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Analyzing Public Opinions Regarding Virtual Tourism in the Context of COVID-19: Unidirectional vs. 360-Degree Videos

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Abstract: Over the last few years, more and more people have been using YouTube videos to experience virtual reality travel. Many individuals utilize comments to voice their ideas or criticize a subject on YouTube. The number of replies to 360-degree and unidirectional videos is enormous and might differ between the two kinds of videos. This presents the problem of efficiently evaluating user opinions with respect to which type of video will be more appealing to viewers, positive comments, or interest. This paper aims to study SentiStrength-SE and SenticNet7 techniques for sentiment analysis. The findings demonstrate that the sentiment analysis obtained from SenticNet7 outperforms that from SentiStrength-SE. It is revealed through the sentiment analysis that sentiment disparity among the viewers of 360-degree and unidirectional videos is low and insignificant. Furthermore, the study shows that unidirectional videos garnered the most traffic during COVID-19 induced global travel bans. The study elaborates on the capacity of unidirectional videos on travel and the implications for industry and academia. The second aim of this paper also employs a Convolutional Neural Network and Random Forest for sentiment analysis of YouTube viewers' comments, where the sentiment analysis output by SenticNet7 is used as actual values. Cross-validation with 10-folds is employed in the proposed models. The findings demonstrate that the max-voting technique outperforms compared with an individual fold.

Keywords: virtual tourism; COVID-19; SentiStrength-SE; SenticNet7; 360-degrees videos; unidirectional videos; optimal sentiment analyses model; convolutional neural network; random forest; max-voting

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1. Introduction

Information science and information technology are closely connected to tourism. In 2014, Pedrana claimed that information technology had supported the tourism revolution by altering conventional tourism and product experiences, culminating in a virtual tourism model [1]. The basic foundation for virtual tourism is the natural tourist landscape. By creating an online environment, people might be able to enjoy immersive travel while staying at home, and the Internet or virtual technology will surpass the appeal of physical discovery [2–5].

Even though the online travel industry has received much attention as a new kind of tourist industry, there are still some disagreements over people's views and opinions of this model. According to Dale, 2016; Julia Lekgau, Harilal and Feni, 2021; Yang et al., 2022 [6–8], virtual tourism has developed a new tourist model with several benefits, for example, recreating the initial chronological arrival of a destination and preserving intangible heritage. It may make tourism more accessible to travelers with physical disabilities, financial constraints, or limited time [9,10]. Opposers dispute the claim that visitors might not have an outstanding virtual adventure because all experiences must engage with the surrounding world to be entirely inspired [5,11]. Some heritage destination administrators are also afraid that the online adventures may jeopardize the factual validity of the place and will refuse to use them.

Even though the virtual travel industry has been available for more than a dozen years, most travellers are still unaware of it and have many comments; some might have positive comments, while others may have negative or neutral comments. In the prior literature, the authors [12] observed that virtual travel problems were centred on non-crisis and ordinary scenarios and recommended investigations to inspect the prospects of virtual tourism during and after crisis settings. Kim et al. argue that virtual travel is a viable option when access to the actual world is restricted [11]. What is the proper perception of viewers toward virtual travel in a crisis? It is still challenging to provide a definitive response. Importantly, elucidating the popular understanding of virtual travel will give additional perspectives and create possible recommendations for the long-term growth of virtual travel.

Since the beginning of COVID-19, worldwide financial and social growth has suffered significantly. COVID-19, in contrast to previous pandemics, has a more extended incubation duration and less frequent signs, and it disperses more rapidly and widely [13]. Avoiding the public and movement is an effective strategy for minimizing transmission of the COVID-19 pandice. In just several months, the approach of the international tourist strategy transitioned from unrestricted travel to limited tourism [14]. Most nations have implemented travel bans [13]. According to OurWorld in Data [15], the highest possible travel ban density might have been around May 2020, as shown in Figures 1 and 2.

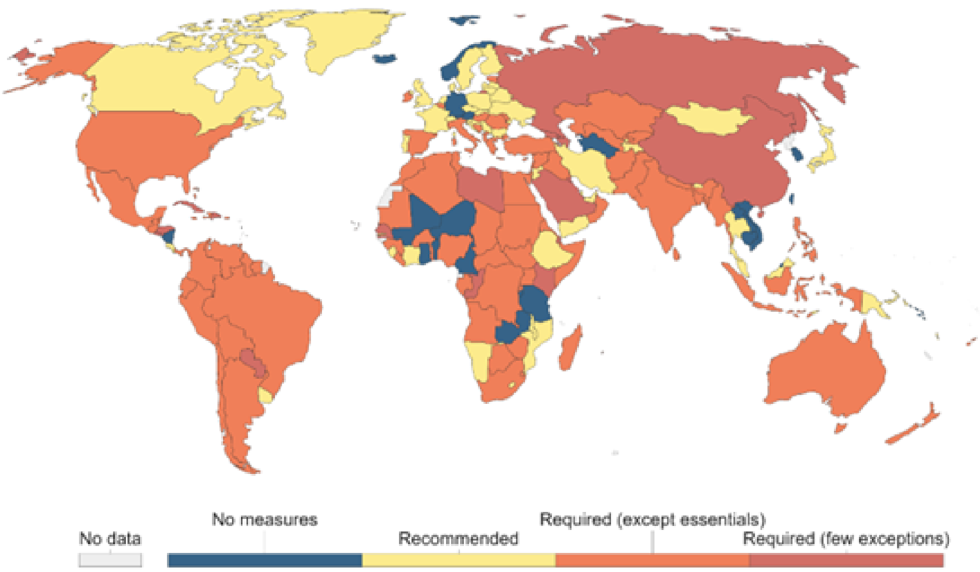

Figure 1. Stay-at-home requirements during COVID-19, 13 May 2020 [15].

