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Improving Sentiment Classification and Fake Video Detection of YouTube Videos Using Custom Metadata and GAN Model

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Abstract:

With the rapid increase in user-generated content, YouTube faces a significant challenge in managing the vast amounts of data, including the proliferation of fake videos published online in a short span of time. Effective sentiment analysis and fake video detection are crucial for understanding user engagement, preferences, and maintaining the platform's integrity. This research aims to improve sentiment classification and fake video detection for YouTube videos using custom metadata and Generative Adversarial Networks (GANs). The proposed methodology focuses on extracting sentiment from user comments and custom metadata associated with YouTube videos. A multi-stage process is employed that includes custom data creation, data preprocessing, feature extraction, and sentiment classification. By integrating domain-specific features and contextual information, our aim is to improve the accuracy and relevance of sentiment analysis. The proposed approach not only facilitates more efficient organization and categorization of YouTube content but also provides valuable insights for detecting fake videos, even with a limited number of user comments. Experimental evaluations on diverse datasets, including a custom dataset and the publicly available YouTube US video dataset, demonstrate significant enhancements in performance compared to existing methods. To further boost model performance, the GANs model is used which performs data balancing and leads to notable improvements in both recall and F1-score metrics, showing an increase of approximately 5% to 6% across all machine learning models. This research addresses the critical need for reliable sentiment analysis and fake video detection in the ever-expanding digital content landscape.

Keywords: YouTube Video Metadata, Machine Learning Algorithms, Generative Adversarial Networks, Sentiment Analysis, Fake Video Detection.

1. Introduction

In the digital age, platforms like YouTube have become ubiquitous sources of user-generated content across a vast array of categories, ranging from entertainment and education to lifestyle and gaming [1]. Effective techniques to examine and interpret YouTube video metadata are becoming more and more necessary as the amount and variety of content continue to expand rapidly. Sentiment analysis is one of the many facets of metadata that makes it an essential tool for figuring out user preferences and involvement. It is critical to stop fake information from spreading on social media sites in order to protect people and society [2]. The spread of fake information via these means carries the risk of causing harm to gullible people, endangering their security, well-being, and financial stability. Furthermore, the spread of fake information damages the credibility of information providers and threatens the foundation of democratic society. The integrity of democratic institutions is seriously threatened by fake data, which has the power to manipulate electoral processes and influence public opinion [3]. Moreover, the polarizing quality of fake information depends societal divisions and promotes conflict and hostility among groups. Fake information can have far-reaching effects on the economy, affecting investor confidence, consumer behavior, and market stability. As a result, stopping the spread of fake information on social media is not just a personal obligation but also essential to maintaining the integrity of democratic ideals, societal harmony, and financial stability.

In today's digital world, the rapid spread of fake information poses a serious problem. Fake information spreads quickly on social media sites and messaging apps, which are frequently powered by algorithms that put interaction above accuracy [4]. These videos / information are often created to garner likes, shares, and views by misleading viewers with fake information. For instance, some creators upload videos claiming to show trailers for new movies that haven't been released yet. These fake trailers are designed to exploit the anticipation and excitement of fans, driving traffic to their channels under false pretenses. Similarly, other fake videos may spread incorrect information on various topics, aiming to sway public opinion or create confusion. The ease of creating and sharing content online has made it difficult to distinguish between genuine and fake videos, posing significant challenges for both viewers and content platforms in maintaining the integrity and reliability of the information presented. As a result, sensationalized or fake data becomes viral and creates echo chambers where people are exposed to information that confirms their pre-existing opinions. The impact is significant, leading to political tensions, divisions in society, and reduced trust in institutions. Echo chambers and filter bubbles worsen the problem by reinforcing biased views and hindering critical thinking. Figure 1 illustrates an example of a misleading thumbnail and user comments. The thumbnail is fake, and upon reviewing user comments, it becomes evident that the spread information is fake.

