

Deep Learning for Sentiment Analysis

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Abstract— The opinions of people and others are one of the main influencers of human behaviour and activities. Therefore, individuals and organizations often consult with others to understand their opinions or attitudes towards a certain topic, before making decisions. Also, for telecommunication enterprises to survive, they need to be attentive to their customers' opinions. Sentiment analysis is a technique that is often used by organizations to categorize and understand the underlying attitude of a person towards an entity, product, topic, etc. Though it has been traditionally performed using text-based sources, it has been suggested that other modalities should be explored. One such alternative to text-based sources is video recordings of people using or reviewing content. Videos can contain multiple modals including text, voice, and facial expressions, which can be used to detect a person's attitude towards a topic. An approach to performing sentiment analysis using affective computing for extracting an opinion holder's affective data based on their facial expressions, and then feeding this data to a deep learning multilayer perceptron neural network, is proposed in the paper. The outcomes of this study indicate that the proposed approach is highly feasible to gain accurate insights into a person's sentiment towards a specific topic.

Keywords— *sentiment analysis, social media analytics, deep feedforward neural network, face emotion detection, convolution neural network, data mining, deep learning.*

I. INTRODUCTION

Opinions play a central role in influencing how humans act and behave. Worldviews, or the way one perceives the world around them, are often formed by the way those people surrounding a person perceive the world. Organizations, like individuals asking their peers for their opinions, often rely on the opinions of their customers when they need to make decisions. This can be done using traditional means such as customer satisfaction questionnaires. However, due to high costs and issues with availability related to obtaining feedback, organizations explored other avenues into their customers' opinions. One such avenue into understanding other's opinions or sentiment is the use of sentiment analysis with the increase of media posted to social media websites, organizations, such as telecommunications enterprises, can gain insight into their customers' opinions. This allows them to identify their strengths and weaknesses, as well as to identify new opportunities and threats. Previous research has been done to determine how telecommunications enterprises can make use of text-based sentiment analysis to improve customer satisfaction and improve the overall user experience.

Sentiment analysis is traditionally done using text-based reviews published to the Internet. Nevertheless, the increase in popularity of social media platforms and the sharing of opinions on these platforms in forms other than text, such as video, audio, and images, has made it necessary to explore these other modalities to use for performing sentiment analysis.

According to the use of videos for performing sentiment analysis has the advantage of including a magnitude of behavioural cues to detect the affective state of the opinion holder. The field of affective computing can help with the identification of human emotions, since it entails calculating what "relates to, arises from, or influences emotions".

Based on this information an approach to accurately perform sentiment analysis using effective computing to identify emotions of opinion holders in videos based on their facial expressions, and a deep learning multilayer perceptron (MLP) neural network, is presented [1].

A literature review covering the topics of sentiment analysis, affective computing, and deep learning neural networks are presented in this paper.

II. LITERATURE REVIEW

For the precise characterization of assumptions, numerous specialists have put forth attempts to consolidate profound learning and AI ideas lately. This area quickly clarified the various scholarly investigations, related information to conclusion examination of web substance and social exercises about clients' assessments and survey, feelings recognition, client audits toward several of issues and item based utilizing profound learning strategies.

Sentiment analysis undertakings could be performed information effectively by executing an audit of various models, for example, speak to profound learning models, that are expanded as of late. The models includes CNN (convolutional neural systems) and RNN (recursive neural system) and DNN (profound neural systems) and RNN (repetitive neural systems) and DBN (profound conviction systems). The segment depicts the efforts of various scientists to actualizing profound learning models speak to for playing out the sentiment analysis. A few analysts have utilized more than one speaks to the model in their investigation, and these are referenced under the speak to cross breed neural system area.

A. Convolutional Neural Networks (CNN)

CNN (convolutional neural system) [4] incorporates pooling layers and advancement as it provides a standard design to delineate sentences of different length into the sentences of fixed length dispersed vectors. For Example. CNN is been executed utilizing Caffe and Python on a Linux machine. As CNN improve its presentation by expanding its size and profundity, so a profound CNN model, enlivened by Google Net is proposed with 22 layers for sentiment analysis. The system with 60 ages has been performed for preparing the system as Google Net has performed 250 ages. For test work, a dataset of twitter consisting of 1269 photographs is chosen and backpropagation is applied. Amazon Mechanical Turk (M Turk) and well known group knowledge is used to mark the photographs. Five laborers were included to create estimation mark for each picture. By changing over Google Net into visual sentiment analysis system, the better element extraction was completed. The steady and dependable phase was achieved by using hyperparameters.

