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Sentiment Analysis of YouTube Video Comments

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ABSTRACT: The explosion of social media has made gauging public opinion easier than ever before. This rich data offers valuable insights for content creators, businesses, and advertisers. This study delves into the world of YouTube comments, employing deep learning to develop a system that automatically analyses sentiment. The focus here is on Long Short-Term Memory (LSTM) networks, a powerful deep learning architecture. Four distinct LSTM-based models are constructed and meticulously evaluated. The core objective is to identify the model that delivers the most accurate sentiment classification (positive, negative, or neutral) for YouTube comments. A comprehensive evaluation process is undertaken, utilizing metrics like accuracy, recall, precision, F1 score, and ROC curves. The analysis reveals that a Bi LSTM model reigns supreme, achieving an impressive accuracy of 89%. To assess the generalizability of these models, they are tested on a separate dataset of IMDB movie reviews. The results are encouraging, with an average accuracy of 87%, indicating their adaptability for sentiment analysis across diverse textual data. Intriguingly, a statistical analysis of YouTube videos is conducted. The findings unveil a clear correlation: videos with predominantly positive comments garner significantly more upvotes and views. However, the link between negative comments and downvotes appears less pronounced. In conclusion, this study underscores the efficacy of LSTMs for sentiment analysis on YouTube comments. By harnessing this technology, content creators and marketers can gain a deeper understanding of audience reception, paving the way for more effective content creation and audience engagement strategies.

KEYWORDS: Sentiment analysis, Emotional Tone, Communication, Natural Language Processing (NLP), Audio, Video, Text Data, Facial Recognition, OpenCV, Google API, Sentiment classification, LSTM, Convolutional neural networks.

I. INTRODUCTION

Emotions and opinions play an essential role in human behaviour, as we often make decisions based on other people's experience and thoughts, since everyone's opinions or subjective and affected by their personal experiences and beliefs, learning about them helps together broader perspective, public opinion has been of interest to organizations, companies and politicians for a long time The collective opinion of people can help predict who will win elections, generate knowledge about the future trends and topics. It also helps determine general opinions about products and services, which helps marketing tips decide on marketing strategy, improving existing or production of new product and improving customer support. Therefore, recognition of sentiment in various fields is of essence. Initially, people's opinions were collected through service or questionnaires about manually reviewed. However, as the usage of Internet increased, people started expressing their opinion online more frequently. The boom of social media platforms in recent years has allowed its users to share all kinds of information and introduce a wider variety and ways to express their opinions Blocks discussion forums, reviews, comments and microblogging services such as Twitter or Facebook, YouTube as rich data sources composed of audio files, videos, images and opinions. One such platform YouTube is currently one of the most popular social media platforms in the world. It allows its users to share their videos or view videos uploaded by other users and provide feedback. And user can provide feedback by supporting or rejecting a video by rating its posterior or negative respectively. Users may further also provide textual feedback in the form of comments posted to videos Each video can hold thousands of comments making used to a platform of interest for text classification and categorization.

II. RELATED WORK

- **Title:** Predicting like-ratio on YouTube videos using sentiment analysis on comments

Authors: MARTIN HYBERG TEODOR ISAACS

Description: Hyberg and Isaacs have written a bachelor's receipts on the topic of predicting YouTube video like proportions from comment sentiment. They also used a simple formula based on the number of comments classified as positive or negative or neutral by supervised learning classifiers for prediction, but their training was only done on

wheats and their classic oil. Only classified comments as positive or negative or neutral They implemented SVM, logistic regression multinomial database classifiers. Their results showed Pearson correlation coefficients between the actual like proportions and the predicted proportions based on their formula for their different classifiers and YouTube channels that ranged from -0.1 to 0.62 their predictor type proportions were almost like all in the 0.3 to 0.8 range. While the actual proposals had a larger spread from about 0.05 to 0.95.

