AI-DRIVEN SENTIMENT ANALYZER

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I. Abstract

The main application of natural language processing is to analyze the author's sentiment within a given context. Sentiment analysis (SA) aims to determine the accuracy of the underlying emotion expressed in the context. It has been employed in various fields such as stock market prediction, social media analysis of product reviews, psychology, judiciary, forecasting, disease prediction, agriculture, and more. Numerous researchers have made significant contributions in these domains, yielding valuable outcomes that facilitate a quick understanding of the overall summary. Additionally, sentiment analysis plays a crucial role in comprehending genuine feedback shared across platforms like Amazon, TripAdvisor, and others.

This comprehensive survey aims to review some of the most important research conducted to date and provide an overview of sentiment analysis models within the domain of emotion AI-driven SA. Furthermore, this work explores sentiment analysis applied to different types of data, including images and speech. Visual sentiment analysis endeavors to understand the emotional impact of images on individuals. Despite being a relatively new field, a wide range of techniques has been developed to address various data sources and topics, resulting in a substantial body of research. Therefore, this paper considers a structured formalization of the problem that is commonly employed for text evaluation and discusses its applicability in the context of visual sentiment analysis. The paper also highlights recent challenges and examines progress towards more sophisticated systems and practical applications, offering a summary of the insights gained from this study.

Keywords: Emotion AI, Sentiment Analysis, multi-lingual, Machine-learning, Neural-Networks, Visual Sentiment analysis.

II. Introduction

Sentiment analysis is the process of identifying the human emotions expressed within a given context. It enables the prediction of an individual's emotions, attitudes, and even their personality, which are conveyed through various means. By recognizing the emotions highlighted in a context, sentiment analysis allows machines to accurately understand and interpret these emotions. In the past, information and opinions were mainly shared in person among family, friends, neighbors, and so on. However, with the advancement of technology, most of these exchanges now take place online, where sentiment analysis plays a vital role. Technological advancements have exposed people to a wide range of perspectives within minutes. For instance, individuals can share their thoughts on social issues or their experiences with products. These opinions encompass movies, hotels, restaurants, and more. As online communication becomes increasingly popular, both individual experiences and the need for sentiment prediction in business settings have grown. This helps businesses better understand the preferences, likes, and dislikes of the general public.

Traditionally, sentiment analysis techniques have primarily focused on analyzing textual content, with limited efforts directed towards extracting sentiments from visual content such as images and videos. Alongside the vast amount of available data, social networks often consist of short and informal messages. Furthermore, people commonly use images and videos, in addition to text, to convey their experiences through popular social platforms. Visual contents provide not only semantic information related to objects or actions depicted in the image but also cues about the influence and sentiment conveyed by the scene. Such information is valuable in understanding the emotional impact beyond the semantic content. Images and videos have become popular means for people to express their emotions and share experiences on social networks, which play a significant role in gathering information about people's opinions and feelings. The images shared on social media platforms reflect the visual aspects of users' daily activities and interests. These user-generated images represent a rich source of information for analyzing user interests. Extracting emotions underlying images perceived by viewers can lead to new approaches in various application fields such as brand perception, customer satisfaction assessment, marketing, and media analytics. The widespread use of personal mobile devices connected to the internet and the growth of social media platforms have introduced a new communication paradigm in which people share multimedia data. Uploading photos to social media platforms has become the new way for individuals to share their opinions and experiences. This presents exciting research opportunities and poses various challenges. The purpose of this paper is to introduce this emerging research topic, analyze related issues, provide a brief overview of current research progress, and discuss key issues and potential advancements and challenges in this area. This paper builds upon our previous work by significantly expanding the number and types of reviewed papers. Sentiment analysis and opinion mining greatly benefit from these innovative approaches, which involve the automated process of perceiving and recognizing human emotions.

The objective of this paper is to offer a comprehensive analysis of various research on AI-driven sentiment analysis and opinion mining of emotions. Additionally, it serves as a comprehensive review of sentiment analysis and opinion mining, encompassing multiple approaches and methodologies, including implicit and explicit information extraction. This review paper includes a taxonomy of sentiment analysis and discusses the pros and cons based on previous research works. It highlights the different stages of sentiment analysis, open issues, research problems, and future directions in the study of sentiment analysis and opinion mining, along with their diverse applications.

III. Types of Sentiment Analysis Models

Text-based model: Textual sentiment analysis, also known as text-based sentiment analysis, focuses on analyzing the sentiment expressed in textual data, such as reviews, social media posts, news articles, or customer feedback. It involves using various techniques and models to determine the overall sentiment (positive, negative, or neutral) conveyed in the text.