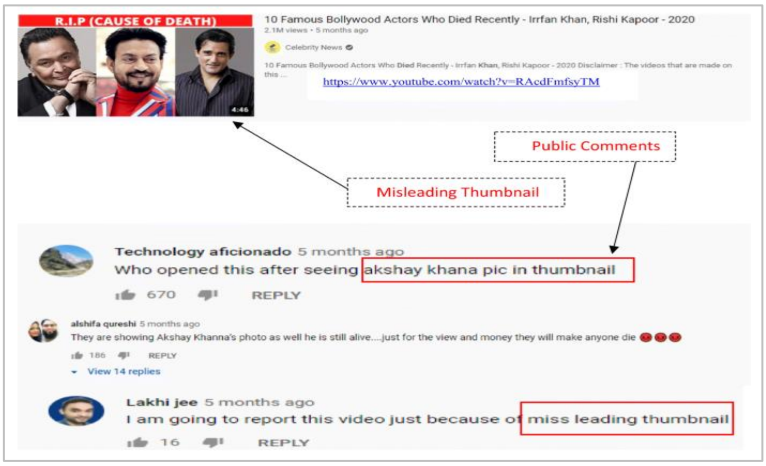

Figure 1: Fake Video Detection using Comments

Various methods have been explored to detect fake news / fake reviews, such as research in [5] , which is conducted using the N-gram and TF–IDF methods for feature extraction as well as various classifiers such as Stochastic Gradient Descent (SGD), Support Vector Machine (SVM), Linear Support Vector Machine (Linear SVM), K-Nearest Neighbor (KNN), and Decision Tree (DT). Ahmed et al. [5] use a dataset called ISOT Fake News where it can be accessed publicly, and they obtained an accuracy of 92% using the Linear SVM classifier. Moreover, Ozbay and Alatas [6] only used TF–IDF as their feature extraction method, a slightly different approach from the study. Authors also tried to use 23 classifiers such as ZeroR, CV Parameter Selection (CVPS), Weighted Instances Handler Wrapper (WIHW), DT, and so on to detect fake news /reviews.

With the success of deep learning in various domains, DL based FND methods have been proposed and attracted significant attention recently. Firstly, deep learning can avoid feature engineering and take full advantages of its strong expressive power to model the features of input news. For example, Ma et al. [7] modeled the sequential relationship between news posts utilizing recurrent neural networks. Yu et al. [8] utilized convolutional neural networks to represent high-level semantic relationships between news posts. Bian et al. [9] leveraged a Graph Neural Networks (GCNs) with both top-down and bottom-up directed graph of rumor spreading to learn its propagation and dispersion patterns. Khattar et al. [10] proposed the multi-modal Variational Autoencoder (MVAE) to extract the hidden multi-modal representations of multimedia news.

While there have been several surveys on fake video detection, most of them categorize existing research based on feature perspectives. Recently, weakly supervised and unsupervised methods have garnered attention to address challenges arising from limited labeled data. This is crucial for real-world applications, particularly given the rapid spread of data on social media also the authenticity of internet videos has grown more and more significant with the growth of digital content development and distribution. Even though comments might provide insightful information and social validation, it might not be enough to rely simply on them to assess a video's validity. By using a thorough analysis that includes source verification, metadata inspection, visual analysis, contextual information, expert opinion, and pattern recognition, we are still able to determine the authenticity of films even with fewer comments.

In this paper, we provide an improved sentiment analysis technique for gathering and labelling YouTube video metadata in several categories. Consequently, there is an increasing demand for automated systems to support metadata collecting and annotation that can precisely analyze the feelings represented in user comments [11]. Our method uses natural language processing (NLP) and other machine learning techniques to extract sentiment from user comments on YouTube videos. We use a multi-step procedure that includes sentiment categorization, feature extraction, and data preprocessing. Furthermore, we incorporate contextual data and domain-specific features to enhance sentiment analysis's effectiveness and applicability in a variety of video categories. We run experiments on a huge dataset consisting of YouTube videos covering several categories like music, gaming, education, and lifestyle in order to assess the efficacy of our strategy. We show notable improvements in terms of robustness and performance when we evaluate our sentiment analysis model's performance against current methods. Additionally, we show how our method can be used to improve the annotation and collection of video metadata by automatically classifying videos according to their sentiment polarity. The adoption of GAN models, such as CTGAN [12], provides a solution to the issue of data imbalance in YouTube video evaluations while also enhancing the overall performance of machine learning models. These methods contribute to dataset balance by producing artificial samples for underrepresented categories. This improves machine learning models' performance, allowing for more precise forecasts and a clearer picture of the attitudes and preferences expressed in YouTube video reviews. The results of this study help to improve sentiment analysis methods that are especially designed for collecting and annotating metadata for YouTube videos. The suggested model can not only analyze sentiment, but it can also find fake videos, even if there aren't many comments. This two-in-one feature makes it easy to tell the difference between fake and positive YouTube video reviews, giving users and content authors useful information. Overall, the contributions of this research work can be summarized as follows;