- **Title:** Incorporating Semantic Knowledge for Sentiment Analysis

Authors: Shitanshu Verma, Pushpak Battacharya

Description: This study aims to expand upon their work by training on YouTube comments include more classifiers, include neural comments in the classification and test several formats for prediction. Kumar Verma and Sahu have returned their course paper, partly on the topic of predicting YouTube videos like proportions from the sentiment of the comments. They used a neural network and added the comment count and view the count beside the comment's sentiment in the prediction. Kumar Verma and Sahu found that on their study, that correlation between the comment and sentiment and video like ratio was weak. The primary focus is on uncovering the current landscape of sentiment analysis applications in the realm of YouTube video content, shedding light on the methodologies used challenges face and potential enhancement for decoding emotional responses in this dynamic digital ecosystem.

- **Title:** Analysing and Mining Comments and Comment Rating on Social Web

Authors: Stefan Siersdorfer, Sergiu Chelaru, Jose San Pedro, Ismail Sengor Altingovde, Wolfgang Nejd

Description: Opinion mining is a form of opinion analysis towards a pattern or mood of a person or a certain subject, these things are often called sentiment. In order to filter every statement or opinion sentiment from the public, the most and easy publishing media that is being used is the internet. Many comments on Ahok's remarks have been made on YouTube. The process of seeking or tracing the natural language to find patterns or moods of society against certain products, people or topics is called Sentiment Analysis. Sentiment analysis is also often referred to like the opinion of mining. Sentiment reasoning can be used to find out how far the performance of Ahok based on the results gained from netizen's comment on YouTube. The result of a classification of weighted values according to the Support Vector Machine (SVM) method has brings us to the conclusion that the value of True Positive rate is 91.1% based on the comments taken from 2015 until 2016. For the further development of this research, further researchers need to take into account that data recording should be very high in number to achieve the accuracy of the results and conclusions on the opinion mining analysis.

III. MOTIVATION

Elevating Emotional Intelligence through Technological Innovations: Harnessing state-of-the-art machine learning techniques, including Recurrent Neural Networks (RNNs), Transformer models, and Deep Reinforcement Learning (DRL), to advance our understanding of emotional nuances across diverse communication mediums.

An Analytical Journey Across Audio, Video, and Text: Exploring emotional landscapes through meticulous analysis of data spanning audio, video, and textual formats, employing advanced computer vision algorithms and sentiment analysis methodologies. Unravelling Emotional Threads and Delving into the intricate emotional tapestry woven within communication channels, deciphering facial expressions through computer vision and extracting sentiments using advanced neural network architectures.

Technology as the Gateway to Emotional Insight: Utilizing sophisticated machine learning methodologies, such as PyTorch for video processing and Deep Speech for transcription, to uncover emotional nuances and enrich communication channels.

IV. OBJECTIVE

Efficiency Enhancement in Sentiment Analysis: The core objective is mainly focused on optimizing sentiment analysis processes through a diverse array of machine learning techniques, including Support Vector Machines (SVMs), Multi-Task Cascaded Convolutional Neural Networks (MTCNN), and Natural Language Processing (NLP) models.

Advancing Facial Expression Recognition: Harnessing machine learning, particularly MTCNN and OpenCV, to recognize facial expressions within video data, and textual data aiming to detect and analyse nuanced emotional cues by scrutinizing features such as the eyes, nose, and lips in visual communication.

Empowering Intelligent System Development: The primary goal is utilizing sentiment analysis insights to develop intelligent systems capable of studying public opinions and categorizing related emotions. This objective involves leveraging machine learning models like SVMs and NLP to classify specific message segments into various emotional states, contributing to the evolution of intelligent systems in understanding and categorizing public sentiment.

V. SYSTEM MODEL AND PROPOSED METHODS

A. EXPERIMENT METHOD AND ENVIRONMENT

Our proposed method is based on comparative research [9] which is a representative study on YouTube spam comment detection. Our method applied six machine learning techniques (i.e., CART (Decision Tree), LR (Logistic Regression), NB-B (Bernoulli Naïve Bayes), RF (Random Forest), SVM-L (Support vector machine with linear kernel), and SVM-R (Support vector machine with Gaussian kernel)) to improve the performance of the Cascaded Ensemble Machine Learning Model aware YouTube Spam Comments Detection Scheme. These performed well in [9] and were significant with 99.9% confidence. We propose an ensemble model combining them and evaluate the performance. The experimental environment used version 3.7.1 of Python and version 0.20.1 of the Cicely Library on Jupiter notebooks [13]– [15].