Image-based model: Image-based sentiment analysis is a method of extracting sentiment and emotion information from visual data, such as pictures and videos. It involves using AI and deep learning algorithms to analyze the visual content and classify it based on the emotions it conveys.

Speech-based model: AI-driven sentiment analysis involves categorizing emotions into positive, negative, or neutral sentiments, with advancements in deep learning enabling direct extraction of sentiment information from speech. Studies have focused on identifying relevant acoustic features in speech-based sentiment analysis**.**

IV. Benefits of Sentiment Analysis Models

Mrs. Mamatha S et al. [5] state that sentiment analysisoffer a range of benefits for businesses, including:

Improvedwebsitedesign: Analyzingemotionsthroughdatacanhelpbusinessesidentifyareasforimprovementin websitedesign andfunctionality.

Enhanced content marketing: Sentiment analysis can help businesses optimize theircontent marketing efforts by identifying which types of content are most popular and which channelsaredriving themosttraffic.

Better user experience: By analyzing user behavior, businesses can optimize website navigation,contentplacement, andotherelements toimprovetheuser experience.

Increased website traffic: By identifying the most effective products and topics of content, sources and optimizing websitecontent,businesses can drivemoretraffictotheirsite.

V. Sentiment Analysis Techniques

Collecting Datasets: This technique involves collection of data from various sources like movie reviews, Product reviews on e-commerce platforms, social media reactions, speeches, songs, pictures with different objects and emotions in them.

Preprocessing-Datasets: This technique involves analyzing the collected datasets divide them into groups and the preprocess them. Remove stop words, duplications of data, tokenizations of text data, labelling image datasets using libraries like NLTK, Label Image, bag of words, libras, etc.

Model-Training: In this technique we train the model selected by us using the preprocessed data sets from various fields through different algorithms like CNN, NLTK, Deep-learning, etc.

Model-Evaluation: Once the training part is completed and models are trained, we evaluate the accuracy of our model by testing them using the test data.

V. Application Development

Boiy, E.; Moens, M.F state that the proposed web Sentiment analysis model will be developedusingthefollowing technologies:

ProgrammingLanguage: Theapplicationwillbedevelopedusingahigh-levelprogramminglanguagesuchasPython andJava.

Web Framework: The applicationwillbe builtusingawebframeworksuchasFlaskorDjango.

Database: TheapplicationwilluseaMongoDBtostoreModels and prediction history.

API Interface: For API interface the application will use swagger open API.

VI. Key Features

Zaki et al. state that sentiment-analyzer-model provides owners with arrange of features to monitor, and analyze their performance. These features include:

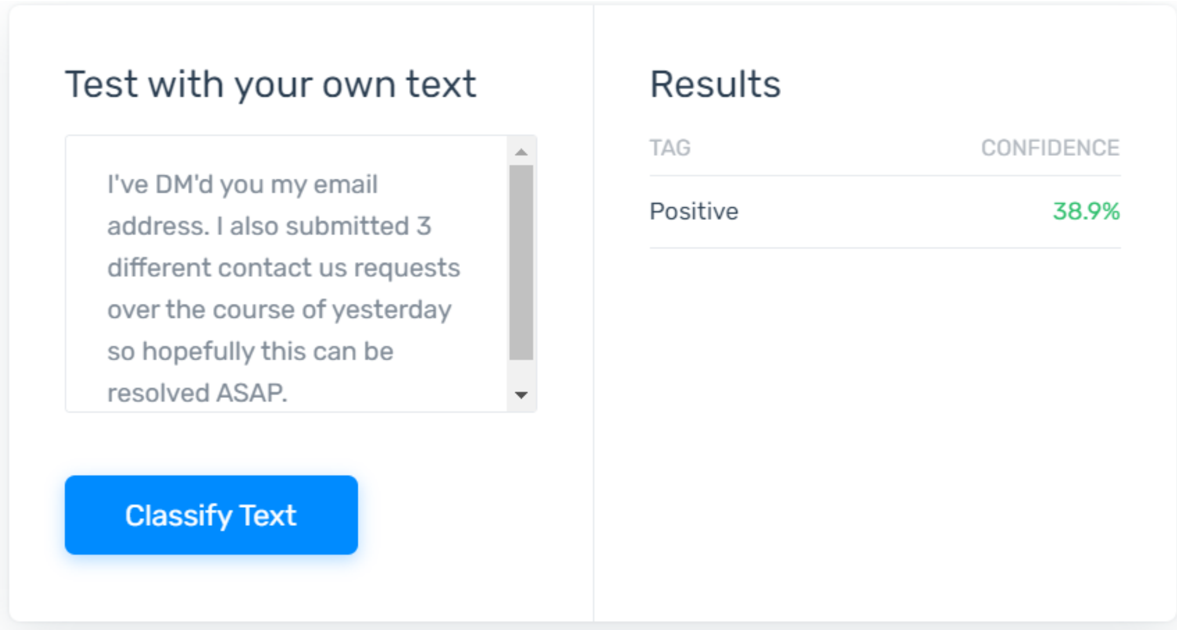
Provides insights into user behavior, including the pages visited, time spent on each page, and the devices used to access the website.

