Geolocation Data and Sentiment Analysis Combined with Deep Learning for Tourism Destination Management

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Abstract

The length of the data makes sentiment analysis on social media platforms like Twitter challenging, typographical errors, acronyms, and special characters. There are several applications for the underlying issue with social media sentiment analysis. An important problem in the tourism sector is the characterization of fluxes, hence sources of geotagged data have already showed promise for geographic research on the sector. The article describes a technique for determining how the general population feels about Cilento, a well-liked vacation spot in Southern Italy. Our strategy is based on a freshly assembled corpus of travel-related tweets.

We intend to present and evaluate In order to describe the spatial, temporal, and demographic tour- ist flows throughout the enormous area of this rural tourism sector and along its coasts, we used a deep learning social geode framework. To distinguish and evaluate the sentiment, we used two specially trained word-level Deep Neural Networks and two character-level Deep Neural Networks. Contrary to many current datasets, our method does not automatically assess the true attitude implied by texts or hashtags. To improve the correctness of the dataset and demonstrate the efficiency of our system, we manually annotated the entire set.

Keywords Deep learning, geotagged social media, sentiment analysis, and tourism

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1 Introduction

User-generated content usage has increased significantly in recent years as a result of the development of Web 2.0 tools and the growth of social media. In light of this, sentiment analysis is currently making substantial headway in a number of sectors, including marketing and financeIt is now widely recognised as a new subfield of natural language processing that evaluates users' opinions and sentiments on a wide range of subjects, enterprises, and experiences. It belongs to the field of affective computing research. (Liu 2015). Sentiment analysis looks for indications of favorable or unfavorable views in texts, either generally or in relation to a particular topic (Nakov et al. 2016). An explicit sentiment score is assigned to each word and phrase in a list of emotion

words and phrases that can be used to characterize the sentiment of textual pieces. In truth, a lexicon-based sentiment analysis's performance is significantly impacted by the sentiment lexicon.
To automatically ascertain the underlying sentiment of a document, algorithms and sentiment analysis techniques have been created (Sun et al. 2017). These algorithms are widely used by businesses to improve decision-making and better understand the attitudes and behaviours of their clients (Valdivia et al. 2019).
Despite the fact that many research have examined various consumer impressions of brands or organisations (Paolanti et al. 2017; Ghiassi et al. 2013), experts have not given much regard to the sentiment associated with tourism at the destination level and its possible effects. The economy, society, and environments of destinations are impacted by tourism in both positive and harmful ways. Lessening the negative social and ecological effects of visitor flux while both enhancing the visitor experience and the quality of life for locals is one of the main goals of sustainable tourism development (Gursoy et al. 2019). Despite the enormous amounts of tourism reviews and posts that could be used for this purpose and the potentials of sentiment analysis, The recourse to this is constrained because it costs money and takes time to carefully and manually extract useful information from the studies.
One of the most well-known social networking services at the moment is Twitter (http://twitter.com). People are able to express their thoughts and feelings about a variety of problems and difficulties they deal with every day. Instant messages are tweets. Twitter offers the chance to access the unprompted opinions of many people on specific things or events.
Approximately 200 billion tweets are sent each year on Twitter, or 500 million every day, 350,000 per minute, and 6,000 per second (Alharbi and de Doncker 2019). Additionally, it is necessary to automatically identify and extract spatial information about tour- ist flows from tweets. It can be challenging to determine how severe localised flooding is. Information gathering and dissemination can be aided by social media, particularly in urban areas. A few of the reasons for selecting Twitter as the case study in this study are listed above.

Travel-related tweets are lighthearted and informal. To process this textual input, effective sentiment analysis techniques must be applied. A felt language tailored specifically for the tourism industry must also be developed. The majority of current techniques for sentiment analysis on Twitter build a classifier from tweets that have been manually labelled with labels for sentiment polarity using machine learning algorithms such as Naive Bayes.Deep learning techniques have been more popular recently, and they can improve classification accuracy, especially when there are many examples of labelled data.
Given the aforementioned objectives, this book offers two unique additions to the field of research. In order to determine attitudes toward a popular tourist site in Southern Italy, we empirically compare the effectiveness of cutting-edge deep learning techniques on one side. The sentiment is categorised using four Deep Neural Networks with customised training (DNNs). These character- and word-based networks were given by Zhang et al.
Four DNN architectures are chosen by experimenting with various parameter combinations and picking the best one. The test factors for word-based DNNs are the size of the lexicon or alphabet and the maximum character limit for tweets (for characters-based DNNs). On the other hand, we show how deep learning architectures enable the inference of spatial, temporal, and demo- graphic aspects of visitor flows using a data-driven approach. This is done by employing geographic data.

Actually, a recent study shows that using sentiment analysis in conjunction with geo-location data might lead to more effective design of tourist attractions (Yan et al. 2020). The approach was tested using a current collection of tweets regarding travel. The dataset and implementation code are available at (XXX.it, hidden for blinding purposes: dataset-tweets-related-cilento). The accompanying phrases or hashtags do not always indicate the true feeling, in contrast to many other datasets. The dataset is more accurate because it was manually calculated by human annotators.

