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Web-based Sentiment Classifier for YouTube Comments

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Abstract: The current paper presents a web-based program that will evaluate the comments posted on YouTube on the basis of an analysis procedure that utilizes sentiment classification methods supported by contextual information gained through video transcripts. The system will first of all extract the comment, then, semantic search is performed to retrieve the most relevant transcript parts, and then the particular aspect is identified to which the user is agreeing, disagreeing, or assuming a neutral situation. A retrieval-augmented plan is implemented together with a language model, which adds the sentiment predictions with a human-readable explanation. This will increase the credibility of interpreting sophisticated remarks, especially those that may mention a particular spoken material in the video. The system aims at backing content creators, moderators, and viewers by providing a more subtle and dependable sentiment analysis.

Keywords: Sentiment Analysis, Natural Language Processing, YouTube Data API, Retrieval Augmented Generation, Naive Bayes.

1 INTRODUCTION

The social networking sites have shifted the channels that people use to express their views, and YouTube has become one of the most important platforms of interaction via video. The huge amounts of user-generated comments, whose number reaches millions of hours of content uploaded daily. These commentaries also give timely information on the satisfaction of the viewer, political perception, product rating, and the opinion of the population in general [1][2].

However, the unstructured nature of discourse in social media makes automated analysis difficult. The YouTube comments are specifically challenging due to their heavy reliance on context [3]. As an example, a remark that would normally be taken as negative by a generic sentiment model would be, that was a terrible implementation. However, in the case where the video in question is a tutorial called How NOT to write code and a commentator agrees with the modeling practice, the attitude towards the video in question must be taken as positive or affirmative.

1.1. Problem Domain

The traditional approaches are usually based on a bag-of-words or shallow neural structure, which process only the text of the comments. These systems are easily susceptible to failure when a comment gives a reference to a particular time-stamp or quote without having to put it in the exact form [4]. Besides, they are characterized by trouble in dealing with sarcasm, where the surface meaning differs from the meaning intended, and by a stance, whether built in agreement or disagreement, rather than a simple affective term, like happiness or sadness.

1.2. Objective

The main objective of the research is to develop a web-based application that would retrieve user comments and video transcripts in relation to the same. The architecture is designed in such a way that it links each comment to the exact video fragment it speaks of and uses a hybrid artificial-intelligence system to obtain sentiment classification on a high-accuracy level. This is eventually aimed at providing the end user with an explainable output, hence allowing the content creator to have a more refined and reliable assurance of the feedback of their audience [5].

2 LITERATURE SURVEY

In order to build the background on this work, a number of classical studies were analyzed in the field of sentiment analysis and opinion mining.

2.1. Machine Learning

The survey study by E. Supriyadi et al. is known as Sentiment Analysis of Movie Reviews with the help of Machine Learning Algorithms [6]. They compared the results of the Maximum Entropy, Support Vector Machine, and Naive Bayes classifiers. Their results showed that, although Naive Bayes is computationally efficient, it is often unable to deal with the informal syntax of social media streams of data.

2.2. Niche Domains

L. M. Gandy et al. suggested a Sentiment Analysis-Based Framework of Evaluating Videos in Internet Telemedicine [7]. They used sophisticated architectures like CNN-BiLSTM-MHA and TF-IDF. Their model was highly accurate, but they consume a lot of computational resources, which makes such deep-learning models inappropriate for use in a lightweight web application.

2.3. YouTube Specific Analysis

P. Gamette et al. had an exploration of how YouTube comments can be sentenced through sentiment analysis with respect to movie trailers using a Naive Bayes classifier [8]. Their experimental findings provided an accuracy of 81 percent on the Money Heist Season 4 data. However, analysis errors made by the authors revealed that the model is not very accurate in classifying comments where the users expressed complex opinions with an element of irony, which cannot be represented by the simple models that are based on probabilistic theories.