B. EXPERIMENTAL OVERVIEW OF THE PROPOSED TECHNIQUE

As shown in Figure 1, we collect 1,983 comments and distinguish 1,369 (70% of total) into training data and 587 (30%) into test data. To classify the spam data, we remove stop words such as articles (i.e., the, a, an) and pronouns (e.g., I, you, it). Additionally, in [9], only BoW vectorization was performed. In this paper, TF-IDF vectorization preprocessing is used to solve the issue that BoW may not find significant meaning in a sentence because it appears frequently in other sentences. References [12] suggests that there is no single technique that performs well on all datasets. The ensemble model achieved good performance in [9]. We carry on the experiment with multiple techniques to find the best classification algorithm, using six machine learning algorithms (i.e., CART, LR, NB-B, RF, SVM-L, SVM-R). We use two ensemble models, ESM-H (Ensemble with hard voting) and ESM-S (Ensemble with soft voting), to train and test our dataset. They predict and evaluate the class.

C. DATASETS

We use open datasets, which can be downloaded from [16]. They consist of comment data on five popular music videos provided in [9]. They contain YouTube ID, comment author, date, comment content, and labeled class (0: Ham or 1: Spam). We only use comment content and labeled class. Each training and testing of the five data sets as shown in Table.1 can result in overfitting, where the five classifiers perform well only on that data and do not apply well to comment data in other videos. Therefore, in this paper, to generalize the result, we include all five video’s datasets. As shown in Fig. 1, we employ 1,983 comments with 1,369 comments (70%) for training and 587 comments (30%) for testing.

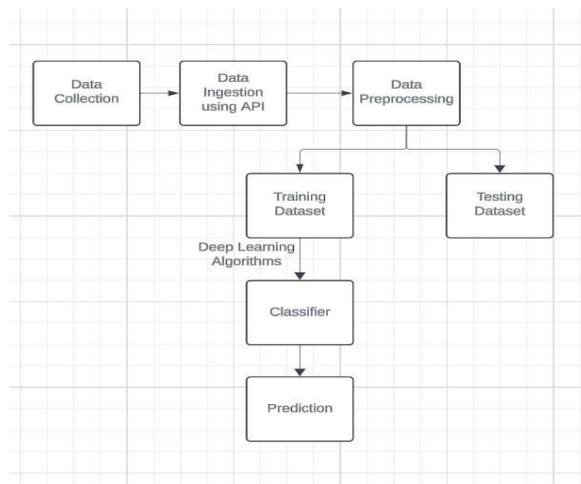


FIGURE 1: Overview of the proposed comment sentiment detection scheme.

Comment : "John likes to watch movies. Mary likes movies too."

1. tokenize
["John", "likes", "to", "watch", "movies", "Mary", "likes", "movies", "too"]

2. Bag of words
BoW = {"John":1, "likes":2, "to":1, "watch":1, "movies":2, "Mary":1, "too":1}

FIGURE 2: "Tokenizing and BoW vectorizing processes."

D. DATA PROCESSING

Since the datasets are text data, pre-processing is employed for the machine learning. We eliminate stop words and list the tokens with comments using the Count Vectorizer function of the Python Psychic Run library. Then we count how often tokens occur and use BoW (Bag-of-Words) and TF-IDF vectorization. The process is presented in Figure 2.

E. THE PROPOSED HYBRID CNN-LSTM MODEL

The suggested hybrid model is detailed in depth in this section. IMDb review dataset is taken first of all because of large samples which can be used for better training and testing. Next, the first step of model training is performed i.e., data cleaning in which unnecessary punctuation is removed, converted uppercase letter to lower case letter, removed html tags and certain emojis from text, articles and conjunctions are also removed. After this, tokenization is performed which breaks the raw text into small parts. Embedding layer is used after the tokenizer, that converts each word into a fixed length vector of defined size. Next, batch normalization layer is used to achieve more stability through normalization of the layers, inputs are re-scaled and recentred. Then, a convolutional layer is utilized for feature extraction. The output of CNN layers acts as input for Max-Pooling layer which performs feature reduction. Then, LSTM layer is used to get a sequence output rather than a single valued output. After this, dense layer with ReLU activation function is added for generalization of output from LSTM layer and later, dense layer with sigmoid activation function is used to classify text messages according to our classification model which is binary i.e., 0 and 1. Sigmoid function is a logistic function that ranges from 0 to 1, as defined by the formula given below –