We saw encouraging accuracy results from our approach, which also supported the applicability of the suggested methodology. The travel and tourism sector does not have anything like our dataset. However, the models chosen are the most effective text classifiers currently on the market and are generic. Additionally, In the reference articles for these networks, additional datasets have been examined. One Word-CNN : evaluated on six distinct datasets, the majority of which were used for sentiment analysis. (2) Word-LSTM was evaluated using WMT'14 datasets (Sutskever et al. 2014). The paper is structured as follows: The state of textual sentiment analysis research is summarized in Section 2, along with suggestions for next research, in Sections 5 and 6.

2 Relatedworks

The research outlines a variety of techniques that analyse tweets using classifiers with the primary goal of determining polarity. The literature is replete with examinations of approaches that point up important differences in both procedures and data sources. The majority of current studies on Twitter sentiment analysis employ supervised techniques.

The feature combinations used to train classifiers (such Naive Bayes. The fundamental component of supervised approaches is the use of recognisedlex-icons of words that are weighted according to their sentiment orientations (Miller1995).

They represent two knowledge-based techniques for determining the emotional polarity of peers' expressions. These techniques rely on semantic data sources. These methods' accessibility and ease of use contribute to their popularity. For their performance, nonetheless, a solid basis and a comprehensive representation are required. Despite the widespread usage of statistical methods in the scientific community.

Deep learning techniques, such as bag-of-words mixed with SVMs, have recently replaced shallow feature representations, which were previously the main techniques for recognising and analysing textual sentiment analysis (Tang et al. 2014). (Bengio 2009; LeCun and colleagues 2015) Deep learning algorithms, Nave Bayes and Artificial Neural Networks (ANN), and Support Vector Machine (SVM) are the three main techniques for categorising sentences.

Using ANN requires more processing time than the other two approaches., but it yields better results overall? SVM and Nave Bayes algorithms are less expensive to compute but have limited performance.

Results from experiments on various datasets have shown that utilizing CNNs improves classification performance. To improve the accuracy of Twitter sentiment analysis, Jianqiang et al. (2018) train a deep neural network using a convolutional approach. The technique makes use of statistical traits and semantic connections among each tweet's words. There are numerous studies that use lexicon-based techniques to conduct sentiment analysis on tourists. The WordNet algorithm (Miller 1995) was used by Serna et al. (2016) to find emotions in tweets about the

Easter and summer holidays.

When undertaking autonomous sentiment analysis in the tourism business, Though few studies accurately analyse content from popular networks like Twitter (Kirilenko et al. 2018). The study of geotagged social media data has shown to produce more detailed spatial, temporal, and demographic information on visitor movements than what is currently known about the patterns of tourist flow in the area, as Chua et al. (2014, 2016) have shown.

The lexicon-based technique establishes polarity by comparing opinion phrases from a sentiment dictionary with the given data. Dictionary-based approaches and corpus-based approaches are the two types of lexicon-based approaches. Machine learning-based techniques such as Naive Bayes (NB), Maximum Entropy (ME), and Support Vector Machines (SVM) have produced excellent results in sentiment analysis.Recently proven useful, particularly for automatically evaluating Twitter data (Lim et al., 2020). Because of its ability to handle massive amounts of data, the technique used in this work is based on Deep Learning, as demonstrated by the advantages and disadvantages in Table 1. DNNs can extract a large amount of data by removing the most important traits. Given that we are dealing with a subjective task like sentiment, this capability is critical in this context.

3 Resources and Techniques

The framework for textual sentiment analysis is introduced in this part, along with the dataset that will be used to test it. Its biggest and most problematic features are always the area's size and orthographic complexity. Southern Italy's Cilento is a popular tourist location. To promote bold development and cohesiveness, local governments have been struggling for many years to come to an agreement on the best regional tourism plan. We have been working on a nationwide initiative (TOOKMC: Transfer of Organized Knowledge Marche-Cilento) since late 2013 to encourage the exchange of best practices in sustainable tourism between Italy's developed and developing regions. This project is sponsored by state and European organizations. Using a dataset of tweets about the Cilento amassed for this study, trained DNNs have been employed for the evaluation, and they have undergone a thorough evaluation. The framework depicted in Figure 1 More information about data collection and DNN settings can be found in the next sections.