Create a YouTube Review Dataset: Develop a comprehensive YouTube review dataset by leveraging the YouTube API key to gather user comments and associated metadata aiming to enhance the classification accuracy of video authenticity, enabling robust detection of fake videos through detailed analysis of limited user reviews and contextual information.

Data Balancing with GAN: Develop and implement improved sentiment classification techniques using custom metadata and Generative Adversarial Networks (GANs) model.

Implement a Multi-Stage Methodology for Analysis: Implement a structured multi-stage process encompassing custom data creation, rigorous data pre-processing, feature extraction, and sentiment classification based on machine learning.

Validate Findings Using Publicly Available Datasets: Validate the proposed methodology and findings by applying them to publicly available datasets, such as the YouTube US video dataset and Evaluate the performance of sentiment analysis and fake video detection methods using metrics like accuracy, precision, recall, F1-score, and confusion matrix.

The remaining sections of the work is organised as follows; Section 2 describe the reviews the literature and provides overview of findings related to detecting fake videos on social media. Section 3 details the related work and data sources, Section 4 explains the proposed methodology along with dataset creation process, flow of model including data processing, techniques for feature extraction, datasets utilized in current models for fake news detection, GAN Model working and Machine Learning algorithms for sentiment classification, Section 5 describes the tools and technologies used and experiment scenarios along with performance parameters and shows the experimental results obtained as well as discussions. Finally, Section 6 presents conclusions and plans for future work.

2. Literature Review

In this section, we have performed a thorough examination of the existing literature based on various feature extraction, natural language processing (NLP), machine learning, deep learning and sentiment analysis techniques. Our exploration covers a wide variety of papers and studies, which represent the most recent trends and breakthroughs in the subject of fake video or review detection.

There is a careful analysis required among the features extracted from the video. The current research has not addressed this problem fully, as they focus only on the content-based solution like, Potthast M et al [13] incorporate several set of handcrafted features like bag-of-words, n-grams, etc., to train the classifier and firstly introduce an automatic clickbait detector, the authors have used the random forest for the prediction of clickbait tweets. Shaikh et al. [14] explores the impact of YouTube on scientific research, proposing models to measure its influence. It discusses metrics such as views, likes, comments, and how these metrics correlate with traditional research impact indicators like citations. Madasu & Elango et al [15] explores various techniques for feature selection in sentiment analysis, aiming to enhance model efficiency and performance. Authors addresses the challenge of selecting the most informative features from large datasets. While Wang et al [16] introduce efficient randomized algorithms for feature selection, focusing on enhancing computational efficiency and effectiveness in feature subset selection tasks.

Zuo et al. [17] develop a context-specific heterogeneous graph convolutional network designed for implicit sentiment analysis, addressing challenges related to capturing contextual information and relationships in sentiment expression across different domains. Zhou G. et al [18] research investigates sentiment analysis models tailored for short texts using deep learning methods. Author addresses the challenges posed by the brevity and contextuality of short text data. Balli et al. [19] applies Natural Language Processing (NLP) techniques to analyze sentiment in Turkish content on Twitter. Author contributes to understanding sentiment patterns specific to Turkish-speaking users on social media. Kumar Donthi et al. [20] research proposes a hybrid approach for sentiment analysis in online social networks, leveraging multiple attributes of data. Author aims at enhancing the accuracy and robustness of sentiment analysis models in the context of social media data. Basiri et al [21] study aims to improve sentiment polarity detection by focusing on identifying specific targets (entities or aspects) within texts.

