✓

e for Table 16 is shown in FIGURE 4, which further highlights the distinctions between our suggested approach and earlier reputation creation systems. Since there are no established evaluation criteria for these kinds of systems, we utilized the same process as in to assess the efficacy of our system's constituents and the output dependability of our system.

System	Review sentiment	Review popularity	Review posting year	Spam filtering	Aspect' reputation
Yan et al. (2017) [3]	✗	✗	✗	✓	✗
Benlahbib and Nfaoui (2019) [4]	✓	✗	✗	✗	✗
Benlahbib and Nfaoui (2020) [6]	✓	✓	✓	✗	✗
This study	✓	✓	✓	✓	✓

other works, such as [59] and [6]. The purpose of our invitation to return was to assess the efficacy of four reputation creation systems: system 1 (our reputation system), system 2 [6], system 3 [4], and system 4 [3]. These 32 users come from a variety of backgrounds (TABLE 17). Based on the effectiveness and helpfulness of each system, the participants were asked to rate their level of satisfaction on a scale of 0 to 10.
In order to strengthen the trials' validity, we invited

three different experts to rate and judge each reputation

system. TABLES 17 and 18 present information about the

participants.Each Volunteer rated the four systems based on their ef_-ciency and helpfulness in supporting them during the decision making process while asking the question of ``which system is more reliable and helpful?''. In

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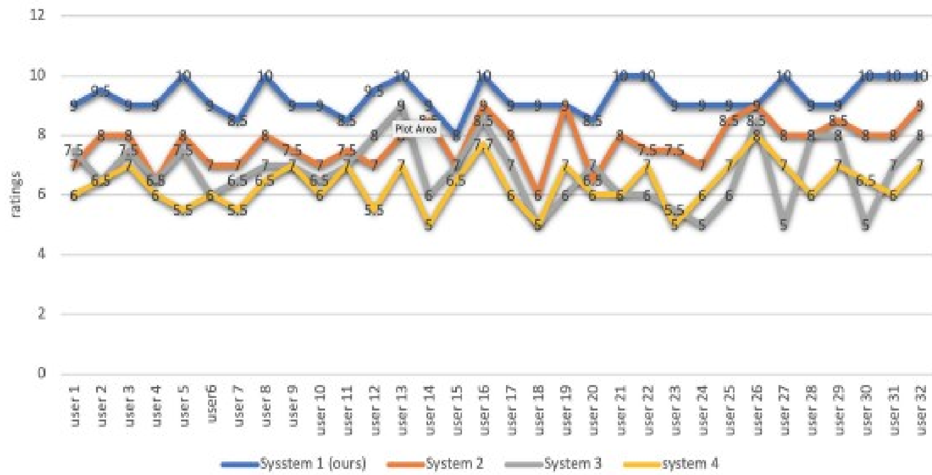
TABLE 19, we calculated the average of all ratings provided by the users for each



Number of users	Background
6	Computer Science PhD students
2	Math PhD students
1	Electrical engineer
1	Undergraduate math student
2	computer science engineers
1	Physics teacher
4	Math teachers
1	Reseach engineer in computer science
1	Electronic engineer
1	Information system engineer
1	Student at the national school of commerce and managment
1	Quality control technician
7	Medical student
1	Housewife

system $\mu = \frac{1}{n}\sum_{i=0}^{n} x$, where $x_1, x_2, \ldots, x_n$ are the observed ratings and n is the total number of ratings. We also measured the coefficient of variation (CV), which is the standard deviation divided by the mean times 100% as shown in Equation 11.

$$CV = \frac{\sigma}{\mu} 100\% \tag{11}$$

where

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2}$$

We denote:

σ: Standard deviation

As we can see, our system was higher-rated among the other systems based on the average rating. Moreover, our proposed system is the only one to get the perfect rating (10 out of 10) from 10 different users. With an average rating of 9.33, our proposed system is ranked first in comparison with the others. System 2 got the second higher rating

Expert	Background
Expert 1	Owner and reputation manager of the streaming website of 'Fushar.tv'
Expert 2	Social media manager of an online store
Expert 3	Computer science professor specialized in business intelligence

with 7.78. In third place, we have system 3 with an average rating of 6.63. Finally, system 4 came in last with an average rating of 6.37, which is close to system 3 since both systems only use the sentiment or semantic features for generating the reputation on an entity. FIGURE 5 displays the ratings given by the users.

We also calculated and compared the coefficient of variation of the users' ratings for each system in order to measure the spread of the ratings. If the ratings all lie close to the mean/average, then the percentage of the coefficient of variation will be small, while if the ratings are spread out over a large range of values, then the percentage coefficient of variation will be large. This will help us determine if the ratings given for each system are balanced. As we can see in TABLE 19, the coefficient of variation of the group of ratings for our proposed system is the lowest compared to the other systems with a value of 6.12%.