The Cilentotook project (http://www.cilentodas coprire.it) is responsible for the dataset's acquisition. Given the length of the data collection period and the size of the geographic area, the Tweets made by visitors to Cilento have been saved.Due to the fact that tourists continue to talk about their vacations long after they have left their vacation places, providing significant information for our study, Data gathering is not just restricted to the Cilento and the vacation season, A customized Python programmer that makes use of the tweepy library (last accessed 2021/01/30 21:45:16), tweepy Python library) gathers tweets. The Twitter streaming API is made simple to use by Tweepy, which also manages authentication, connections, sessions, and message reading. Applications of a spatial filter based on scripts that run in a Dockers container

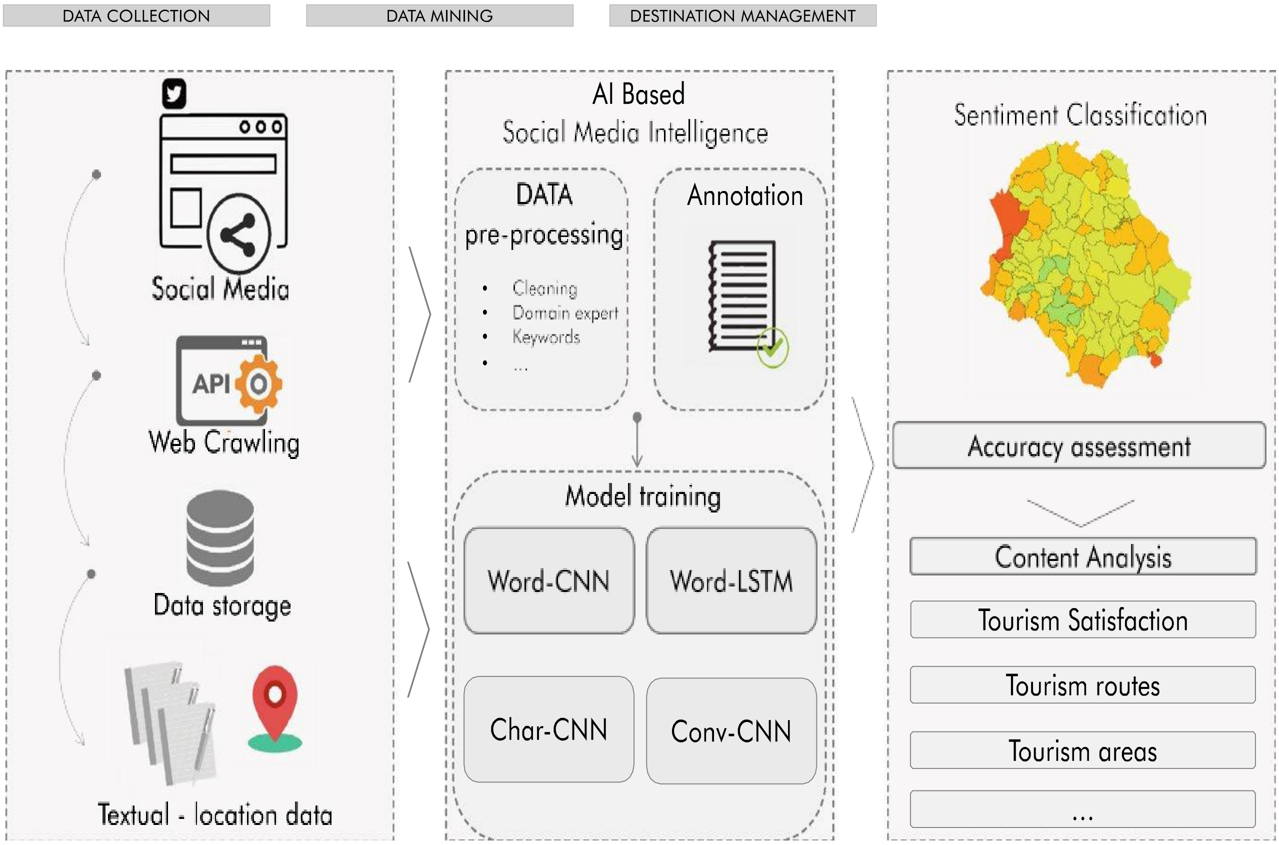


Fig. 1 The proposed research framework's workflow

A tweet on Twitter can be "geotagged" as it is being published by users. Based on precise location given to a Twitter Place, geotagging is used. The size of the location region is determined by the latitude and longitude coordinates, This could be described as a "bounding box." Geographic data of this kind is referred to as tweet location. It offers the highest degree of precision when it comes to geographic location .The biggest flaw in "tweet locations" is that often only 1% to 2% of tweets are geotagged. A database contains all of the tweets. Every tweet creates a record that includes the text and metadata. The following details are provided:

• id: unique tweet id;

from user: the user's username who posted the tweet;

- to user id: the username of a potential recipient of the tweet;
- loc.lat: the tweet's sending location's latitude;
- loc.lon: the tweet's sending location's longitude;
- sent at: the time the tweet was sent;
- text: the tweet's text

Actual sentiment of gathered tweets (in Italian and English) has been painstakingly checked by human annotators, compared to automatically produced labels using hashtags, delivering a more accurate and quieter dataset.The following geotagged Twitter information about Cliento's neighbourhood is part of the dataset: 2200 tweets with uplifting messages; 3720 tweets with neutral attitude; 4442 tweets were critical in nature.