2.4. Statistical Measures

J. Oh et al. have also dealt with the issue of categorizing YouTube comments based on sentiment, which makes use of statistical indicators in order to help content creators [9]. Their results highlighted the importance of the instruments that will help to improve the level of user interaction, thus corresponding to one of the main impetuses behind the given research proposal.

2.5 Ensemble Models

S. In et al. also examined the sentiment analysis of videos on YouTube about cryptocurrency and used a stacked ensemble model (Decision Tree, k -Nearest Neighbour, Random Forest, and XGBoost), which achieved 94.2 percent accuracy [10]. The technique was successful, but it has been using only the textual nature and has not taken into account the financial background that is implicit in the video contents- a fact that is assumed to play a role in the user's feelings.

Gap Identification: It is important to note that none of the reviewed systems inquired or processed the video transcript to feed the sentiment identification of the comments. In line with this, the proposed system helps deal with this methodological weakness in particular.

3 SYSTEM ANALYSIS

3.1. Problem Statement

The existing sentiment analysis instruments are afflicted with a so-called Context Blind Spot. Such systems interpret the written text of the comments, but do not realize what particular aspects of the video the commentary is about. These obstacles are listed below:

- No Contextual Awareness: The models do not have the ability to associate pronouns like " it " or " that " in a comment with the corresponding event or part of the video [11].
- Stance Detection Failure: There is a severe challenge in detecting between a user who criticizes the video creator herself and a user who criticizes one of the issues covered by the creator.
- Sarcasm: The tools show a high level of false positives when faced with sarcastic praise, which hampers the quality of sentiment inference [12].

3.2. Proposed Solution

It is suggested to create a so-called Context-Aware Sentiment Classifier, which will break new ground by showing the concurrent matching of the textual comment stream with the video transcript stream. The key innovations that the given framework provides are: Key Advantages:

- Context Retrieval: The search techniques based on semantic vectors would be used to find the transcript segments that are semantically related to the contents of the comment.

- Aspect-Based Understanding: Finding the specific topical aspect that the user is dealing with, so that fine-grained sentiment analysis becomes possible, with regard to specific content elements.
- Hybrid Logic and Explainability: The system not only uses a hybrid methodology to provide the computational expediency of an offline Naive Bayes model combined with the lexical sensitivity of VADER, but also provides efficiency and accuracy. This approach is also supported by the focus on explainability, because the system provides clear justifications of its classifications, for example, the recognition of a positive sentiment as the direct correspondence of the current section of the video transcript. The proposed Women's Safety Device with GPS Tracking and Alerts is designed as a compact, wearable embedded system that ensures rapid emergency detection, real-time location tracking, and instant alert communication. The methodology integrates manual and automatic triggering mechanisms with GPS–GSM communication and IoT-based cloud monitoring to enhance system reliability during critical situations.

4 System Architecture

The system is a micro-modular system that is specially designed to be deployed on the web. It has three major parts: the Frontend (user interface), the Backend API, and the Intelligence Engine.