B. Recursive Neural Network (RNN)

RNN consists of tree like structure that is settled before preparing and the hubs can have various frameworks. There is no requirement for recreation of contribution to RNN. For Example. The proposed research constructs a Treebank for chines assessments of social information to conquer the insufficiency of named and enormous corpus in existing models. To anticipate the names at sentence level for example positive or negative, the Recursive Neural Deep Model (RNDM) was proposed and accomplished superior than SVM, Nave Bayes and Maximum Entropy. At that point baselines with incredible edge. Right now, model containing RNTN (Recursive Neural Tensor Network) and Sentiment Treebank is proposed to accurately explain the compositional impacts at various degrees of expressions, that is, positive and negative expressions.

C. Affective computing

The field of affective computing is concerned with giving computers the ability to detect, process, express, communicate and respond to human emotions. Emotions play a major role in human's everyday lives. It influences cognition, perception, communication, and rational decision making. Therefore, it is an important aspect to consider when designing computer systems.

Humans interact with each other using their facial expressions, body gestures, and speech. By incorporating these methods of communication affective computing leads to advancements in the area of human computer intelligent interaction. Thus, interfacing with a computer can move beyond the traditional use of a keyboard and mouse [5].

Computers can be made aware of emotions by detecting emotions through facial expressions, body gestures, speech, and other physiological signals. For this paper, the Affective AI software development kit (SDK) was used to detect facial expressions [2].

a. Text Classification

CNN's can be utilized to extract the data from the sentences. This data can be utilized for the classification of sentiments. For example: If a writer is happy or sad? or are the movies good or not?

III. DEEP LEARNING FOR NEURAL NETWORKS

Deep learning emerged from the field of machine learning in 2006 [11]. It broadly refers to machine learning techniques using neural networks which (1) consist of multiple layers of nonlinear nodes, and (2) which uses supervised or unsupervised learning methods at consecutive higher levels of abstracted layers for feature representation.

Supervised deep learning refers to deep learning techniques where the collected data is labelled before feeding it to the deep learning neural network [12]. On the other hand, unsupervised deep learning can be classified as the techniques that do not require a human to label the dataset and are usually focused on the capturing of the high-order correlation within the observed data. The most basic form of a deep learning neural network is also named as the multilayer perceptron neural network, which is based on the Perceptron proposed by Rosenblatt in 1950 [9, 10]. An MLP consists of an input and output layer and contains multiple hidden layers in between these layers. It receives an input which is then mapped to a category, by successively sending the input values from one layer of nodes to the next layer of nodes.

Emotions detection on social media websites is exceptionally powerful for quantifying the state of mind of people on a particular point, news, or item. It include a wide scope of utilizations, including distinguishing mental conditions, for example, uneasiness or recognize melancholy in clients. However, it is a challenging assignment to recognize useful emotions' detection features from a huge corpus data of text since emotions are very supplemented in abstract, with constrained fuzzy boundaries that might be communicated in distinct terminologies and ways of understanding meaning. To handle the issue, paper includes a hybrid proposition of TensorFlow based deep learning with Keras for emotion detection on a large-scale data of imbalanced social networking' data. Initially, pre-processing phase is carried out to gather valuable features in raw social activities without noisy data. Secondly, the entropy weighting technique is utilized to figure the significance of every method. Thirdly, the class balancer is applied in order to balance the classes. Fourthly, application of Principal Component Analysis is done to transform highly mathematical and correlated features to normalized ones. At last, the TensorFlow based deep learning with Keras algorithm is carried out to find out high-quality features and analyse data for classification of emotions. The methodology proposed is analysed on that dataset of all social activities review collected from the website 'kaggle'. The proposed approach is compared to another state-of-the-art algorithms on different training industries ratios. It is demonstrated that the proposed algorithm outperformed amongst other social techniques [6].

IV. SOCIAL MEDIA ANALYTICS

In these years, social media, discussion forums, online blogs and other methods of online communication tools have affected everyday life, particularly the way individuals express their opinions and remarks. The derivation of required information (like people's opinion about company brands) from the enormous unstructured data is important for several organizations and associations. The product surveys are significant for entrepreneurs as they can make business decisions appropriately to consequently group clients' reviews towards offered services and products. The implementation of sentiment analysis is not only restricted to a product or a movie review however could be implemented to various fields, for example news, politics, sport and so forth.