We used a subsampling strategy to ensure that the proportions of each class (1/3, 1/3, 1/3) were equal before splitting the data into training and testing. After class balancing, they all have 3200 samples in total. The following criteria were used by two reviewers (annotators).

if it includes words (verbs, adjectives), such as "to love," "to admire," "pleasure," or "beautiful," which by themselves have a positive connotation;
- if at least two "!" are used to support the assertion;
- If it includes common likeness indicators like "happy smiles" and "thumbs up,"
• Neutral: If neither a positive nor a negative attitude is present.
• If it contains words (verbs, adjectives) with negative connotations, such as "hate," "ugly," or "disgusting," it is seen as negative.
When words having positive connotations but negativity meanings are used; if the negative idea is strengthened by the point "!" appearing at least twice; if it includes symbols such as "ad facets" or "thumbs down";
Only a small number of the edited tweets experienced arguments or conflicts between the annotators. There was usually a second round of mutual conflict followed by a consensus.

DNNs for textual sentiment analysis

Four DNN architectures have been used to compare the effectiveness of sentences categorization with various parameter settings. DNNs that work at the word level include convolutional neural networks (CNN) and long short-term memory (LSTM) recurrent neural networks (Word-CNN and Word-LSTM, respectively). ConvNets and Char-CNN are the other character-based DNNs With regard to the Word-CNN and the Word-LSTM, a dictionary using the "index," "word," and "frequency" data structures has been created using all of the terms from the complete text dataset that were left unanswered. The frequency with which a word is used throughout the dataset as a whole determines where it appears in the index. Therefore, the terms that are used the most frequently will be listed first.

Three models of CNN are as follows:

• Static: conditioned vectors are used in the model. According to Kim (2014), all word vectors will remain static, not changed.

• Non-static: similar to the prior model, but each task requires fine-tuning of the pre-trained vectors.

• Random: in accordance with the reference work (Kim 2014), all word vectors are randomly initialised and updated during training.

Using 100 billion words from Google News, the publicly accessible word2vec vectors were trained, were specifically used to build the pre-trained vectors. Utilizing the continuous bag-of-words architecture, the 300-dimensional vectors were trained (Mikolov et al. 2013b). When terms are absent from the list of words that have already been trained, random initialization is employed. The initial stage of processing can be summed up as follows:

• Words are created and added to a lexicon; a tweet is made up of several words. A word vector, which is a fixed-size vector made up of real integers, is created for each word. In order to identify each user in each tweet.

• These features serve as the inputs for two convolutional layers that are running simultaneously and have varied kernel dimensions in order to extract distinct features. An embedding layer extracts a collection of features for each ID from the arrays of integers that make up a CNN's inputs (embedding dim).

• The classification stage is followed by an aggregated distribution of the parallel arm properties to a fully linked final layer.

The unreplied terms from the whole text dataset were utilized in the second technique, which is for character-based DNNs, the following data structure to build an alphabet or dictionary: "index," "word," or "character," "frequency." Kim won't be mentioned again, and the dictionary will only contain new phrases, according to not-replied (2014). The word or letters are positioned according to the index by taking into account how frequently they are used across the full dataset. As a result, the words or characters that appear the most frequently (hirer frequency) are placed first. The text processing method known as word embedding transforms each sentence into a real vector domain (Mikolov et al. 2013a, b). In a high-dimensional space, Real-valued vectors are used to encode words.where the proximity in the vector space corresponds to the similarity in meaning between words. Positive integer word representations can be effectively transformed into a word embedding by an embedding layer utilising Keras (http://keras.io).

On our dataset, the networks were trained from scratch. Other freely available Twitter datasets for the travel sector do not contain tweets in both Italian and English. Because of this, we decided against leveraging the networks' pre-training on other datasets to improve them.Our dataset was divided into 20% for validation and 80% for training for each model. The automatic partition construction kept the emotional balance of both tweets. For the various learning rates, batch sizes, epochs, optimization strategies, etc., the default values from the repositories were used.and loss functions for each model's training hyperparameters. No optimization of the hyperparameters has been done. Hyperparameters have been adjusted for both types of networks. Several dictionary sizes and word counts have been tested for the Dictionary-Based, obviously employing the terms that appear most frequently in the dataset. All further network hyperparameters have been set to the values specified in the cited references. The Character-based network, for instance, maps each word onto a 32-length real valued vector. Finally, since the sequence length (number of words) of each phrase fluctuates, we limited each phrase to N words by clipping larger phrases and padding shorter phrases with zero values.