Al-Shammari et al [22] explores the classification of fake news using machine learning algorithms like Random Forest and Decision Tree (J48), focusing on improving accuracy in detecting misinformation and enhancing information credibility. Vishwakarma et al [23] conduct a comprehensive review of deep learning architectures used for sentiment analysis across various applications, highlighting advancements, challenges, and future directions in the field. Li et al. [24] presents a Convolutional Neural Network (CNN) based model for detecting misleading videos. It contributes to combating misinformation by automating the detection process using deep learning techniques. Yang et al. [25] employ sentiment lexicons and deep learning techniques to perform sentiment analysis specifically for Chinese e-commerce product reviews, aiming to extract nuanced sentiment expressions and improve understanding of customer feedback. Yan et al. [26] proposes a sentiment analysis model, combining Convolutional Neural Networks (CNN), Bidirectional Gated Recurrent Units (BiGRU), and Attention Mechanism (AT). It focuses on analyzing sentiment in student texts, possibly aiming to understand educational sentiments or feedback. Suratkar et al. [27] focuses on detecting deep fake videos using transfer learning, a method where a model trained on one task is adapted for another related task. It is crucial for addressing the growing concern of misinformation and manipulated media.

Bourou et al. [28] review the application of Generative Adversarial Networks (GANs) for synthesizing tabular data, specifically focusing on their use in an Intrusion Detection System (IDS) dataset, aiming to generate realistic synthetic data for enhancing cybersecurity research. Smith et al. [29] discuss the evolving role of Generative Adversarial Networks (GANs) in anomaly detection within network security, examining their potential applications, challenges, and future research directions in detecting network anomalies and improving cybersecurity measures.

These studies showcase the diverse applications of sentiment analysis, machine learning and deep learning techniques across different platforms and domains for effective fake video and reviews detection. In this paper, we focus on fake video detection using YouTube video reviews and metadata.

3. Existing Methods and Data Sources

In this section, the reviewed work is presented. The work shows the various algorithms used for sentiment analysis and fake review classification using machine learning techniques. Machine learning algorithms includes Random forest, Naive Bayes, KNN and Decision Tree;

Random Forest

The Random Forest Algorithm [32] [35], widely used in Machine Learning, is frequently applied in supervised learning to address Classification and Regression assignments. It is a well-known fact that a forest consists of many trees, and the greater the number of trees, the stronger its ability to withstand challenges. Likewise, an increase in the quantity of trees within a Random Forest Algorithm leads to improved accuracy and problem-solving skills. Random Forest is a classification model comprising multiple decision trees constructed on different parts of the dataset and aggregating the predictions to enhance the dataset's overall accuracy. Ensemble learning relies on combining multiple classifiers to address complex problems and enhance the model's effectiveness.

Naive Bayes

Naïve Bayes [35] is a classification method that relies on Bayes' Theorem and assumes independence among predictors. In basic terms, a Naive Bayes classifier assumes that the existence of a specific feature in a class is independent of the existence of any other feature. The Naïve Bayes classifier is a widely used supervised machine learning technique for tasks like text classification. It is part of the generative learning algorithms family, indicating that it represents the input distribution of a specific class or category. This method relies on the belief that the characteristics of the input data are independently linked to the class, enabling fast and accurate predictions to be made by the algorithm.

In statistics, naive Bayes are simple probabilistic classifiers that apply the Bayes theorem. This theorem is based on the hypothesis's likelihood given the available facts and past knowledge. The naive Bayes classifier operates under the assumption that every characteristic in the input data is unrelated to every other feature. This is a condition that is often not met in real-world scenarios. The naive Bayes classifier is still widely used despite this simplification because of its potency and solid performance in a range of real-world situations. It should be noted that, despite being simple models of Bayesian networks, naive Bayes classifiers can achieve great accuracy when paired with kernel density estimation. By approximating the probability density of the input data using a kernel function, this technique helps the classifier perform better in complex scenarios with a non-defined data distribution. As a result, the naive Bayes classifier is a powerful tool in machine learning, particularly for applications such as sentiment analysis, spam filtering, and text classification.

K Nearest Neighbor

KNN [33] is a well-known supervised machine learning method that is frequently used for regression and classification. Based on supervised learning, it is a simple machine learning technique. By assuming similarity between the new and available data, the K-NN method assigns the new example to the category most similar to the existing categories. Saves all the existing data and categorizes a new data point according to its similarity. This indicates that when new data is introduced, it can be easily sorted into a suitable category using the K-NN algorithm. K-NN is a non-parametric technique, indicating it does not rely on any assumptions about the underlying data. It is known as a lazy learner algorithm as it postpones learning from the training set and instead stores the data until classification, where it finally acts on the dataset. During the training phase, the KNN algorithm simply saves the dataset. When new data is introduced, it is classified into a category that closely resembles the new data.