To an instance, in case of online political discussions, individual's opinions for particular candidate or political party can be recognized with the help of sentiment analysis. In this context, the wide use of sentiment analysis has been made in divergent languages by utilizing conventional and advanced machine learning algorithms. However, constrained research is till now carried out to create models for Per-sign language [5].

V. SENTIMENT ANALYSIS

Opinions of individuals are a vital factor that needs to be considered by organizations before they make decisions. People often review products or provide their opinions on specific issues through blog posts, or discussion forums. Because of the increased availability of content on the Internet and social media there exists a wealth of data that may be used by them[2].

Data scientists can analyse this data to mine for patterns that could be of interest to organizations. These patterns are used to understand customers, and to improve an organization's sales and marketing strategies. Sentiment analysis refers to discovering the opinions, or sentiment towards a certain object, fact, or attributes. A sentiment consists of four components, i.e. the entity, the aspect, the opinion holder, and the aspect's sentiment. Thus, sentiment analysis should successfully extract these components from the given source [4].

A. Characteristics of Sentiment Analysis:

It incorporate various featured values including trigrams and bigrams with combinations and polarities. In this way, opinions can be inspected in both positive and negative perspective with the utilization of various support vector machines (SVMs), alongside training algorithms.

neural network aids sentiment analyses to figure out the consideration of number of labels. To incorporate extraction of data at context level, conditional dependencies amongst various edges and nodes from the a non-cyclic graph operated by Bayesian networks are considered. Optimization of sentences and words, data exactness could be achieved on the social media sites. The utilization of data tokenization is done at word root level to create positive and negative sides of data fed. Algorithms are being utilized to diminish the errors occurred in sentiment analyses to accomplish a more significant level of accuracy of data gathered from social media [3].

B. Sentiment Analysis is a multidisciplinary Field:

The sentiment analysis is referred to as a multidisciplinary field and technologies since it incorporates various fields and the statistical analysing for data and computational linguistics, data recovery, semantics, machine learning, artificial intelligence and natural language processing. The categorization of approaches for sentiment analysis could be made as three different levels: i) feature or aspect level; ii) document level; and iii) sentence-level. Sentiment analysis can be applied as two different strategies, these are, lexicon based documentation and machine learning based algorithms, deep feed forwarding input output techniques.

The sentiment analysis includes the processing of huge amount of data and automatically predicting sentiments into positive or negative. The analysis is carried out at as: at the document level or the sentence level. A document level process the entire document in order to classify the sentiments into positive or negative, while, at the sentence level is utilized to categorize the sentiments expressed in the sentence for analyses. It has been seen in literature that the automated feature extraction based on deep learning outperforms other state-of-the-art manual feature engineering-based classifiers, for example, Support Vector Machine (SVM), Multilayer Perceptron (MLP), or Naive Bayes (NB) and so forth. One of the significant algorithms in deep learning is the autoencoder which for the most part includes reducing the amount of feature dimensions taken for review. The primary point of dimensionality information decrease is to acquire a lot of head factors to improve the elite of the great methodology. like, CNN's have been demonstrated to be specific in sentiment analysis. Be that as it may, little work has been completed to misuse profound learning based include ripper-sensation for Persian sentiment analysis. Right now, present two deep learning models (deep autoencoders and CNNs) for Persian supposition examination [8].

A. Data Collection:

The proposed approach makes use of affective data that are extracted from video recordings. Therefore, affective data (specifically facial expressions), were collected from nine participants, consisting of Honours and master's Computer Science students. The group consisted of 1 female and 8 male participants.

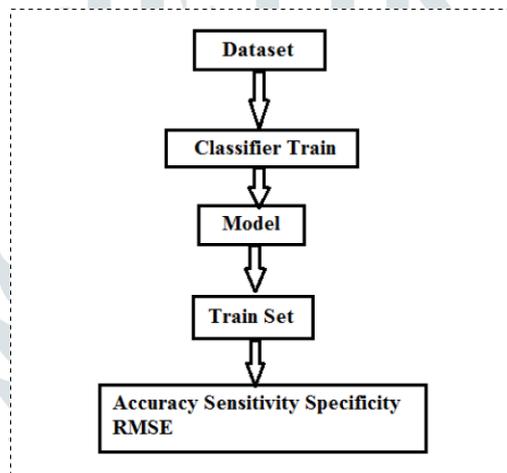
Three text passages were identified that would evoke one of three main reactions, or sentiment, from the participants. The three categories for the passages were classified as positive, neutral, and negative. The participants were informed that they would be recorded as they read the passages. However, they were only informed afterwards about which metrics were to be extracted from the videos (i.e. emotions), as to prevent

them from possibly being self-conscious about their reactions, and to not be influenced to react in a certain way. After recording the participants, each video was processed using the Affective SDK to extract the 43 metrics indicating a probability that the participant is experiencing that metric. Therefore, 43 input values for the MLP were generated at each frame that was analysed. Table I provides an example of values for four of the extracted metrics at five consecutive frames [2].