Table 2 A comparison of the DNNs' architectures' performance DNNs

Parameters	Metrics

	Sentences length	Dict/Alph length	Accuracy	Precision	Recall	F1-score
Word-CNN	128	1000	0.776	0.776	0.776	0.776
	128	3000	0.778	0.778	0.778	0.778
	128	5000	0.767	0.767	0.767	0.767
	128	10000	0.776	0.776	0.776	0.776
	200	1000	0.779	0.779	0.779	0.779
	200	3000	0.767	0.767	0.767	0.767
	200	5000	0.766	0.766	0.766	0.766
	200	10000	0.780	0.780	0.780	0.780
	280	1000	0.774	0.774	0.774	0.774
	280	3000	0.776	0.776	0.776	0.776
	280	5000	0.760	0.760	0.760	0.760
	280	10000	0.784	0.784	0.784	0.784
Word-LSTM	128	1000	0.750	0.750	0.750	0.750
	128	2000	0.751	0.751	0.751	0.751
	128	3000	0.751	0.751	0.751	0.751
	128	5000	0.752	0.752	0.752	0.752
	128	10000	0.731	0.731	0.731	0.731
	200	1000	0.758	0.758	0.758	0.758
	200	2000	0.751	0.751	0.751	0.751
	200	3000	0.751	0.751	0.751	0.751
	200	5000	0.752	0.752	0.752	0.752
	200	10000	0.724	0.724	0.724	0.724
	280	1000	0.755	0.755	0.755	0.755
	280	2000	0.757	0.757	0.757	0.757
	280	3000	0.755	0.755	0.755	0.755
	280	5000	0.758	0.758	0.758	0.758
	280	10000	0.724	0.724	0.724	0.724
Char-CNN	128	70	0.843	0.843	0.843	0.843
	128	100	0.847	0.847	0.847	0.847
	128	200	0.846	0.846	0.846	0.846
	128	345	0.846	0.846	0.846	0.846
	200	70	0.840	0.840	0.840	0.840
	200	100	0.846	0.846	0.846	0.846
	200	200	0.848	0.848	0.848	0.848
	200	345	0.845	0.845	0.845	0.845
	280	70	0.843	0.843	0.843	0.843
	280	100	0.842	0.842	0.842	0.842
	280	200	0.847	0.847	0.847	0.847
	280	345	0.845	0.845	0.845	0.845

Table 2 (continued)

DNNs	Parameters		Metrics			
	Sentences length	Dict/Alph length	Accuracy	Precision	Recall	F1-score
ConvNets	128	70	0.761	0.761	0.761	0.761
	128	100	0.769	0.769	0.769	0.769
	128	200	0.786	0.786	0.786	0.786
	128	345	0.776	0.776	0.776	0.776
	200	70	0.777	0.777	0.777	0.777
	200	100	0.782	0.782	0.782	0.782
	200	200	0.783	0.783	0.783	0.783
	200	345	0.779	0.779	0.779	0.779
	280	70	0.793	0.793	0.793	0.793
	280	100	0.788	0.788	0.788	0.788
	280	200	0.798	0.798	0.798	0.798
	280	345	0.799	0.799	0.799	0.799

We looked at a number of M and N combinations to conduct different tests, alternate amounts for the reference alphabet have also been investigated. By changing the character count of the alphabet and the maximum character count for each tweet, additional tests based on character level have been carried out using neural networks. The alphabetic characters are classified according to how frequently they are used using distinct numbers. When a character count restriction is implemented, the less frequently used characters are subsequently removed. This most recent assessment was a test. Our objective is to evaluate the degree to which categorization performance was impacted by the size of the dictionary and the alphabet (for character-based models) (for word based model). Because they only appear once in the sample, the results demonstrate that some of these emoji are not particularly significant.

Our work made use of a different kind of coding from that employed by Kim (2014), Zhang et al. (2015), and others who used one-hot vector encoding. This array must first be rebuilt in reverse order in order to build an array of numbers from an array of characters, such as the tweet. The number zero serves as a visual cue for the gaps and erased characters in a tiny alphabet. The performance of DNNs in comparison to human coding is used to evaluate the sentiment analysis. The sentiment indicated in our data sets was evaluated by human annotators using the same criteria, resulting in two independent human classifications for each textual record. To categorise the textual features as being negative, neutral, or positive, we have selected annotators with sentiment analysis expertise who have been uniformly trained and given a clear set of guidelines. The classifications of the other raters were unknown to the raters. The following metrics have been used to compare the DNNs performance to human raters.

Additionally, all of the tweet-related emoji are now included in the alphabet. Despite the fact that each emoji is a character, the first two networks use them as words. The result of the word embedding serves as the input for the second component of each DNN architecture.

4 Results

The test results that were performed on our dataset are shown in this section. In the experiments, only tweets that had achieved approval from both annotators regarding the tone of the text and image as a whole were used.

Additionally, three variants of the DNNs—static, non-static, and random—have been examined. However, utilising pretrained "word2vec" vectors, only the best outcomes (non-static) were implemented. It uses a transfer learning process, starting with vectors that have already been taught and refining them with training on our dataset. The old dataset heavily influences the static example, while the other two cases include random initialization of the vectors for training.

Static, non-static, and random DNN versions have all been researched. Pretrained "word2vec" vectors were only used to implement the best outcomes (non-static). It uses a transfer learning method, starting with vectors that have already been learned and refining them through training on our dataset. The static example is significantly influenced by the old dataset, whereas the initialization of the vectors for training in the other two cases is random.. The results of the experiment show how closely length affects grading results. Some tweets have been seen to be composed of several portions, the first of which has the indicated sentiment and the remaining sections providing the supporting details. As a result, we increased our research while reducing the maximum length of the tweets.