$$y(x) = 1 / (1 + \exp(-x)).$$

F. Evaluation Metrics

Upon building the model, its efficacy is evaluated using several indicators of effectiveness such as 'accuracy', 'precision score', 'ROC', 'AUC score', and so on. The efficacy of a model made up of statistics or machine learning is assessed using indicators of assessment. Any undertaking necessitates the assessment of machine learning systems. A model is capable of being evaluated via a variety of evaluation measures. Models are examined in this research based on accuracy and ROC score since quality indicators solely are not able to determine the optimum strategy. Certain measurements have been addressed below:

- Accuracy Score: It is the proportion of appropriate forecasting to overall forecasts.

$$(TP + TN) / (TP + TN + FP + FN)$$

- Precision Score: The degree of accuracy is determined by how many good predictions for classes are really affirmative class forecasts.

$$TP / (TP + FP)$$

Where TP = True Positive, TN = True Negative, FP = False Positive and FN = False Negative

- Receiver Operating Characteristic (ROC) Score: It corresponds to the region beneath the contour, that gauges how well a system for classification can distinguish amongst several distinct categories. It has a value spectrum of 0 to 1, with 1 denoting optimal performance or the highest achievable effectiveness and 0 signifying the system's most minimal effectiveness.

- Early Stopping: It is a technique which is used to avoid overfitting. In this, by specifying patience value, model will continue to train until the validation loss stops decreasing.

VI. SYSTEM ARCHITECTURE

- Real-time Analysis
- YouTuber/Content Creators engagement within the system
- Multimodal Integration
- Social Trend Identification
- Verify the Quality of content