In addition to the 32 voluntary users, we also asked three experts (TABLE 18) to rate the four systems based on their helpfulness and functionality. The results are shown in TABLE 20. As we can see, all the experts favor our proposed reputation generation system by giving it a higher rating score compared with the other systems. With an average rating of '8.83', our proposed system takes first place, then system 2 in second place with an average rating of '7.5', next is system 3 in third place with an average score of '6.83', and finally system 4 in the last place with an average rating

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	System 1 (ours)	System 2 [6]	System 3 [4]	System 4 [3]
User 1	**9**	7	7.5	6
User 2	**9.5**	8	6.5	6.5
User 3	**9**	8	7.5	7
User 4	**9**	6.5	6.5	6
User 5	**10**	8	7.5	5.5
User 6	**9**	7	6	6
User 7	**8.5**	7	6.5	5.5
User 8	**10**	8	7	6.5
User 9	**9**	7.5	7	7
User 10	**9**	7	6.5	6
User 11	**8.5**	7.5	7	7
User 12	**9.5**	7	8	5.5
User 13	**10**	8	9	7
User 14	**9**	8.5	6	5
User 15	**8**	7	7	6.5
User 16	**10**	9	8.5	7.7
User 17	**9**	8	7	6
User 18	**9**	6	5	5
User 19	**9**	9	6	7
User 20	**8.5**	6.5	7	6
User 21	**10**	8	6	6
User 22	**10**	7.5	6	7
User 23	**9**	7.5	5.5	5
User 24	**9**	7	5	6
User 25	**9**	8.5	6	7
User 26	**9**	**9**	8.5	8
User 27	**10**	8	5	7
User 28	**9**	8	8	6
User 29	**9**	8.5	8	7
User 30	**10**	8	5	6.5
User 31	**10**	8	7	6
User 32	**10**	9	8	7
Average	**9,33**	7,78	6,63	6,37
Coefficient of variation	**6.12%**	10.12%	16.10%	11.90%

	System 1 (ours)	System 2	System 3	System 4
Expert 1	**9**	8	7	6.5
Expert 2	**8.5**	7	6.5	5.5
Expert 3	**9**	7.5	7	6
Average	**8.83**	7.5	6.83	6.0

of "6.0" FIGURE 6 presents a comparison of the average evaluations from professionals, demonstrating that our method is more dependable on building and promoting one's reputation rather than making use of the previous systems. Furthermore, we asked the experts send in an evaluation outlining their ideas about the proposed method, as seen in TABLE 21.

Part Six. TALK

One possible definition of the system proposed in this article is an advanced tool for decision-making that has the potential to generate values that represent the credibility of an organization (i.e., products, services, movies, hotels, etc.) depending on reviews and feedback made public on the web. The proposed system can accommodate perspectives from several platforms for the first time, thanks to its ability to manage platform properties with a high level of adaptability.

To top it all off, our system is now more resistant to attacks by spammers thanks to the inclusion of an opinion spam filter in the proposed reputation system. This filter identifies and removes opinion spam based on the characteristics of the actions of spammers, leading to the creation of trustworthy reputation values. Another important feature is the ability to extract and use SOTA aspect-based sentiment analysis methods to investigate the characteristics of the target entity. Posting duration, popularity characteristics, and views are also part of the system for the objective of establishing credibility, which enhances its reliable and trustworthy. An alternative visualisation method in which case the final result of such efforts to improve their reputation

procedures are shown in an interesting, participatory
interface, leading to more convenient online decision-making
process for normal customers as well as business owners.
Section VII. The verdict is in.
Our work here proposes a reputation system with the potential to
creating numerical reputation values for a certain product
and everything that goes into it (excellent, movie, hotel, service, etc.).
on online comments and viewpoints. The data that is entered
all eyes were on these four things that weren't
employed in previous systems. And first, it works on all major platforms.
compatibility, enabling the proposed system to collect and
take into account comments made via various platforms (Facebook:
(Twitter, Amazon, TripAdvisor, etc.) and managing
and harmonizing the features of these kinds of systems. The following
Opinion spam filtering is the first, and it involves opinions that are
are detected and eliminated in line with the behaviors of spammers
certain traits, maintaining only authentic perspectives. Lastly, there is
by using a sentiment-analysis method grounded on SOTA characteristics
requested LCF-ATEPC to obtain and evaluate
features of the literary perspectives. Finally, we brought in
the previous results in addition to a benchmark for evaluation period
when analyzing the popularity score by computational means
so that the target item may likewise get a reputation value
in terms of the traits that determine the worth of the entities' reputations. The interior also has a detailed portrayal of reputation.
system that demonstrates the full-scale results of the reputation production process. For the purpose of determining how well our reputation system, and 32 individuals, including 3 experts, were invited.
choosing the most effective system out of the four SOTA
by the provision of quantitative evaluations of contentment, reputation management to all systems. When it comes to reputation, our way is tops.
rating of average satisfaction among experts and users. On the inside of
We want to investigate our future efforts' effectiveness.
proposed approach of striving to generate more than the
reputation-related figures, such as increasing the system's capacity to
provide a concise summary of the benefits and
negative aspects of the target audience. In addition, our goal is to broaden
Bilingual material will be addressed using this technique.
Advocates for Mentors

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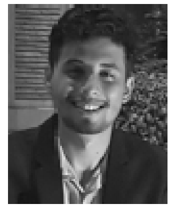

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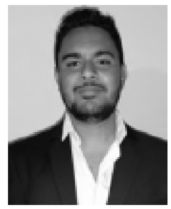

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