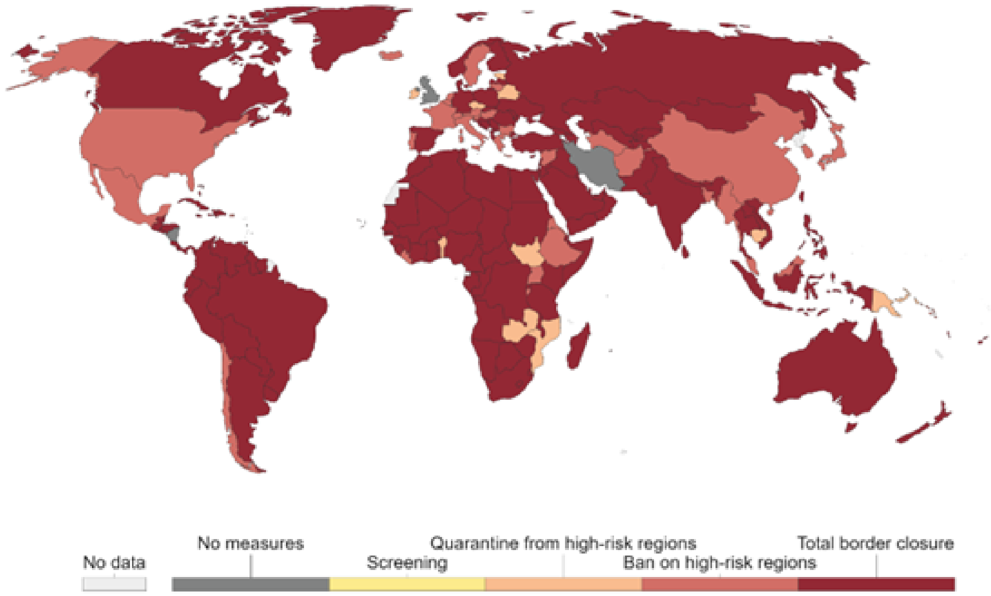

Figure 2. International travel controls during COVID-19, 13 May 2020 [15].

Youtube is the largest video platform in the world [16]. It produces millions of metadata in audio–video content that enables researchers to operate NLP and investigate opinions and sentiments [17]. The analysis of feedback in the form of comments left by viewers on Youtube channels is an essential source of unstructured data for further research [18,19]. Additionally, Youtube is a dedicated video-sharing platform that amasses a significant amount of data that can be channeled to study the sentiments of individuals (also known as opinion mining) towards a product or phenomenon [20].

Comments from Youtube videos have been historically studied to mine individuals' opinions regarding trending topics [21]. Dubovi and Tabak (2020) in their study involving knowledge co-creation from Youtube videos revealed that "comments went beyond information sharing to argumentative negotiation, reaching a higher level of knowledge construction" [22]. They have further added that Youtube comments provide an informal setting for science discussions. Yu, Wen, and Yang (2020) extracted comments from Youtube videos to explore the visitation intention of individuals wth respect to suicide tourism [23]. Their study reveals that unobserved social proclivities can be revealed from mining Youtube video comments. Similarly, Raja Chakravarthi et al.(2021) examined Youtube comments to identify hate/violent speech against the lesbian, gay, bisexual, transgender, and queer community [24]. Compared to content from other content sharing platforms such as Snapchat, Instagram, and Imgur, content from Youtube is more generationally diverse and far-reaching [24]. Furthermore, comments from Youtube videos have been investigated to understand a plethora of sociocultural processes and societal norms such as cyberbullying of overweight people [25], anti-NATO sentiment [26], ethnic insults [27], and misogyny [28]. The antecedents presented herewith provide substantial empirical merit to the current study's authors to adopt Youtube commentaries as their preferred medium of analysis.

This study investigates public opinions regarding virtual tourism in the context of COVID-19 via watching YouTube [5]. The percentage of viewers who watch 360-degree videos vs. unidirectional movies was measured. We also summarized the frequency of watching videos during the peak of COVID-19 compared with other periods. Such problems have not yet been addressed and must thus be investigated further.

Regarding the relevant dataset for this research, online comments from YouTube were collected using Python. There are two kinds of videos that were collected, one is 360-degree [29], and the other is unidirectional videos. Each video should have two more million views and more than one thousand comments. Furthermore, a five-level sentiment analysis technology [5] to investigate the features and laws of public opinion toward online travel and the SentiStrength-SE [30] tool was applied in this paper.

2. Related Works

Sentiment analysis (SA), often known as opinion mining, is a natural language approach for examining people's feelings on a particular product or problem [31]. SA is the automatic examination of an online document, such as a blog, remark, review, or comment, to decide if it is a solid positive, positive, negative, strong negative, or neutral (Pang & Lee, 2008). SA may be used to predict polarity results [32], give product information to businesses and organizations, automate product descriptions or summaries in reviews, and even forecast the stock market on online shopping sites [33].

In general, the categorization of emotions is crucial in contemporary SA research. This method assigns the opinion polarity of words and phrases that express sentiments to identify a document's subjectivity/objectivity orientation, positive, negative, or neutral [34]. Two types of sentiment classification strategies are reported in the literature, supervised and unsupervised SA [33]. This type of classification is related to the method used by the computer to generate sentiment classifications. Machine learning techniques such as support vector machine (SVM), maximum entropy, k-nearest neighbour, Naïve Bayes, Decision Tree, and Artificial Neural Network are utilized [20,33,35,36]. The supervised learning approach makes use of labelled training data that have been annotated by hand, as well as testing data.

On the other hand, the unsupervised technique does not require labelled training data. The current paper's primary methods are linguistics-based and lexicon-based [37]. The lexicon-based approach entails statistically calculating feelings based on the text's semantic orientation of words or phrases [38]. The fundamental premise behind lexicon-based techniques is that the most critical indicators of emotion in the natural language literature are words that communicate opinions. A pre-compiled lexicon of positive and negative phrases is necessary for this strategy.