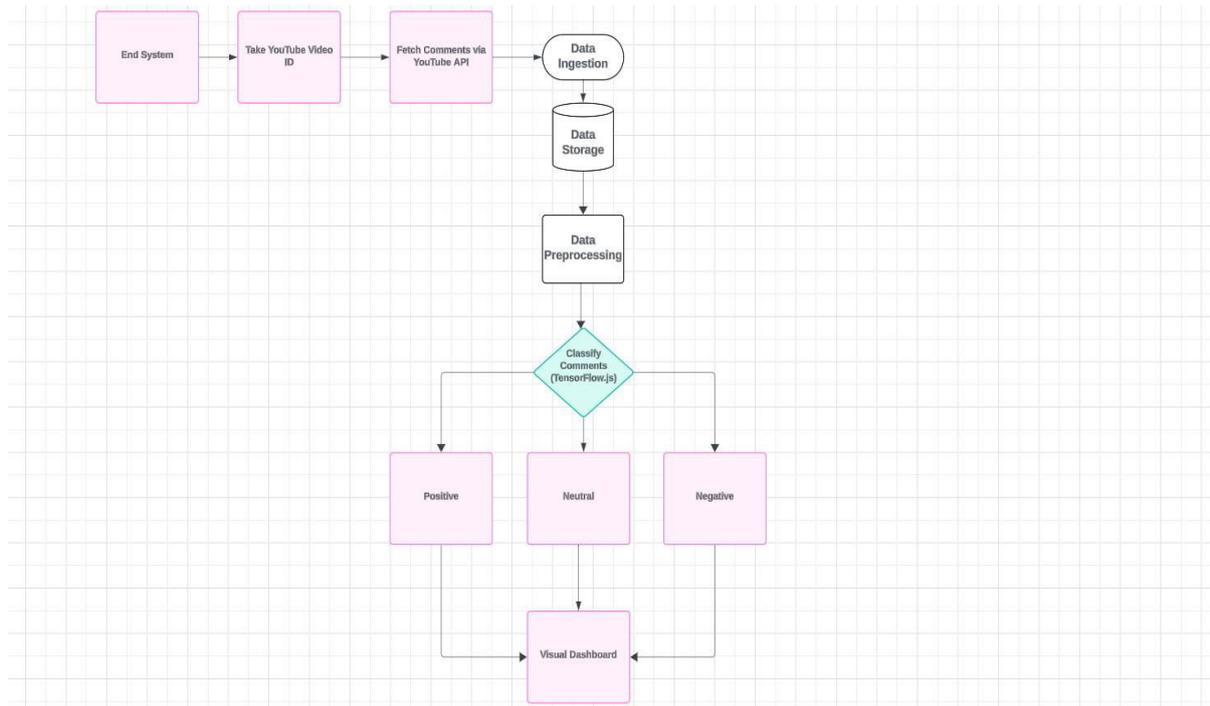


FIGURE 2: Working Model of System

VII. SYSTEM REQUIREMENTS

Software Requirement:

- OS: Windows 11
- Programming Languages: Python, HTML-CSS, JAVASCRIPT, PHP
- Development Environment: VS code
- Libraries: NLTK, Scikit-learn, OpenCV, pandas
- Database: Google YouTube API Key

Hardware Requirements:

- Computing Resources: access to systems with sufficient computational power (CPU/GPU), RAM, and storage.
- GPUs (Graphics Processing Units): deep learning models,
- Storage: models, and generated content.
- Internet Connectivity: model repositories, and APIs.

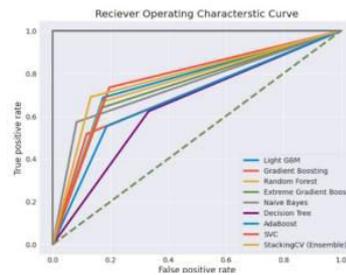
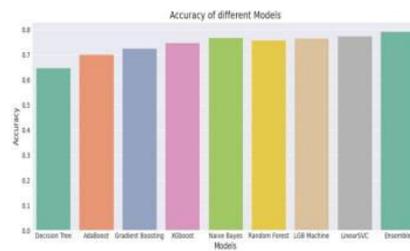
VIII. RESULTS AND DISCUSSION

A. Machine Learning Results: In machine learning, some bagging and boosting models are trained for sentiment analysis along with a variation of SVM classifier i.e., Linear-SVC which outperformed all other machine learning models as shown in the table 1. Also, an Ensemble model of top three best performing models is trained naming: Linear-SVC, Random Forest and LGB machine in case of Amazon Reviews Dataset gave the best scores. Results, after applying different machine learning models are as follows:

1) Amazon Reviews Dataset: Table-1 delineates the most efficient model that gave evidently decent results with an Accuracy of 0.791, Precision Score of 0.689 and ROC Score of 0.779 when trained on Amazon reviews dataset was the Ensemble model of the following three models i.e. LGB Machine, Naive Bayes and Linear-SVC.



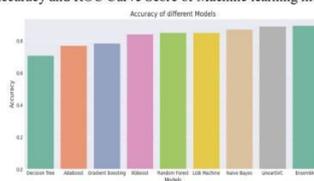
S.No	Models	Accuracy	Precision Score	Roc Scores
1	Decision Tree	0.648	0.622	0.642
2	AdaBoost	0.701	0.552	0.682
3	Gradient Boosting	0.725	0.767	0.699
4	XGboost	0.748	0.739	0.734
5	Naive Bayes	0.769	0.839	0.744
6	Random Forest	0.758	0.743	0.747
7	LGB Machine	0.766	0.747	0.756
8	LinearSVC	0.774	0.734	0.769
9	Ensemble	0.791	0.689	0.779

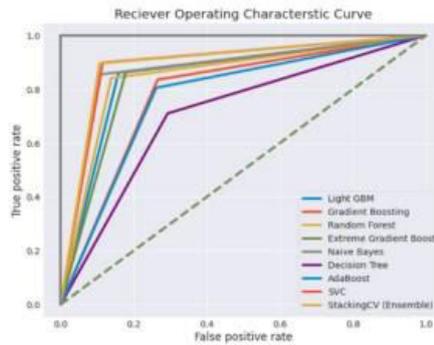


2) IMDb Reviews dataset: Table 2 clearly depicts the three most efficient models when trained on IMDb reviews dataset gave reasonable results, namely, LGB Machine, Naive Bayes and Linear-SVC. Ensemble model of these three is made to get the best possible results among machine learning models for IMDb reviews dataset. With the Ensemble model we get an Accuracy of 0.894, Precision Score of 0.898 and ROC Score of 0.894.