Table 2 displays the results of the experiments. When considering sentences that have the same length in characters, notably for the Word-CNN, a larger lexicon reduces accuracy. This tendency can be explained by the fact that tweets with fewer repeats have less discriminative power. On the other hand, a dearth of dictionaries makes it difficult to amass a significant number of discriminatory words. This is a result of "stopwords" like articles, prepositions, and conjunctions dilating and weakening the most prevalent words. Trimming the data to the first N tweets yields a marginal improvement in the final accuracy. This pattern may exist as a result of the fact that only a small portion of a tweet's useful language is needed to determine its mood. On the other hand, too much truncation results in the misclassification of a feeling because too much information is lost.

The results of the Word-LSTM show that, in contrary to what happens with CNN, sentences of the same length are more accurate when their lexicon is broader.
It would seem that a recurrent neural network can recognise less discriminative vectors of characteristics given that they are linked to words that are either too common (stopwords) or not

very frequent. Results from recurrent neural networks typically perform worse than results from CNNs.

Contrary to what happens with dictionary-based CNNs, the results for the Char-CNN and ConvNets show that larger alphabets boost accuracy for a given length of the sentence in characters. In this instance, the accuracy is decreased by trimming the alphabet by removing the less common characters.

The result is that a character-based network outperforms a dictionary-based network. This characteristic results from the fact that tweets frequently contain mistakes and purposeful word alterations intended to emphasise messages. A kernel in the convolutional layers could therefore eliminate these artefacts, making character-by-character analysis more trustworthy. Terms that are based on dictionaries are not treated the same way as these artefacts.

Inter-annotator agreement is widely used to assess the quality of a dataset and the difficulty of the classification problem because sentiment estimation is a subjective endeavour in which various people may assign different sentiments to tweets. More reliable metrics of agreement include the Kendall and Cohen coefficients (Kirilenko et al. 2018). To determine how well the categorization results of the DNNs and the hand annotation agree, we calculated and O. (ground truth). They were not informed of the classifications made by the other raters. Table 3 summarizes the findings. The results of these assessments of the inter-annotator agreement also demonstrate that, generally speaking, the four approaches have produced successful results. They consistently achieve values above 0.6 for the Cohen coefficient and the Kendall coefficient, respectively. The Char-CNN approach was the most effective; its Kendall, Cohen, and final coefficient values were all greater than 0.76, and its ratio of opposing classifications did not surpass 0.023.Discussion and results

To better comprehend the results of the investigation, we employ spatial data. To determine the sentiment-based ranking, we deduced the semantic meaning of a tweet from its geographic position. Because it makes it easier for people to acquire and comprehend complex data, data visualisation is crucial. Data visualisation employs statistical visuals, charts, information graphics, and other techniques to display information simply and effectively. However, numerical data, such as a piece of quantitative information, is represented by dots, lines, bars, and cartograms. geo-localized and categorised tweets can be viewed on a map. In particular, a geodatabase that incorporates tweets has been developed. The original mongoDB database's fields were retained when exporting tweets as a table, but an additional field called sentiment was added to indicate the sentiment of each tweet, including whether it was positive, negative, or neutral. A map of a specific place can also be loaded, and tweets from that location can be overlaid on the map. The longitude and latitude of each tweet serve as the coordinates for that tweet. Many different emotions can be expressed through colour. Tweets that were posted in the Campania region are shown in Figure 2a. The other half of Campania is depicted in green, and the five macroregions of the Cilento are shown in purple. Green indicates a positive attitude, yellow indicates a neutral attitude, and red indicates a negative attitude in a tweet.

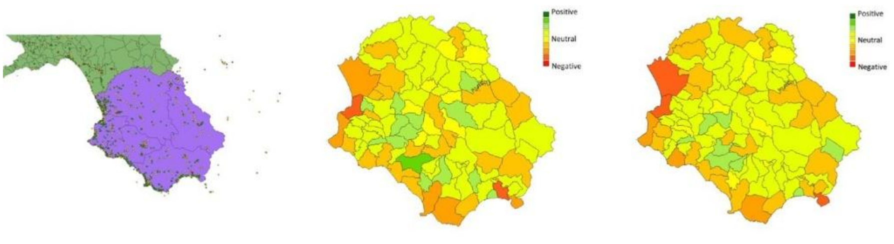
The geodatabase also makes it possible to run queries like "average mood of tweets in a region," which is a sporadic and tiny area. If the tweets are positive or negative, a colour gradient from green to red can be used to depict the outcome on a region's map.

Figure 2b's map displays the overall sentiment of the tweets that each Cilento municipality generated. To bring focus to the unfavourable tweets, the nonlinear colour spectrum was used. The negative attitude would not have been apparent on a linear scale because there were fewer negative tweets than positive or neutral ones.