SentiWordNet [39] is another well-known lexical resource intended exclusively for sentiment classification and analysis applications. Based on linguistics, the SA divides natural language information into more than individual constituent words and sentences. It also detects their syntactic structures to determine a syntactic part-of-speech category, such as an adjective or verb phrase, most likely to be mentioned in an opinion. Each word's polarity score in the text is employed to categorize the emotion of the textual material. For example, if a phrase in the lexicon matches a positive emotion score, the material's positive polarity score is increased. As a result, if the positive polarity score surpasses the negative polarity score, the substance is deemed positive; otherwise, it is termed negative. A substantial study has been conducted to locate frequently used words reflecting sentiment in an online review using a learning lexicon-based technique and natural language processing to reveal typical terms that indicate opinion mining [34,40].

Thet et al. [30] suggested a linguistic approach for the SA of topic postings in discussion forums based on clause-level opinion analysis. SentiWordNet, a purpose-built domain lexicon (movie review domain), obtained the above word emotion ratings. The emotion score for each phrase was then calculated by analysing the natural language syntactic relationships of words, using syntactic dependency trees and taking pattern rule into account.

Thelwall et al. [41] created the SentiStrength technique enhanced by machine learning to evaluate consumer behaviour and sentiment strength in textual data. Islam et al. utilized SentiStrength to create a database to classify specific content in the double polarity (positive or negative), and SentiStrength identified 298 positive and 465 negative phrases [30]. In addition, Alrehaili et al. adopted SentiStrength to classify positive and negative sentiments based on the comments of YouTube videos for kids [39]. However, SentiStrength-SE also includes domain-specific phrases in the software development area that do not contain any sentiments [30]. According to [42,43], SentiStrength-SE is more efficient than the general-domain lexicon at detecting sentiment polarity in application circumstances. Based on the advantages of SentiStrength-SE, this article will use it to classify polarity sentiment.

Last but not the least, SenticNet7 was proposed by E Cambria et al. [44]. It is a level of acquaintance used by the sentic computing structure for concept-level sentiment analysis [45]. It involves polarity recognition and emotion identification by leveraging the denotative and connotative information in connection with phrases and multi-word expressions rather than depending exclusively on term co-occurrence frequency ranges. Furthermore, Sentic APIs (sentic.net/api) are a set of application programming interfaces built to handle numerous sentiment analysis activities in various languages. Because all APIs are built on the Sentic Computing Structure, they use a combination of SenticNet and deep learning.

On the other hand, various sentiment analysis techniques have been adopted, ranging from tree-based classifiers to neural network-based methods [20,36,46]. They include Naïve Bayes, Decision Trees, Random Forest, Support Vector Machines, Gradient Boosting, Multiplayer Perceptron, and Convolutional Neural Networks.

- Multi-layer Perceptron (MLP) is a feedforward network [47,48]. Its components have three layers: input, hidden, and output. It is wholly connected, with each node linked to every node in the before and the following layer. The input layer will receive a list of factors, for example, factor 1 to factor k, as a list dataset for training. MLP might be trained to learn new things. A set of the training dataset, consisting of a group of input and output vectors, is required for training. It is continually provided with training data while training, and the network's weights are modified until the proper input–output mapping is achieved. Pattern categorization, recognition, prediction, and approximation are MLP's most typical uses. In 2020, M. Almaghrabi et al. adopted this model to improve sentiment analysis in Arabic and English languages [49]. Moreover, Xia et al. (2021) also used MLP in Tweet sentiment analysis of the 2020 United State Presidential Election [50].
- The Naïve Bayes Classifier is a technique based on Bayes Theorem [35,46]. The Naïve Bayes classifier works on the idea that the existence of one attribute in a class has nothing to do with the presentation of any other feature. For massive data sets, the Naïve Bayes model is beneficial. Naïve Bayes is renowned for outperforming even the most complex classification systems due to its simplicity. According to Kausar et al. [46], Google currently uses it to determine whether or not an e-mail is spam.
- Decision Trees are a classification method commonly utilized in the scientific world [46]. Text is classified into sentiment polarity using the decision tree. It belongs to the category of machine learning. Several studies [20,33,35,36] use decision trees to sort positive, negative, and neutral comment categories.
- Support Vector Machine (SVM) might be the most famous machine learning technique [46]. Since the 1990s, it has been popular and is still the leading strategy for a high-performance algorithm. It is a discriminant classifier that builds an ideal hyperplane for new sample classification by using labelled training data. The SVM model can predict unknown input based on the training.
- Random Forest (RF) is a branch of artificial intelligence that can be used for regression and classification [46]. It also performs reasonably well in the contexts of dimensional-reduction approaches, incomplete data, outlier values, and other critical processes in data discovery. It is an ensemble classifier in which a group of poor models is combined to create a better model. Each tree assigns a categorization to a new object's various attributes. The forest selects the categorization with the most votes and averages the outputs of the different trees. In 2019, Karthika et al. used RF to classify positive, neutral, and negative customer opinions [51]. They also stated that RF outperformed SVM. Furthermore, Ravinder Ahuja et al. (2019) conducted an investigation that showed that RF might perform more accurately than DT, SVM, and Naïve Bayes [52].

- Moreover, deep learning-based approaches, particularly convolutional neural networks (CNNs), have demonstrated consistent performance across many applications in medical image processing and documenting classification problems in recent years. As mentioned by Rani et al. (2019), CNNs are four-layer feedforward neural networks [53]. The first is the input layer, representing sentences $n \times k$ in size. The second layer is the convolutional layer, followed by the global max-pooling layer, and finally, the fully connected layer, which produces output results. The convolutional layer is CNN's primary building block because it performs most computations. A feature extraction layer extracts local features using filters, then produces a feature map using the convolutional kernels function and sends it to the pooling layer. In 2022, Priyanka Malhotra et al. presented research in the area of medical image segmentation using CNN [54]. They highlighted the benefits and drawbacks of the most widely used deep learning-based models used for the segmentation of medical lesions. Similar research was also studied by Sarvamangala et al. (2022), they stated that CNN is a common method for resolving medical image problems [55]. In addition, Chetanpal Singh et al. proposed CNN approach for sentiment analysis of COVID-19 reviews on Twitter [56]. The authors stated that their approach outperforms SVM and RF. Furthermore, Hoc et al. (2022) studied MLP, deep learning, and the multiple regression model in terms of software effort estimation; they showed that the deep learning approach leads to higher accuracy than the other [57]. Based on this discussion, we use the CNN approach to build a classification model based on collected datasets. The performance of CNN approach also compared with RF model.