Customer service: Customers expect fast and personalized customer experiences. When they reach out to customer support, they want to feel listened to, Sentiment analysis tools uses (NLU) to detect words, expressions, and emotional tones in text that denote urgency. Take a look at the example below:

Social-media monitoring: Social media conversations helps you learn what customers are sayingabout your product or service. But, with so many things posted in a second, it is hard to stay up to speed. sentiment analysis makes sure you never miss an online mention of your brand, and 24/7 monitoring means you can act right away.

Better understanding of customers: The application provides information on the reviews of products, brands including search engines, social media, and referral links.

User behavior: The application



Different models: The application provides a one stop solution for all kinds of analysis be it textual, visual or speech.

VII. Methodology

According to the Prof. Almeida Pradoetal.[9], sentiment analysis application was developed using a combination of programming languages, including Python, Java. The applicationuses Swagger APIfor api interface. The database used is MongoDB.

Thedevelopmentofthe webtrafficanalyticalapplicationinvolvesthe followingsteps:

Requirement gathering: The first step in developing the application is to gather requirements fromwebsite owners and marketers. The requirements will include the features they need to analyze content traffic, such as real-time data analysis, user behavior analysis, customer service analysis, andmarketinganalysis.

System design: Once the requirements are gathered, the next step is to design the system. The system design will include the architecture of the application, the database schema, and the algorithms used for data analysis, libraries used for data preprocessing.

Application development: After the system design is completed, the application development process will begin. The application will be developed using programming languages such as Python andJava,and thedatabase willbecreated using MongoDB.

Testing: Once the models are developed, they will undergo evaluation to ensure that it meets the requirements and accuracy levels and is free from bugs and errors.

Deployment: After the testing is completed, the application will be deployed on a server and madeavailableto the users.