TABLE I: SAMPLE OF DATA EXTRACTED FROM PARTICIPANT VIDEOS

Timestamp (s)	Disgust (%)	Fear (%)	Surprise (%)	Brow Raise (%)
8.48	99.92004	99.57072	95.69440	28.01171
8.52	99.91998	99.57033	95.68865	27.95599
8.56	99.91998	99.57021	94.37222	28.73918
8.60	99.92001	99.57047	93.46150	29.60226
8.64	99.91998	99.57097	91.47912	29.15755

The pre-processing of all the videos created a dataset consisting of 132261 data points. This may be due to each participant having a different reading speed. However, it is believed that this did not influence the results. Before it was presented as input to the MLP, the order of the extracted data points was randomised, and the data were grouped into three datasets, i.e. training-, validation-, and test datasets, in a relation of 70%, 20%, and 10%, respectively [4].



B. Experiment results and discussions:

In our research, 8 distinct classifiers are been considered for the comparative analyses of performance of classifiers and selection of best classifier that produces best results amongst all. Educational dataset is considered from Callboard 360 dataset repository, and is given as input to several classifiers specifically SVM, MLP, Decision Tree, K-star, Bayes Net, Simple Logistics, Multi-class Classifier and Random Forest. Training of data set for each classifier is performed and a Model is obtained, which is then checked against test data to obtain the outcomes. The outcomes are computed and assessed in the form of factors including Accuracy, RMSE, Specificity, Sensitivity and ROC curve area.

TABLE II. RESULT ANALYSIS INVOLVING DIFFERENT CLASSIFIERS USING EDUCATIONAL DATASET

Methods	Accuracy	RMSE	TP	FP	ROC
SVM	78.75	0.35	0.78	0.12	0.86
MLP	78.33	0.34	0.78	0.12	0.89
Random Forest	76.66	0.33	0.76	0.13	0.89
Simple Logistics	77.21	0.34	0.76	0.13	0.88
Decision Tree	75.83	0.36	0.75	0.13	0.83
K-Star	73.75	0.38	0.73	0.14	0.87
Multi-Class Classifier	70.62	0.37	0.70	0.17	0.85
Bays Net	70.20	0.37	0.70	0.16	0.84

VII. CONCLUSION AND FUTURE WORK

Telecommunication enterprises can make use of sentiment analysis to gain a better understanding of their customers' opinions. Since the number of non-text media, such as videos, and audio, being published to the Internet has drastically increased with the use of social media, new modalities of performing sentiment analysis should be explored. Possible improvements can be made to current applications of sentiment analysis by making use of effective data and deep learning neural networks.

Sentiment analysis is being utilized broadly for a wide of scope of genuine applications, going from item audits, studies input, to business knowledge, and operational enhancements. Be that as it may, most specialists are dedicated to English-language just, where data vital is additionally accessible in different dialects. Right now, center around creating sentiment analysis models for the Persian language, explicitly for Persian motion picture audits. Two deep learning models (profound autoencoders and profound CNNs) are created and contrasted and the cutting edge shallow MLP based AI model. Reproductions results uncovered the outperformance of us proposed CNN model over autoencoders and MLP. In the future, we expect to abuse further developed profound learning models, for example, Long Short-Term Memory (LSTM) and LSTM-CNNs to additionally assess the exhibition of our created novel Persian dataset.

The results indicate that using affective data and a deep learning MLP to perform sentiment analysis is feasible. However, it should be further investigated as to which metrics would produce the best results for performing sentiment analysis.

Possible future work includes performing further experiments in terms of the architecture and number of inputs used by the MLP. Also, as only nine participants were used, the number of participants can be increased to create a larger dataset that is more representative. Alternative methods to extract other forms of affective data from the videos may also be explored. Furthermore, the problem can be approached using other types of neural networks, such as recurrent neural networks, convolutional neural networks, as well as ensembles of neural networks, as to determine the most suitable type for this problem.

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