3. Problem Statement

Recently, exceptional methods for determining text polarity have been proposed by scholars. They usually divide comments into five categories: strongly positive, positive, negative, strongly negative, and neutral [20,34,36,37,40,41,58]. The positive class includes documents that use positive language. In contrast, the negative class includes documents in which the user has a negative attitude toward virtual tourists, and the neutral class consists of neither positive nor negative documents. We used SentiStrength-SE and SenticNet7 to identify the five polarity classes in this study. For such a purpose, we employed a variety of arguments driven by participants' attitudes when travelling to scenic destinations via YouTube as an input dataset.

4. Research Questions

The following research questions (RQs) should be answered in this study:

1. RQ1: How do sentiments differ between users exposed to 3D and unidirectional videos?
2. RQ2: How does the performance differ between SenticNet7 and SentiStrength-SE?
3. RQ3: What is the most precise classification algorithm to gauge the performance of the sentiment analysis CNN-based model?

5. Data Collecting

In this section, we studied six videos from Angel Falls, Sahara Desert, and Victoria Falls, where three videos for each are 360-degree, and three other ones are the same places are unidirectional. Each place has a video with at least 1000 comments and more than two million views. Their comments were collected on 6 April 2022.

Table 1 shows they are categorized into six datasets ranging from Dataset 1 to Dataset 6. In addition, Dataset 7 is an aggregate of comments from six datasets, which are considered in this study. The SentiStrength-SE python library and natural language tool kit (NLTK) have been selected for coding.

Table 1. List of six videos for case study.

No	VideoID	Type	Description
Dataset1	L_tqK4eqelA	360°	Angel Falls, Venezuela
Dataset2	etSgGjaSM	unidirectional	Angel Falls, Venezuela
Dataset3	RdFkC6Gtb5A	360°	Sahara Desert, Africa
Dataset4	LMHfYnS65w0	unidirectional	Sahara Desert, Africa
Dataset5	WsMjBMxpUTc	360°	Victoria Falls, Mosi-oa-Tunya, Zambia & Zimbabwe
Dataset6	iywqpda7d8k	unidirectional	Victoria Falls, Mosi-oa-Tunya, Zambia & Zimbabwe

The three significant attractions were selected because they are all on the UNESCO world heritage sites list [59]. Interestingly, all of the usually destinations are transnational (spanning across one or more countries). Individually speaking, Victoria Falls, which falls at the cross-border between Zambia and Zimbabwe, attracted 639,000 visitors in 2019 [60]. Angel Falls, which is the world's largest free-flowing waterfall located in Venezuela, recorded 429,000 tourists [61]. The Sahara Desert, which spans the northern African region, received around 12 million visitors [62].

6. Used Methods

6.1. Comment Gathering

This section aims to present the collection of comments on specific YouTube videos. This work was completed with the help of Python programming. It uses the web API's HTTP GET function to retrieve comments from a video depending on its URL. However, the retrieved comments differ in terms of the languages and concepts used by the users. As a result, we had to undertake further cleaning on this unclear commentary to construct the data sets.

6.2. Data Pre-Processing

Comment content obtained from YouTube might feel messy, such as incomplete sentences, emojis, and different languages. These are unnecessary for sentiment polarity categorization. Such comments should be recognized, and these characters should be removed from the dataset. The NLTK library and python programming were adopted to carry this out. Following the extraction of the comments, the following adjustments were made:

- We eliminated any terms that are not relevant to the suggested methodology, such as hyperlinks, dates, special characters (*, /, !, @, #, ?, &, %), and various languages (Arabic, Hindi, Vietnamese, etc.).
- We removed all punctuation, for example, the period ("."), space (" "), commas (","), semicolons (";"), dash ("-"), etc.
- The most common words such as "the," "is," "this," and "that", called stop words, were removed from comments.

6.3. Sentiment Analysis Classification

Research on the subjectivity (neutral vs. emotionally loaded) and polarity (positive vs. negative) of a text is known as sentiment analysis [31]. It is based on sentiment lexicons, which are large collections of words that have each been annotated with a positive or negative orientation (i.e., prior polarity). The overall sentiment of a text is thus calculated based on the polarity of the words it contains. As mentioned above, SentiStrength-SE is a popular tool to carry out sentiment analysis. It works without additional applications or devices [30]. This technology detects emotional responses, emojis, negating words, booster words, slang, and idiomatic expressions. SentiStrength-SE generates a range of [−5, 5] for each sentence. According to [63], SentiStrength-SE measures five classes of sentiment, from strongly negative to strongly positive (see Table 2).

Table 2. Sentiment analysis classification.

No	SentiStrength-SE	Class
1	−5 to −4	Strongly negative
2	−4 to −1	Negative
3	−1 to 1	Neutral
4	1 to 4	Positive
5	4 to 5	Strongly positive

The sentiment analysis classification is presented in Table 2. This table uses the SentiStrength-SE approach to define positive, negative, or neutral polarity. A text is positive if the emotion score ≥ 1 and strongly positive if it is larger than 4. In addition, it is strongly negative if the score is less than -4 and negative if it is in the range of -4 to -1. Otherwise, it is neutral.