Steps of the KNN algorithm:

- Choose the number of neighbors, labeled as K.
- Determine the Euclidean distance for K closest neighbors.
- Select the K nearest neighbors using the distance that has been calculated.
- Decide the classification or numerical value of the data point based on the majority vote or average of the K neighbors.

The core equation in KNN is the Euclidean distance between two data points:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (1)$$

Here, x and y represent feature values for the two data points. The class or value of the unclassified point is determined by the majority class of its K nearest neighbors.

Decision Tree

Decision Tree [36] is a supervised learning technique applicable for classification and regression tasks, but typically used for classification. A classifier based on trees is utilized, where dataset features are represented by internal nodes, decision rules are shown by branches, and the final result is displayed in leaf nodes. A Decision tree consists of two nodes, namely the Decision Node and Leaf Node. Decision nodes are used to make choices and have multiple branches, whereas Leaf nodes are the outcomes of those choices and do not contain any further branches. Decisions or assessments are conducted according to the attributes of the given dataset. It is a visual representation used to explore all possible results of a situation or choice, taking into account unique conditions. Named a decision tree because it looks like a tree, it starts with the root node and expands into branches, creating a treeshaped structure. A decision tree inquires, then generates subtrees depending on the response (Yes/No) provided.

Data Sources:

USVIDEO Dataset

YouTube, the renowned video sharing platform, curates a compilation of its top trending videos, as noted by Variety magazine. The USVIDEO [34] selection process involves a blend of user interactions, including views, shares, comments, and likes, rather than sheer view counts alone, as emphasized by Variety. These trending videos encompass a diverse array of content, ranging from popular music videos like the iconic "Gangnam Style," to celebrity performances, reality TV highlights, and the spontaneous viral videos synonymous with YouTube's culture. The dataset presented here captures a daily record of YouTube's top trending videos, offering an extensive and continuously updated repository of trending content. It covers several months of data across various regions including the US, Great Britain, Germany, Canada, and France, with up to 200 trending videos listed per day. Additionally, the dataset now incorporates data from additional regions including Russia, Mexico, South Korea, Japan, and India, expanding its scope and diversity. Each region's data is contained within separate files, comprising key information such as video title, channel title, publish time, tags, views, likes, dislikes, description, and comment count. Furthermore, the dataset includes a category_id field, which varies across regions. To obtain the specific categories for a given video, users can refer to the associated JSON files provided for each region within the dataset, enhancing the richness and granularity of the available information. Figure 2 shows the data sample of USVIDO dataset.

	video_id	trending_date	title	channel_title	category_id	publish_time	tags
0	2kyS6SvSYSE	17.14.11	WE WANT TO TALK ABOUT OUR MARRIAGE	CaseyNeistat	22	2017-11-13T17:13:01.000Z	SHANtell martin
1	1ZAPwfrtAFY	17.14.11	The Trump Presidency: Last Week Tonight with J...	LastWeekTonight	24	2017-11-13T07:30:00.000Z	last week tonight trump presidency|"last week ...
2	5qpjK5DgCt4	17.14.11	Racist Superman | Rudy Mancuso, King Bach & Le...	Rudy Mancuso	23	2017-11-12T19:05:24.000Z	racist superman|"rudy"|"mancuso"|"king"|"bach"...

Figure 2: USVIDEO Dataset Sample

4. Proposed Methodology

Figure 3 depicts the overall configuration diagram of the proposed fake video detection model. Section 3.1 outlines the dataset description, Section 3.2 provides the proposed methodology, Section 3.3 provides detailed explanations of the Algorithm and model used. The process start with the creation of thorough **Dataset for YouTube video** comments starts with obtaining an API key from the Google Developers Console. This key allows access to the YouTube Data API for retrieving comments. Entering the URLs of desirable YouTube videos into a data collection tool starts the process of gathering data. This is then followed by using the API to retrieve comments and extract information, ensuring that the dataset is complete and accurate. Storing this metadata together with distinct identifiers in a CSV file enables systematic analysis. The API is utilized to download comments, which are then stored alongside their corresponding identifiers for the purpose of creating structured datasets.