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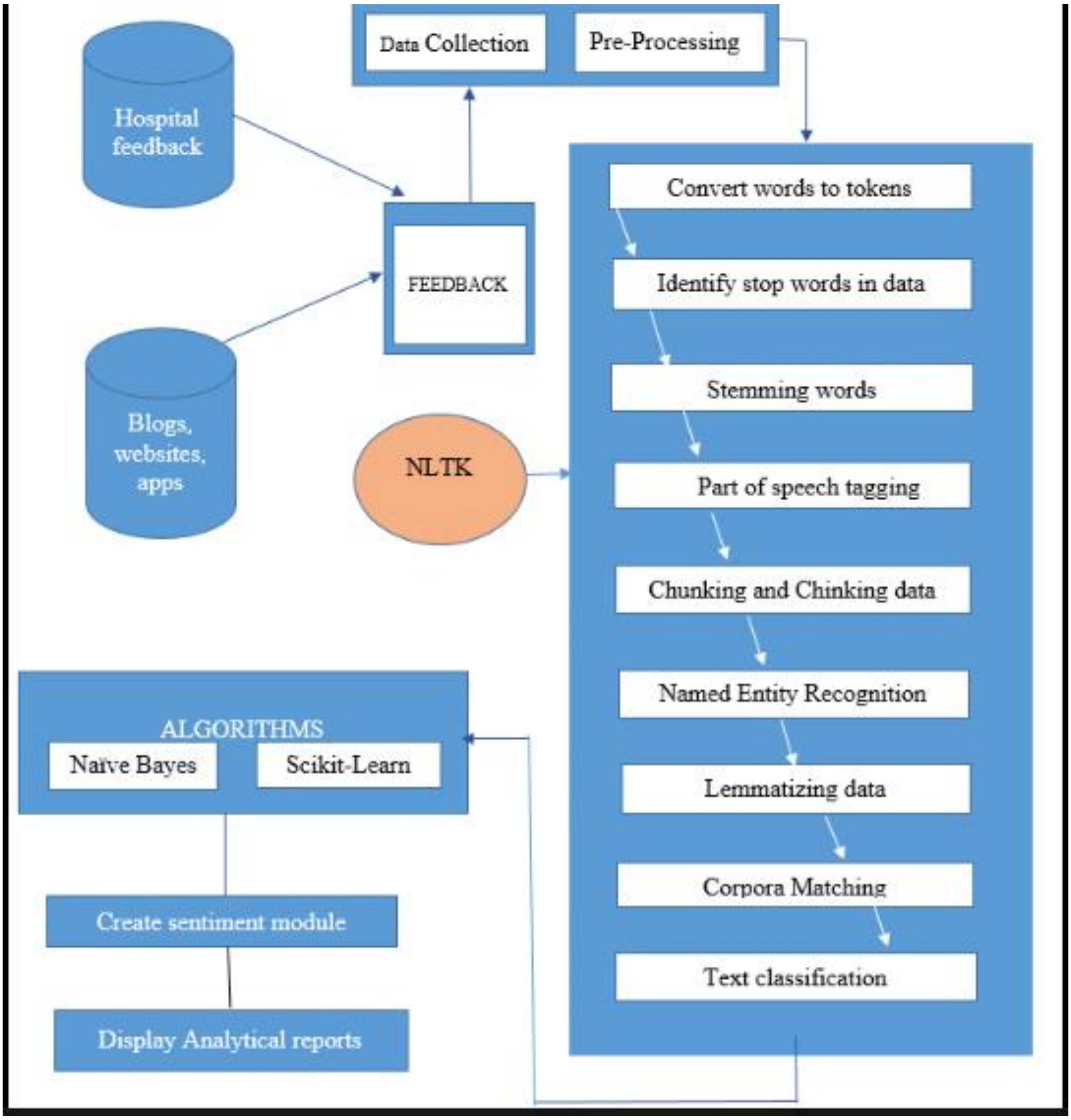
Data Flow Diagram



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1.Sentiments-lebelling

2.API's Structures

```
> gradle
v src
  v main
    v java
      v com.sentiment.analyzer
        > config
        > constant
        > controller
        > dto
        > logic
        > mongo
        > service
        > utils
          SentimentAnalyzerApplication
    v resources
        static
        templates
        application.properties
        bootstrap.yml
```

```
package com.sentiment.analyzer;

import ...

@SpringBootApplication(exclude = MongoAutoConfiguration.class)
@ComponentScan(value = "com.**", basePackages = {"com.**"})
@EnableDiscoveryClient
public class SentimentAnalyzerApplication {

    public static void main(String[] args) { SpringApplication.run(SentimentAnalyzerApplication.class, args); }

}
```

```java
package com.sentiment.analyzer.utils;

import java.util.UUID;

1 usage
public class CommonUtils {
    5 usages
    public static String generateUUID() {
        return UUID.randomUUID().toString();
    }

}

```

```java
no usages
@FeignClient(name = "model-service", path = "/api/model/")
@Headers("Content-Type: multipart/form-data")
public interface ModelService {

    no usages
    @PostMapping("/image/dataset")
    void createImageModel(FormData formData);

    no usages
    @PostMapping("/voice/dataset")
    void createVoiceModel(FormData formData);

    no usages
    @PostMapping("/audio/dataset")
    void createAudioModel(FormData formData);

    no usages
    @PostMapping("/text/twitter/dataset")
    void createTwitterModel(FormData formData);
}
```

```
@Slf4j
@Component
public class MongoClientConfiguration {
    2 usages
    private static ConcurrentHashMap<String, MongoClient> mongoClients = new ConcurrentHashMap<>();
    5 usages
    @Autowired
    private MongoProperties mongoProperties1;


    4 usages
    public MongoClient getMongodbClient() {
        log.info(":::::: MongoDB connection Started ::::::");
        CodecRegistry pojoCodecRegistry = CodecRegistries.fromRegistries(MongoClient.getDefaultCodecRegistry()
                CodecRegistries.fromProviders(PojoCodecProvider.builder().automatic(true).build()));
        MongoClientOptions.Builder mongoClientBuilder = MongoClientOptions.builder().writeConcern(WriteConcern
        MongoCredential mongoCredential = MongoCredential.createCredential(mongoProperties1.getMongodbUsername
        List<ServerAddress> serverAddressList = new ArrayList<>();
        serverAddressList.add(new ServerAddress(mongoProperties1.getMongodbHost(), mongoProperties1.getMongodb
        try {
            return new MongoClient(serverAddressList, mongoCredential, mongoClientBuilder.build());
        } catch (Exception e) {
            throw new RuntimeException();
        }
```