SenticNet 7 is built in four sections, as mentioned in [44]. Lexical substitution is a technique for identifying groups of concepts that have similar meanings (primitive sets). Second, the compelling similarity is applied to these semantically related sets to refine them. Then, each primitive set is named after its most representative term and paired with its semantic inverse (e.g., ACCEPT versus REJECT). Finally, primitive sets are refined further by examining the multidimensional path taken by each antithetic primitive pair. Sentic API (supported by sentic.net/api/) can be used to analyse the sentiment analysis. The structure of API is 'https://sentic.net/api' + LANG + '/' + APIKEY + '.py?text=' + "input text". Special formatting, ampersands, hashtags, semicolons, and braces are not required for "input text". However, in the preprocessing phase, they should be replaced with colons (:) or removed entirely. Currently, this API is supported by several "LANG", such as English (en), Spanish (es), Portuguese (pt), French (fr), German (de), Italian (it), Indonesian (id), and Vietnamese (vi). However, we need to request SenticNet system to receive APIKEY.

6.4. Sentiment Analysis Proposal

This section discusses NLP-based sentiment analysis based on user comments from selected YouTube videos to extract sentiment polarity classification. As illustrated in Figure 3, the suggested procedure is broken down into five parts. Firstly, the comment collection and preparation module take data (comments) from given YouTube 360-degree/unidirectional videos and performs some linguistic pre-processing to prepare for the following procedure. To start collecting data from YouTube, we went to the Google Developers Console and obtained a YouTube Data API key [64]. According to [19], the new Data API keys have a daily quota of 10,000 queries, allowing users to access public YouTube videos. The YouTube Data API is available in a variety of computer languages. This study focuses on Python gathering comments using the Requests module to make API requests. Secondly, the processed text is subjected to NLP-based algorithms to produce data sets. The regular expression (re library) is used to remove messy words, for instance, hyperlinks, dates, and special characters. Moreover, the most common words, or stop words ("the", "an", "a", "a", etc.), are eliminated by the Natural Language Toolkit (NLTK) Python library, version 3.7. As mentioned in Section 6.3, we used SentiStrength-SE and SenticNet7 to analyse sentiment polarity in the next step. As a result, the collected datasets generate sentiment polarity based on the relevant comments.

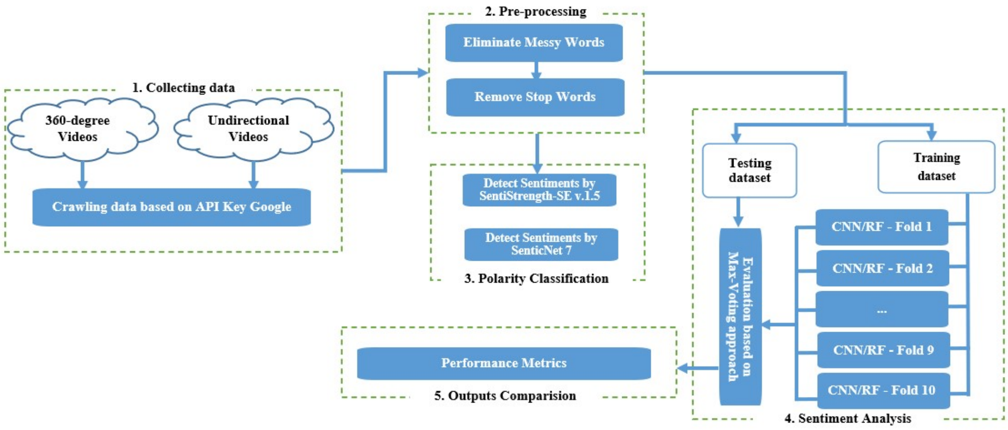

Figure 3. The flow diagram of opinion mining of YouTube comments.

In the following step, the collected datasets were used for both training and testing with a ratio of 80 and 20, respectively. Cross-validation with 10 folds is adopted in the training process for CNN and RF models, where nine distinct folds are chosen as the training dataset and the other one is used as the validation dataset. Each experiment was executed for 200 epochs with a batch size of 32, and the learning rate was 0.001. The purpose was to determine whether a specific comment had various attitudes based on the polarization of key characteristics. Thus, each comment is encoded by one-hot encoding with three given valid labels, negative ([1, 0, 0]), neutral ([0, 1, 0]), and positive ([0, 0, 1]), which are a kind of binary outputs. As a result, we have ten distinct groups, namely Fold 1 to Fold 10. Fold 1 stands for the output of a model that uses Fold 1 as validation and is similar to the other nine different folds. A max-voting approach was adopted to combine each output obtained from each group [65,66]. It might be a suitable approach to integrate predictions from many outputs because the outputs of those predictions are in binary forms. It involves each predictive model making a prediction and casting a vote for each sample. The final prediction consists of the sample that received the most votes.

6.5. CNN Architecture for Sentiment Analysis

Figure 4 represents the CNN architecture for sentiment classification based on collected comments data analysis. CNN receives input in the form of sentences depicted as a matrix. Each row of the matrix symbolizes a single token, which is usually a word but might also be a character. In other words, each row is a vector representing a word. These vectors usually generated word embedding (word2vec) by using GoogleNews-vectors-negative300.bin. They could also be one-time vectors that index the word into a dictionary. The output is fed into the embedding layer.

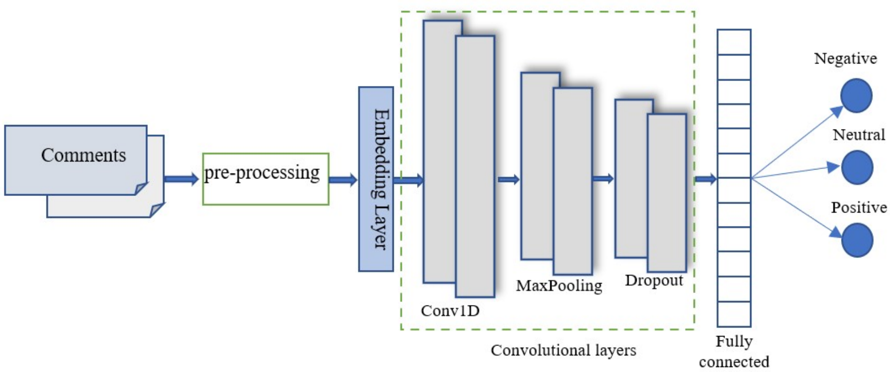

Figure 4. The proposed CNN architecture for sentiment analysis.