Preprocessing encompasses the elimination of duplication, whitespace, and the standardization of text. Further **Dataset Cleaning** entails the removal of emojis, punctuation, and stopwords, thereby improving the quality of the dataset. **Feature extraction** is conducted to gain deeper insights into the dynamics of content and engagement. This process includes the identification of variables such as categorization, sentiment, and topic modelling. Ultimately, sophisticated methods like **GANs** are employed to generate synthetic data, guaranteeing the durability and usefulness of the dataset for future research tasks. After balancing the data **train-test split** is performed with 80% - 20% train test split ratio and the data is passed to the various **machine learning algorithms** to detect the video is fake or valid. Following details shows the steps involved in proposed methodology; Figure 3 shows the working flow or proposed methodology.

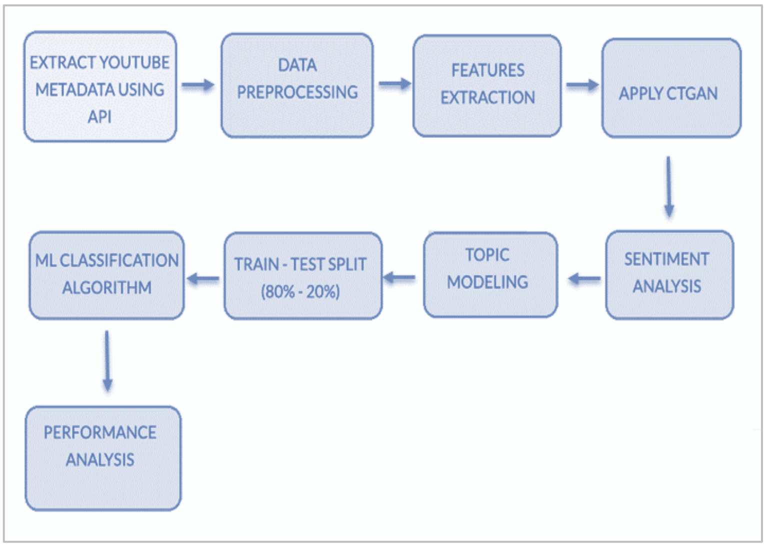

Figure 3: System Flow of Fake Video Detection

4.1 Dataset Creation Process

Self-Created Dataset of YouTube Video MetaData

As part of our methodology, we utilized the YouTube Data API along with a set of 2,000 + diverse YouTube video URLs spanning various categories such as politics, entertainment, sports, and more, to create comprehensive metadata for our dataset. With the acquired API key for authentication, we initiated the process by inputting each video URL into our data collection system. Leveraging the capabilities of the YouTube Data API, we systematically retrieved crucial metadata associated with each video, including titles, upload dates, views counts, and relevant tags or hashtags. By systematically processing URLs from a range of categories through the API, we ensured a broad representation of content types within our dataset. This diverse selection enabled us to capture a wide spectrum of viewer interests and preferences across different genres and topics. The structured metadata, organized alongside unique identifiers, facilitated efficient management and analysis of the dataset, empowering us to delve deeper into the trends and patterns within the YouTube content landscape across various categories. The utilization of diverse categories enriched our dataset, providing a comprehensive snapshot of the YouTube ecosystem's dynamics. This approach enabled us to construct a robust dataset primed for further exploration and analysis, driving insights into audience engagement, content preferences, and broader trends within each category and the platform as a whole.

YouTube MetaData Creation Process:

Generate API Key: In order to obtain an API key for the purpose of producing a dataset pertaining to comments on YouTube videos, required an access to the YouTube Data API via the Google Developers