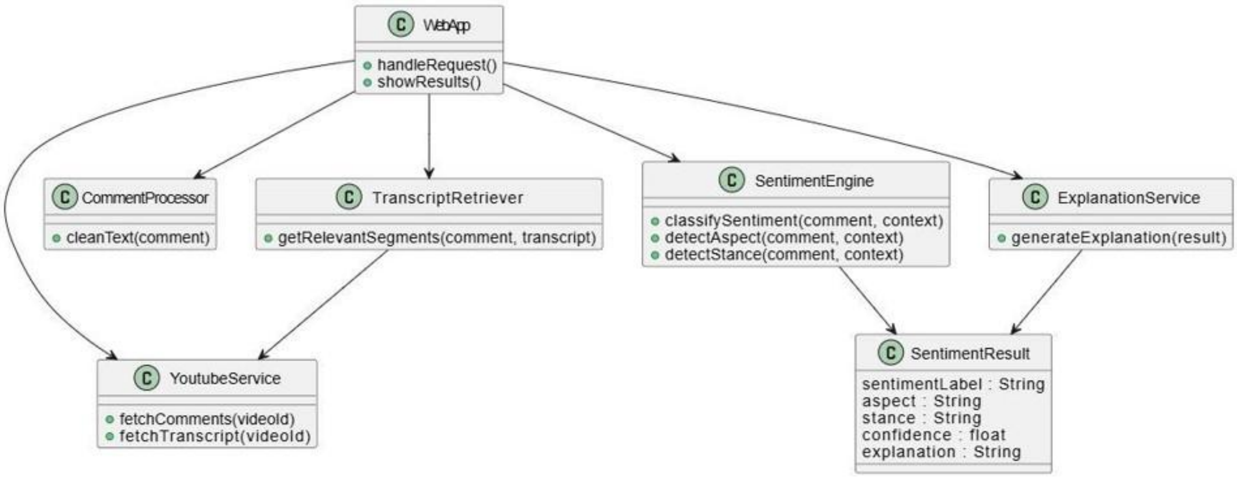

Fig. 1. System Architecture Diagram demonstrating the flow between WebApp, CommentProcessor, TranscriptRetriever, and SentimentEngine.

- User Input & Video URL Module: User input and video URL module: It is the first module in the application. The end-users are presented with a simplified HTML/CSS interface where they are required to input a YouTube URL. The module performs regular expression-based validation to ensure that the URL is a valid YouTube link and extracts the unique Video ID.
- Comment Retrieval Module: The module recognizes the connection with the YouTube Data API, namely, sending requests to the comment-Threads endpoint. It narrows down unimportant metadata to the text Display field (text body of the comment), as well as other relevant author data. The structure allows pagination so that a large enough sample size of comments is accrued.
- Caption Extraction & Context Module: Caption Extraction and Context Module: This module plays a very crucial role. It appeals to the YouTube Transcript API.
  - Fetching: The system gets captions that are either automatically generated or uploaded by hand.
  - Chunking: As there is continuous contiguity in the transcript, the module divides it into semantic portions; that is, blocks of three sentences to maintain the local context.
  - Embedding: The resultant pieces are converted into the form of a set of vectors in order to enable later comparisons of similarities mathematically.
- Text Preprocessing Module: Before analysis, normalization of the comments and fragments of transcripts has been performed:
  - Lowercasing all text.
  - Elimination of special characters and non-ASCII emojis (when possible, changed to the textual version of the same).
  - Tokenization (dividing sentences into words).
- Offline AI Sentiment Module (Naïve Bayes): Offline AI Sentiment Module (Naïve Bayes): To ensure that the system does not overly depend on the paid external AI services, a custom Naive Bayes classifier is used. This model is a

probabilistic one that estimates the probability of a comment being positive, negative, or Neutral, according to the frequency of words in its training set.

- VADER Sentiment Validation Module: Valence Aware Dictionary and sentiment Reasoner (VADER) is used as a validating mechanism. VADER has been manually adjusted to handle textual content of social media; it considers orographic variants like capitalizing (e.g., the word GREAT expresses more polarity than the word great), punctuation (i.e., repeat exclamation marks like in formulae or/and), and emotive characters like an emoji. It is a comparative analysis run between the result obtained by the Naive Bayes classifier and the compound sentiment score produced by VADER. The Context Module is called to adjudicate a dispute between the two sources in case there exists a discrepancy between the two sources.

The main processing logic is in the form of the Retrieval Augmented Generation (RAG) paradigm, which is adequately modified to achieve classification. The Use case diagram is shown in Fig. 2.