Table 3 Comparison of two humans'agreements

and the Cilento-related DNNdataset of tweets	Se n- le ngth	Dict/Al ph length		C
Word-CNN	128	1000	0.664	0.724 0.030
	128	3000	0.666	0.719 0.034
	128	5000	0.651	0.699 0.038
	128	10000	0.664	0.697 0.042
	200	1000	0.669	0.731 0.029
	200	3000	0.65	0.706 0.034
	200	5000	0.649	0.707 0.033
	200	10000	0.671	0.699 0.044
	280	1000	0.66	0.720 0.031
	280	3000	0.664	0.717 0.035
	280	5000	0.64	0.690 0.040
	280	10000	0.675	0.706 0.041
Word-LSTM	128	1000	0.625	0.676 0.042
	128	2000	0.626	0.677 0.043
	128	3000	0.627	0.676 0.044
	128	5000	0.627	0.674 0.043
	128	10000	0.597	0.646 0.050
	200	1000	0.637	0.688 0.040
	200	2000	0.626	0.679 0.042
	200	3000	0.627	0.686 0.039
	200	5000	0.628	0.680 0.041
	200	10000	0.586	0.629 0.058
	280	1000	0.633	0.688 0.040
	280	2000	0.635	0.696 0.034
	280	3000	0.633	0.687 0.039
	280	5000	0.636	0.699 0.035
	280	10000	0.586	0.646 0.049
Char-CNN	128	70	0.765	0.811 0.018

128	100	0.77	0.808 0.021
128	200	0.769	0.808 0.021
128	345	0.769	0.809 0.020
200	70	0.76	0.802 0.020
200	100	0.769	0.805 0.022
200	200	0.771	0.805 0.023
200	345	0.767	0.806 0.021
280	70	0.765	0.808 0.019
280	100	0.763	0.798 0.023
280	200	0.771	0.808 0.021
280	345	0.767	0.808 0.020



(a) (b) (c)

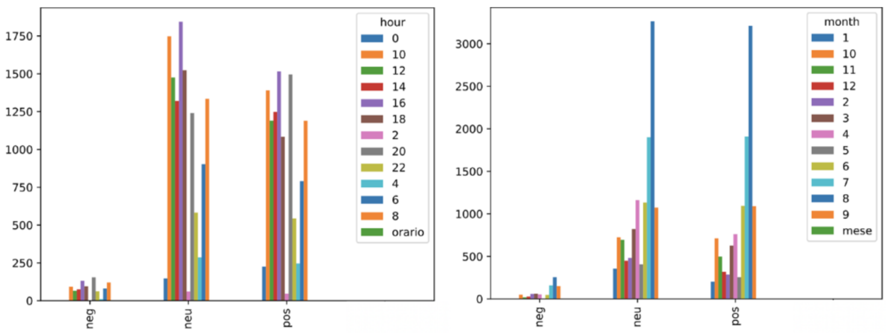
Fig. 2 Geotagged tweet sentiment analysis as data visualisation.

The depiction of tweets from the Campania area, the average sentiment of tweets from each Cilento municipality on a map.

As an illustration, If a municipality is highlighted in red, it indicates that the average mood of all tweets sent from that location was only negative. For example, if a municipality is highlighted in red, it means that the dataset's average sentiment for all tweets mentioning that place is only ever negative. The nonlinear color scale was chosen to highlight the importance of negative tweets.
The created graph provides more specific information on the connections between various macro-regions. The green (positive), yellow (neutral), and red (negative) circles' sizes are equal based on the quantity of tweets related to the particular macro-region. The arches, whose thickness is inversely correlated with the number of tweets, depict the "direction" of the tweets. The graph clearly and immediately displays the analysis' results. It became apparent that all macro-regions have a tendency to talk positively about themselves. In contrast, tweets directed at other macro-regions are less common and, when they do occur, are generally neutral in tone.
There are, however, cases where neighboring macro regions routinely talk badly about one another. The type of tourist experience or location the user is referring to at the time the tweet is posted on Twitter can therefore be determined by analysing the text of tweets. The study's conclusions have some practical implications. We believe that the mapping of visitor sentiment might provide useful data on the destination's online reputation, seen as a brand,to destination managers and policymakers.

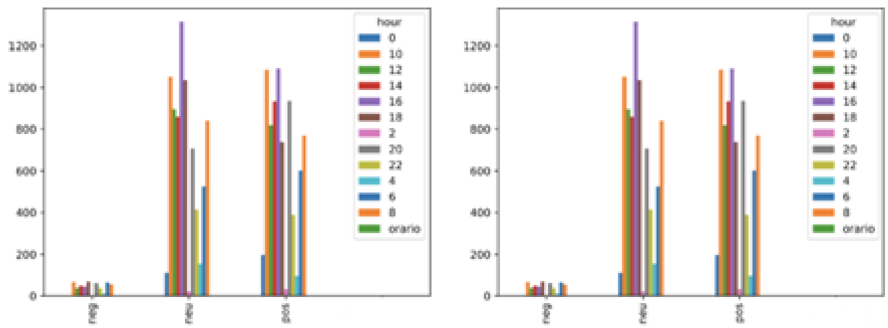
The reputation of the destination brand has a big impact on Ghafari et al. claim that brand loyalty and image are related (2017). Additionally, they discovered that one aspect of the entire destination brand equity is the representation of the travel brand (Keller et al. 2008). Additionally, this fits with the findings of Mazurka's 2019 study, who emphasized the importance of efficiently maintaining a travel destination's brand reputation to improve its allurement. With the exception of a few crucial areas where the presence of negative tweets is more relevant, our findings suggest that the presence of primarily positive or neutral tweets may help to improve the reputation of the destination brand online. Additional research has been committed to comparing tweets about rural areas and the shore in order to draw important conclusions and data regarding the more popular phrases tweeted about.