Next, a group of filters is employed to a sliding window of length h over each phrase in the convolution layers. These filters are adopted for each probable window of words in the phrase. These filters produce several feature maps. Finally, the previous layer's output is passed to a fully connected softmax layer. Because are three classes (negative, neutral, and positive) to measure the error probability between the prediction and the actual label, the cross-entropy function is used in the softmax layer.

7. Performance Metrics

We used three different evaluation methods to assess our proposed methodology, including Precision, Recall, and F-Measure [46,67]. Their formulas are given below:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{1}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{2}$$

$$\text{F}_1\text{-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

These measurements range from 0 to 1, with 0 representing the lowest theoretical and 1 representing the highest academic scores. The worst score is the one we receive from guessing at random. The best score may be less than one in practice because we can only aspire to replicate human achievement in some circumstances. There may be confusion about the correct categorization, such as in sentiment analysis.

8. Results and Discussion

Tables 3 and 4 present the percentages of sentiment analysis for seven datasets, from dataset 1 to dataset 6, where dataset 7 contains six results. Sentiment analysis for those datasets is executed by using the SentiStrength-SE and SenticNet7 approaches. The results indicate that the sentiments between 360-degree and unidirectional videos range from strongly negative to strongly positive on the sensitivity scale in Table 1. The sentiment analysis using those approaches shows a substantial difference between the viewer sentiments of a virtual-reality-enabled video and a unidirectional one. As can be seen, the percentage of positive comments obtained from dataset 1 is lower than that obtained from dataset 2 using both approaches. The analysis results on dataset 3 vs. 4 and dataset 5 vs. 6 also give similar outcomes. Furthermore, the proportion of viewers who have neutral opinions when watching 360 videos appears to be higher than that of unidirectional videos. This may be because 360-degree videos appear no more interesting than unidirectional videos on YouTube. From these findings, we can answer RQ1 by saying that the unidirectional video garnered more positive sentiments than the other.

Table 3. Percentage of sentiment analysis result based on Sentistrength-SE.

Dataset	Strongly Negative	Negative	Neutral	Positive	Strongly Positive
Dataset1	0.00%	4.50%	54.43%	40.09%	0.98%
Dataset2	0.41%	6.63%	42.96%	49.59%	0.41%
Dataset3	0.00%	1.90%	58.57%	38.57%	0.95%
Dataset4	0.72%	8.49%	54.82%	34.10%	1.87%
Dataset5	0.52%	7.63%	54.86%	35.59%	1.04%
Dataset6	0.08%	2.97%	37.09%	58.57%	1.29%
Dataset7	0.26%	5.61%	48.21%	44.81%	1.10%

To measure the level of agreement between SentiStrength-SE and SenticNet7 among seven given datasets based on the same categories, we employed the Matthews correlation coefficient (MMC). It was introduced by Brian W. Matthews (1975) [68], and its score can reveal the agreement between two raters based on the same categories [69]. Table 5 presents the scores of MMC between the two approaches. As can be seen in this table, their scores range from 0.37 to 0.518. These results might reveal that there is some agreement between the two approaches, the most moderate agreement comes from dataset 3, and the least agreement comes from dataset 4.

Table 4. Percentage of sentiment analysis results based on SenticNet7.

Dataset	Strongly Negative	Negative	Neutral	Positive	Strongly Positive
Dataset1	0.26%	13.68%	20.05 %	64.70%	1.31%
Dataset2	1.10%	10.11%	14.56 %	72.21 %	1.02%
Dataset3	0.21%	15.25%	26.09%	56.12%	1.37%
Dataset4	1.15%	20.05%	14.61%	61.71%	2.04%
Dataset5	0.52%	20.43%	20.00%	57.34%	1.40%
Dataset6	0.12%	9.07%	12.23%	76.31%	2.03%
Dataset7	0.32%	14.45%	16.92%	67.11%	1.20%

Table 5. MMC score between SentiStrength-SE and SenticNet7.

	Dataset1	Dataset2	Dataset3	Dataset4	Dataset5	Dataset6	Dataset7
MMC score	0.441	0.447	0.518	0.37	0.458	0.45	0.448

However, the ratios of neutral attitude obtained from SentiStrength-SE among the six videos ranged from 37.09% to 58.57%, whereas the corresponding ratios obtained from SenticNet7 were lower, ranging from 12.23% to 26.09% (see Tables 3 and 4). By contrast, the ratios of positive and negative comments found by SenticNet7 might be higher than those from SentiStrength-SE. These findings can allow us to answer RQ2 by saying that SentiStrength-SE might be unable to identify the proper polarity of the comments compared with SenticNet7. This issue might come from limitationsof the dictionary used; the new dictionary SenticNet's method might have significantly outperformed SentiStrength-SE. Based on these findings, we encourage researchers to consider modern techniques (such as SenticNet7) for sentiment analysis in the future.