VIII. Challenges and Limitations:

Sentiment analysis, the process of determining the emotional tone of a piece of text, comes with its own set of challenges and risks. Here are some of the key challenges and risks associated with sentiment analysis:

1. **Subjectivity and Context:** Sentiment analysis relies on understanding the context and subjectivity of language. Textual data can be ambiguous, and accurately capturing sentiment requires considering the context, sarcasm, irony, and cultural nuances. Different individuals may interpret the sentiment of the same text differently, making it challenging to achieve consistent results.

2. **Domain-Specific Challenges**: Sentiment analysis models trained on generic data may struggle to perform well in domain-specific contexts. Language, terminologies, and sentiments vary across different domains, such as finance, healthcare, or social media. Adapting sentiment analysis models to specific domains requires domain-specific training data and fine-tuning.

3. **Online Slang and Emojis**: Online conversations often include slang, abbreviations, and emojis, which can be challenging for sentiment analysis models to interpret accurately. Understanding the sentiment associated with specific slang terms or emojis requires up-to-date knowledge of evolving language patterns and trends.

4. **Multilingual and Cross-Cultural Sentiment Analysis:** Sentiment analysis becomes more complex when dealing with multilingual or cross-cultural data. Different languages have unique linguistic structures, expressions, and sentiment indicators. Cultural variations and regional differences further complicate sentiment analysis tasks. Developing robust models that can handle multiple languages and cultural contexts is a significant challenge.

To mitigate these challenges and risks, ongoing research and development are necessary to improve sentiment analysis models, address biases, enhance language understanding capabilities, and account for cultural and contextual variations.

Additionally, human review and validation are essential to ensure the accuracy and fairness of sentiment analysis results.

IX. Future Scope

In this paper, an outline of emotion AI-pushed SA in numerous domains changed into provided. also, this surveyreviewed the merits, demerits, and scope of the special methods that have been considered. A sizable advantageof SA is that it presents the precise emotion this is underlined in the context. conventional methodologies, whichinclude device-mastering-based totally approaches, lexicon-primarily based analysis, and ontology-primarily based analysis, were considered for experimentation to evaluate performances. Inside the taken into consideration pattern statistics, the thing-primarily based on otology method, SVM, and term frequency carried out high accuracy and provided better SA outcomes in every class. Destiny studies guidelines in addition to limitations highlighted for the advantage of future researchers. even though the outcomes confirmed better accuracy for the pattern information considered, those effects can also range while its miles applied to different applications. Deep studying techniques also can be considered for evaluating the performances as part of the future work which may additionally carry extensive modifications to the results.

We hypothesize that review photos contain sentiment alerts. certainly, the base version achieves higher accuracies than random. We similarly check out the roles of item-orientation and consumer-orientation. a few photograph capabilities can also code for superb sentiment for some items, and yet code for poor sentiment for others. Experiments display that the object-orientated CNN achieves even better accuracies, specially whilst item-orientation is included at better tiers of abstraction. Experiments for user-orientation yield comparable effects. As destiny paintings, we would analyze how assessment text will be used with overview snap shots for multi-modalsentimentanalysis.

X. Case Study

According to Liu, B ,Sentiment analysis and opinion mining[7] the sentiment analysis model is based on detection and labeling of the sentiments according to the dataset provided to it and then do the modeling part to it , the model gives us the predicted score in which we decide that the percentage score of the model.
The models give us 3 types of predictions in which there are positive (+), Negative (-), And Neutral (0)
So, all the positive and negative scores are labeled through the model and there are also several specific emotions connected to the positive (+) and Negatives (-), Thus through this way our sentiment model works.

XI. Conclusion

The major aim of our work is to perform sentiment analysis of the different forms of data on a single platform. Performing sentiment analysis on data obtained from different sources is a huge challenge because of the amount of ambiguity involved, it becomes difficult for automatic detection of emotions from these data sources. The system proposed by us also attempts to extract actual emotions from the provide data. This type of analysis can be very helpful for different organizations and marketing teams to gain actual and detailed feedback from their users; thus, it can be widely used in business purposes. This project is a small step towards the efficient automation of sentiment Analysis by focusing on ambiguous data.

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