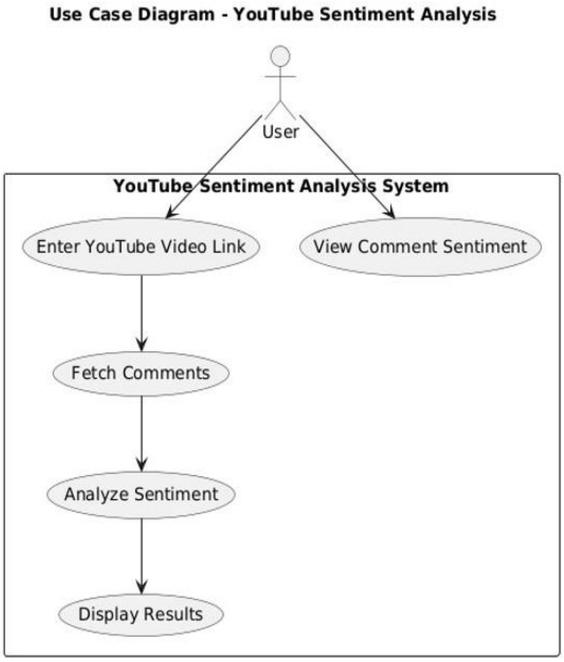

Fig. 2. Use case Diagram for the YouTube Sentiment Analysis System.

5 Results and Discussion

The real-time YouTube videos that were used to evaluate the system were of different categories. The performance along different scenarios is outlined with the use of subsequent subsections.

A. Scenario A: Negativity

Out of such a condition of the experiment, the user comments, which revealed implicit negativity, were analyzed. The statement that was categorized under Negative was, Once a cheater, always a repeater!!!. The system was able to accept the negative sentiment towards the subject even without the lexical expression of hate, as the subject did not have classic hate words.

B. Scenario B: Slang and Emojis

In this case, the application of slang in the social-media discourse was studied. The positivity of the comment he was predicted to make is, that he took it like a champ lol!.

The utterances that were properly decoded by the VADER model include the word lodl and the heart emoji ('!3) as affirmative signs, hence overriding the potential ambiguity. The fact that VADER interprets the term champ as sarcastic can come about as a result of making assumptions about the use of such a term.

C. Scenario C: Contextual Relevance

Comment: "He pays all these taxes and can no longer have decent jackets", all this money thinking of these governmental institutions? Prediction: Negative. Despite what seems to be a neutral set of lexical items, the proper context gives a feeling of displeasure with the fiscal allocation of the government; thus, the proper context can be properly put in the model to provide a negative impression.

D. Comparative Analysis

A comparative analysis was carried out on the proposed system and a traditional system, given in Table 1, a keyword-based type of approach. The proposed system has a better performance in terms of dealing with ambiguity, but it has a small overhead processing cost.

Table 1. Performance Analysis

Feature	Existing System	Proposed System
Context Awareness	No	Yes (via Transcripts)
Sarcasm Detection	Poor	Moderate to High
Stance Detection	No	Yes (Agree/Disagree)
Latency	Low	Medium (API Calls)
Explainability	Black Box	Logic-based Output

6 CONCLUSIONS

The paper managed to create, design, and model a Web- Based Context-Aware Sentiment Classifier that was adapted to the content of YouTube. The study also filled in vital gaps in the traditional text-only models, namely, the lack of contextual richness, by means of implementing the video transcripts into the context of the sentiment analytical processes. By using a hybrid approach based on offline machine-learning approaches and a sentiment lexicon known as VADER, the strategy obtained a good trade-off between precision and scalability of computation. The setup guaranteed high performance and, at the same time, efficient utilization of resources. The resulting system is of great importance to content makers since it lets them sift through large comment feeds to determine which types of feedback are genuine user feedback and which types of noise. In addition, the offline architecture ensures that the underlying inference logic can be made portable and secure, hence protecting sensitive users' information. The proposed improvements to this system will include Multilingual Support, Real-Time Processing, and LLM Integration. Multilingual support, which will be implemented by integrating translation APIs, will allow comments in languages other than English, as illustrated in some of the test results. Real-Time Processing requires adjustments to the architecture to enable live-stream chat analysis with web sockets. LLM Integration can be achieved by replacing the Naive Bayes model with a localized large language model (e.g., Llama or Mistral) to support more profound reasoning.

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ETHICS STATEMENT

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

STATEMENT OF CONFLICT OF INTERESTS

The authors declare that they have no conflicts of interest related to this study.

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