On the other hand, the study has classified the sentiment analysis based on datasets obtained from SenticNet7 by deploying the CNN and RF models. Tables 6 and 7 present the performance metrics of CNN-based and RF-based models based on 10 folds, and the 10-folds-based max-voting approach. As can be seen, the accuracy obtained from CNN and RF models based on dataset1 in 10 folds is in the range of 0.68–0.73 and 0.68–0.77, respectively, while when the max-voting approach is used, the accuracy increases to 0.73, and 0.78, respectively. Similarity, precision, recall, and F1-score achieved from dataset1 by employing this approach also outperform an individual fold. Significantly, the precision obtained from dataset5 in 10 folds is in the range of 0.52 to 0.65 for the CNN-based model and 0.52 to 0.65 for the RF-based model. However, when the max-voting method is used, the precision improves to 0.67 and 0.66 for CNN-based and RF-based models. These findings are similar to those for the rest of the datasets. We can answer RQ3 by saying that the majority voting approach provides the most robust parameters of model selection in terms of Accuracy, F1 Score, Recall, and Precision.

Furthermore, the accuracy obtained from the CNN model based on dataset 3 and dataset 5 is better than that obtained from the RF model. As can be shown in Table 7 at the max-voting section, the accuracy of the CNN model for dataset3 is 85% and 67% for dataset5, compared with 75% and 66%, respectively, obtained from the RF model. In addition, the F1 score was obtained from those datasets given the similarity results.

Although the Random Forest approach slightly outperformed the CNN-based model compared with other datasets, these differences are insignificant.

Last but not least, there are several researchers who have compared performance between RF and CNN approach in terms of sentiment analysis. According to Gordeev, D., the RF algorithm outperforms other machine learning classifiers in terms of consistency and robustness, but it performed poorly for the Russian language [70]. He also stated that CNN classifiers (and deep learning in general) are viewed as more insightful and promising. Furthermore, Shaheen et al. studied machine learning methods such as RF, CNN, and Naïve Bayes in terms of sentiment analysis [71]. They conducted that RF outperformed all other approaches. They discovered that RF outperformed all other methods. However, they also stated that CNN was discovered to be useful for a specific dataset.

Table 6. Performance metrics CNN vs. RF (from Folds 1 to 5).

Dataset	Accuracy		F1 Score		Recall		Precision	
	CNN	RF	CNN	RF	CNN	RF	CNN	RF
Fold 1								
Dataset1	0.73	0.72	0.73	0.72	0.73	0.72	0.73	0.71
Dataset2	0.84	0.87	0.84	0.87	0.84	0.87	0.85	0.87
Dataset3	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82
Dataset4	0.73	0.72	0.73	0.72	0.73	0.72	0.73	0.72
Dataset5	0.65	0.64	0.65	0.64	0.65	0.64	0.65	0.64
Dataset6	0.80	0.80	0.80	0.80	0.80	0.80	0.83	0.82
Dataset7	0.74	0.74	0.74	0.74	0.74	0.74	0.76	0.75
Fold 2								
Dataset1	0.72	0.69	0.72	0.69	0.72	0.69	0.73	0.72
Dataset2	0.76	0.85	0.76	0.85	0.76	0.85	0.82	0.85
Dataset3	0.78	0.85	0.78	0.85	0.78	0.85	0.78	0.85
Dataset4	0.68	0.71	0.68	0.71	0.68	0.71	0.67	0.71
Dataset5	0.64	0.65	0.64	0.67	0.64	0.66	0.64	0.70
Dataset6	0.80	0.76	0.80	0.69	0.80	0.76	0.81	0.76
Dataset7	0.72	0.74	0.72	0.74	0.72	0.74	0.73	0.75
Fold 3								
Dataset1	0.69	0.72	0.74	0.72	0.69	0.72	0.69	0.72
Dataset2	0.74	0.78	0.75	0.78	0.74	0.78	0.74	0.82
Dataset3	0.86	0.78	0.86	0.78	0.86	0.78	0.86	0.78
Dataset4	0.65	0.68	0.67	0.68	0.66	0.68	0.66	0.68
Dataset5	0.58	0.63	0.59	0.63	0.58	0.63	0.58	0.63
Dataset6	0.80	0.79	0.81	0.79	0.80	0.63	0.80	0.80
Dataset7	0.76	0.71	0.78	0.71	0.76	0.71	0.76	0.72
Fold 4								
Dataset1	0.68	0.69	0.68	0.69	0.68	0.69	0.69	0.71
Dataset2	0.76	0.76	0.76	0.76	0.76	0.76	0.78	0.77
Dataset3	0.75	0.75	0.75	0.75	0.75	0.75	0.80	0.80
Dataset4	0.72	0.71	0.72	0.71	0.72	0.71	0.73	0.72
Dataset5	0.63	0.62	0.63	0.62	0.63	0.62	0.64	0.63
Dataset6	0.79	0.80	0.79	0.80	0.79	0.80	0.81	0.80
Dataset7	0.75	0.77	0.78	0.77	0.75	0.77	0.76	0.78
Fold 5								
Dataset1	0.69	0.68	0.69	0.68	0.69	0.68	0.70	0.69
Dataset2	0.79	0.79	0.79	0.79	0.79	0.79	0.81	0.82
Dataset3	0.59	0.64	0.59	0.64	0.59	0.64	0.59	0.64
Dataset4	0.51	0.54	0.51	0.54	0.51	0.54	0.53	0.54
Dataset5	0.58	0.59	0.58	0.59	0.58	0.59	0.59	0.59
Dataset6	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82
Dataset7	0.73	0.73	0.73	0.73	0.73	0.73	0.74	0.74

Table 7. Performance metrics CNN vs. RF (from Folds 6 to 10 and voting based on 10 folds).