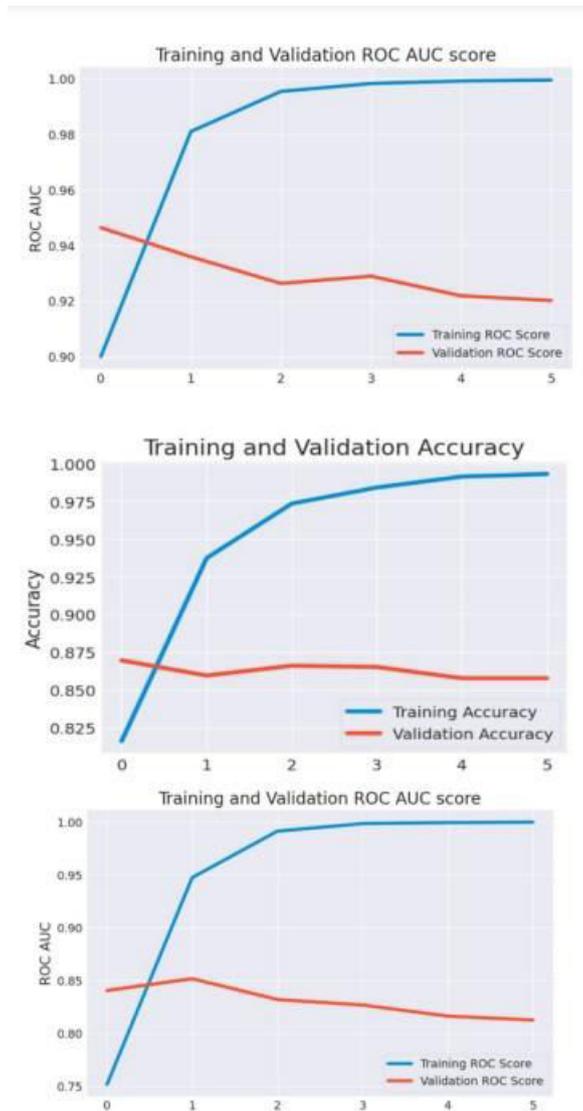
S.No	Models	Accuracy	Precision Score	Roc Scores
1	Decision Tree	0.708	0.709	0.708
2	AdaBoost	0.771	0.805	0.771
3	Gradient Boosting	0.784	0.756	0.785
4	XGboost	0.842	0.827	0.842
5	Naive Bayes	0.872	0.805	0.872
6	Random Forest	0.851	0.857	0.851
7	LGB Machine	0.851	0.843	0.851
8	LinearSVC	0.891	0.898	0.891
9	Ensemble	0.894	0.898	0.894

Table 2: shows the Accuracy and ROC Curve Score of Machine learning models for IMDb Reviews





B. Deep Learning Results Bidirectional LSTM Model, which is a variant of LSTM model, scored with good accuracy of 77% and ROC score of 0.81 for Amazon Reviews dataset and for IMDb dataset, 85.5% accuracy and 0.92 ROC score were the results. Results are:





IX. CONCLUSION

This project introduces that Sentiment analysis is a powerful tool for YouTube channel owners. It provides insights into audio sentiment, helps optimize content and can be used for brand reputation management and comment moderation. By implementing sentiment analysis with tensorflow.js, youtubers can better understand their audience and improve overall quality of their content. Beyond YouTube sentiment analysis applications in various domains, including social media monitoring, customer feedback analysis and market research. Its versatility makes its valuable tool for anyone looking to get deeper insights into textual data and leverage those insights for decision making. So, whether you are a content creator or business owner, sentiment analysis can be a valuable addition to your toolkit.

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