Who emphasized the value of successfully protecting a tourism destination's brand reputation to increase its attraction ,According to our findings, the existence of mainly positive or neutral tweets may contribute to a better online reputation for the destination brand. Additional research has been committed to comparing tweets about rural areas and the shore in order to draw important conclusions and data regarding the more popular phrases tweeted about. The words "piove," "abbandonati," and "rifiuti" were most frequently used The terms "Christmas," "cenadinatale," and "auguridinatale" are the ones that are used most frequently throughout the winter. Scams, particularly in vacation homes, are linked to the unfavorable feeling of that era. Figures 3 and 4 present some data and contrast the tone of tweets on the interior and coastal regions.



(a) (b)

Fig. 3 Tweet analysis of the inland region's sentiment. Figure 3a depicts the state of mind using an ourly analysis.



(a) (b)

Fig. 4 Comparison of sentimental tweets about the beach. Based on the month, Figure 3a shows analysis

5 Conclusion and next projects

Social media sentiment analysis is a challenging but rewarding task that helps firms better understand tourist movements. To categorize the sentiment of tweets on the Cilento region of southern Italy that are pertinent to tourism, deep learning has been developed .A tweet's mood may be detected by four trained DNNs. The experiments using a recently assembled dataset provide excellent accuracy and demonstrate the worth and viability of our method. For gathering and analyzing the geographic, temporal, and demographic characteristics of visitor flows, the last one is beneficial. . It also makes it possible to describe tourist movement in rather sophisticated ways and to identify the demographic characteristics of different tourist groups. Therefore, by utilising these insights, tourism business owners and local governments could adopt a larger perspective of the perceptions of tourists. In addition, because online user-generated content is crucial for travel planning and destination selection

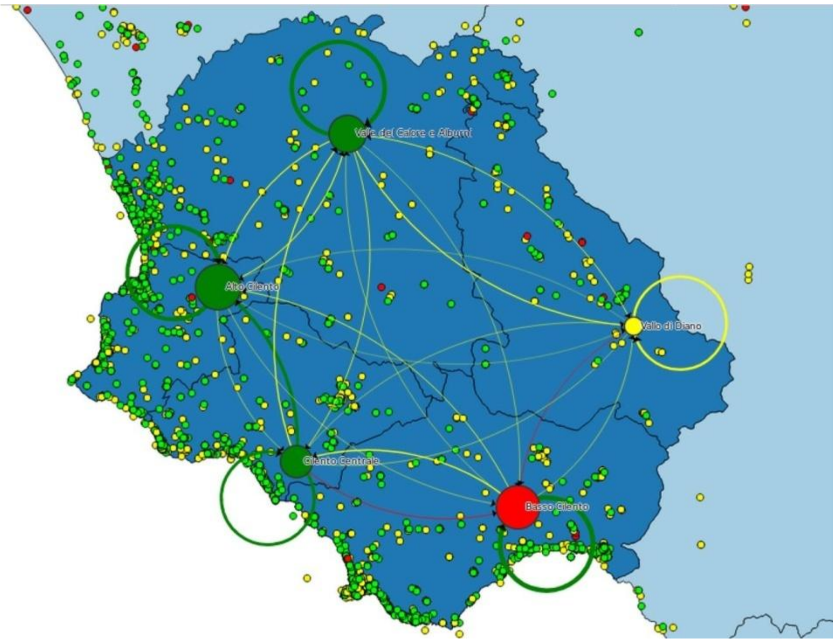


Fig. 5 A visual illustration of the relationships between several macro regions

According to (Litvin et al. 2008; Yoo and Gretzel 2011), they aid in building a company's reputation. However, it is important to emphasize that relying just on sentiment analysis's data may be restricted or even misleading given the actual circumstances. Consequently, a more detailed study that considers the content of each tweet in the sample is needed. In light of this, content analysis coupled with ongoing sentiment tracking will help tourist industry participants improve their marketing choices (Valdivia et al. 2019). Future work on this subject will involve deeper content analysis in order to better understand the motivations behind a given statement. We believe that by implementing this method, It may be possible to improve the prevalent customer satisfaction and dissatisfaction models currently used in the travel and tourism sector, which can only give a partial picture of the overall trip experience. (Fig. 5)

More research will be put into expanding the dataset we use and extracting more useful information to enhance our technique. By contrasting the suggested DNNs with other textual sentiment analysis systems already in use, we will widen the evaluation even more. It was fascinating to examine the generalizability of the strategies in our work with a group that was mostly multilingual. The following step will be to test the same methodologies on datasets that only contain that one language.

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