Dataset	Accuracy		F1 Score		Recall		Precision	
	CNN	RF	CNN	RF	CNN	RF	CNN	RF
Fold 6								
Dataset1	0.69	0.68	0.69	0.68	0.69	0.68	0.70	0.69
Dataset2	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79
Dataset3	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65
Dataset4	0.58	0.55	0.58	0.55	0.58	0.55	0.57	0.53
Dataset5	0.52	0.52	0.52	0.52	0.52	0.52	0.53	0.52
Dataset6	0.79	0.77	0.79	0.77	0.79	0.77	0.78	0.76
Dataset7	0.73	0.74	0.73	0.74	0.73	0.74	0.75	0.75
Fold 7								
Dataset1	0.73	0.77	0.73	0.73	0.73	0.77	0.73	0.71
Dataset2	0.72	0.78	0.74	0.78	0.72	0.78	0.72	0.77
Dataset3	0.86	0.69	0.86	0.69	0.86	0.69	0.86	0.69
Dataset4	0.68	0.64	0.68	0.64	0.68	0.64	0.68	0.64
Dataset5	0.61	0.60	0.62	0.64	0.61	0.64	0.61	0.64
Dataset6	0.80	0.71	0.80	0.71	0.80	0.71	0.80	0.72
Dataset7	0.75	0.70	0.75	0.70	0.75	0.70	0.77	0.71
Fold 8								
Dataset1	0.74	0.75	0.74	0.75	0.74	0.75	0.75	0.76
Dataset2	0.82	0.79	0.82	0.79	0.82	0.79	0.81	0.78
Dataset3	0.85	0.73	0.85	0.73	0.85	0.73	0.85	0.73
Dataset4	0.67	0.66	0.67	0.66	0.67	0.66	0.67	0.71
Dataset5	0.67	0.61	0.67	0.61	0.67	0.61	0.68	0.61
Dataset6	0.77	0.80	0.77	0.80	0.77	0.80	0.78	0.82
Dataset7	0.75	0.72	0.75	0.72	0.75	0.72	0.77	0.73
Fold 9								
Dataset1	0.74	0.75	0.74	0.75	0.74	0.75	0.75	0.76
Dataset2	0.81	0.79	0.81	0.79	0.81	0.79	0.80	0.78
Dataset3	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73
Dataset4	0.66	0.66	0.66	0.66	0.66	0.66	0.67	0.71
Dataset5	0.58	0.61	0.58	0.61	0.58	0.61	0.58	0.61
Dataset6	0.83	0.80	0.83	0.80	0.83	0.80	0.84	0.82
Dataset7	0.73	0.72	0.73	0.72	0.73	0.72	0.74	0.72
Fold 10								
Dataset1	0.68	0.71	0.68	0.71	0.68	0.71	0.66	0.68
Dataset2	0.70	0.71	0.70	0.71	0.70	0.71	0.71	0.72
Dataset3	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59
Dataset4	0.64	0.67	0.64	0.67	0.64	0.67	0.67	0.67
Dataset5	0.57	0.56	0.57	0.56	0.57	0.56	0.56	0.56
Dataset6	0.80	0.80	0.80	0.80	0.80	0.80	0.82	0.82
Dataset7	0.74	0.72	0.74	0.72	0.74	0.72	0.74	0.72
Max-voting								
Dataset1	0.75	0.78	0.75	0.76	0.75	0.76	0.76	0.78
Dataset2	0.73	0.74	0.73	0.74	0.73	0.74	0.74	0.75
Dataset3	0.85	0.76	0.85	0.76	0.85	0.76	0.85	0.77
Dataset4	0.66	0.68	0.66	0.68	0.66	0.68	0.66	0.69
Dataset5	0.67	0.66	0.67	0.65	0.67	0.65	0.67	0.66
Dataset6	0.72	0.73	0.72	0.73	0.72	0.73	0.74	0.75
Dataset7	0.71	0.72	0.71	0.72	0.71	0.72	0.72	0.73

9. Conclusions and Future Work

This study aimed to shed light on three significant research inquiries. Firstly, the investigation aimed to gauge the latent disparity between 360-degree and unidirectional videos as prescribed by [72,73]. It was revealed from the SenticNet7-powered sentiment analysis of comments extracted from three popular tourism-related YouTube videos that 360-degree videos, to some extent, appeal to viewers but apparently do not have a significant influence on the viewers when compared with unidirectional videos. Furthermore, 360-degree videos were unsuccessful in actuating extreme sentiments such as strongly negative and strongly positive sentiments. Instead, unidirectional videos were observed at a higher volume. This observation is corroborated by [74], who found that 360-degree videos have a minor capacity to influence the intention to take mountain walking trips.

The following research question revolved around identifying the optimal sentiment analysis model. According to a study by Kausar et al. [75], it was recommended that the efficacy of the sentiment analysis algorithm must be estimated by deploying multiple machine learning classifiers. This study investigated the efficacy of the sentiment analysis model through a recent state-of-the-art method to solve the research question. As discussed in the Related Works section, the CNN technology proved to be the optimal algorithm for estimating performance metrics. In the extant literature, the CNN model with a max-voting approach based on cross-validation has been highly adaptive when a clear separation between the data classes exists and is relatively memory-efficient [76]. Last and not least, the study attempted to investigate viewer engagement with 360-degree videos during COVID-19. The authors analysed comment traffic from 2019 to 2020, when different countries imposed tourism-related restrictions. We showed that viewer engagement for 360-degree videos was higher than in previous years. The study detected high traffic in the subjects' YouTube videos depicting Angel Falls, Sahara Desert, and Victoria Falls when their countries imposed travel bans.

The study contributes in two ways. For academic, it serves the need to investigate text analyses and natural language processing models through different sentiment analyses and achieve desirable performance matrices. This will further help in advancing the model selection procedure. The study would recommend that tourism marketers and planners capitalize on text-mining technologies such as SenticNet7 and analyse tourist sentiments. Currently, the usage of NLP in the tourism industry is focused only on marketing purposes [75,77,78]. It can be used for tourism forecasting and recommender systems [79]. Furthermore, 360-degree videos can be compounded with Virtual Reality capabilities to promote niche forms of tourism such as adventure, nature-based, and sports. Future studies are encouraged to deploy advanced NLP modelling techniques such as CNN-LSTM [80,81], which have assisted the world of digital humanities in understanding sentiments towards law enforcement during the #BlackLivesMatter movement.

Moreover, as mentioned in the discussion section, CNN and RF employed in sentiment analysis should be studied more in the future.

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