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Console. Upon arrival, initiate the creation of a fresh project, activate the YouTube Data API, and generate an API key with suitable privileges, such as the ability to read video comments. This key grants the application the ability to authenticate and gain access to YouTube's API, thereby enabling it to retrieve and analyze video comments for the purpose of creating dataset.


```
{'URL': 'https://www.youtube.com/watch?v=fxVRDC-6lwo',
 'Title': 'Teri Baaton Mein Aisa Uljha Jiya Full Movie | Shahid Kapoor | Kriti Sanon | New movie',
 'Channel Title': 'APNA MOVIES',
 'Date': '2024-01-21T04:27:48Z',
 'Views': '631231',
 'Likes': '6113',
 'Dislikes': 0,
 'Comment Count': '164',
 'Category ID': '1',
 'Comments Disabled': False,
 'Ratings Disabled': False,
 'Tags': ['teri baaton mein aisa uljha jiya shahid kapoor',
  'teri baaton mein aisa uljha jiya',
  'teri baaton mein aisa uljha jiya trailer',
  'New movei',
  'new movie',
  'shahid kapoor movies',
  'shahid kapoor and kriti sanon',
  'teri baaton mein aisa uljha jiya song',
  'laal peeli ankhiyaan shahid kapoor\nshahid kapoor movie',
  'New movies',
  'Trending no. 1',
  'Viral new south movie'],
 'Description': 'Teri Baaton Mein Aisa Uljha Jiya Full Movie | Shahid Kapoor | Kriti Sanon | New
```


Figure 4: Extracted YouTube Video Metadata

Input YouTube video URLs: To generate a dataset pertaining to comments on YouTube videos, enter the URLs of the appropriate YouTube videos into your data gathering tool or script. Next, employ the YouTube Data API to obtain the comments linked to each video URL. By consolidating and scrutinizing these remarks, you can construct your dataset for subsequent investigation or analysis pertaining to YouTube video.

Extract metadata from YouTube video: Extracting YouTube video metadata entails obtaining crucial information such as the video's URL, title, upload date, view count, hashtags, and tags, among others. Furthermore, it involves handling scenarios where metadata may be absent, such as when the title or tags are missing. This is done by identifying these cases and potentially using other available data sources to guarantee the dataset's completeness and accuracy. This is particularly useful when analyzing YouTube video comments.

Store metadata with unique ID (URL_ID) in CSV file: In order to generate a dataset pertaining to comments on YouTube videos, it is necessary to store metadata together with a distinct identifier (URL_ID) in a CSV file. The metadata may encompass details such as the title of the video, the name of the channel, the date of upload, and the number of views. By utilizing the URL_ID as a point of reference, you can effectively arrange and examine the comments in conjunction with their related video metadata. This enables smoother browsing and analysis of your dataset.

Download comments related to YouTube video: Use the YouTube Data API, notably the comments Threads list function, and provide the video ID for the desired video to download comments associated with a YouTube video for the purpose of creating a dataset. You can collect extensive data for your dataset pertaining to YouTube video comments by using this API call to retrieve all comments linked to the video, including with responses and metadata like commenter usernames and timestamps.

```
Enter the YouTube video URL: https://www.youtube.com/watch?v=fxVRDC-6lwo
Comments:
Nice movie forever
It was great 👍 👌
This is the movie Jersy
Krti ka to kuj btaye hi ni 😮
Movie name to sahi dal Diya kro
Movie name to sahi dal Diya kro
This is jursy movie
Ye to jarsi h
Yr movie ka name kuch v de diye 😂😂
🖤🖤🖤🖤🖤🖤🖤🖤🖤 such a master piece...
Itna hi upload karne ka shauk h toa real name dallo na movie ka
```

Figure 5: YouTube Video Extracted Reviews

Store comments with unique ID(URL_ID) in CSV file: Once the YouTube video comments have been downloaded, save them in a CSV file with the comments and their unique identification (URL_ID). The YouTube video's URL or ID may serve as this identifier. You may keep a structured dataset and make it easier to analyse and correlate comments with the corresponding films for research or insights by giving each comment a unique ID.

4.2 Methodology

Figure 6 shows the detail flow of proposed system architecture.

4.2.1 Dataset Loading

Loading datasets into a data analysis tool involves preparing the data for analysis, here two datasets are used; the first dataset comprises self-generated YouTube video data stored in a CSV file, while the second dataset consists of US video review data. Each dataset requires specific handling to extract and structure the information effectively for subsequent analysis or modeling tasks. Each row in dataset represents a video URLs, along with attributes like video title, views, likes, and reviews. Loading this dataset involves reading the CSV file and ensuring the data is correctly formatted for analysis.

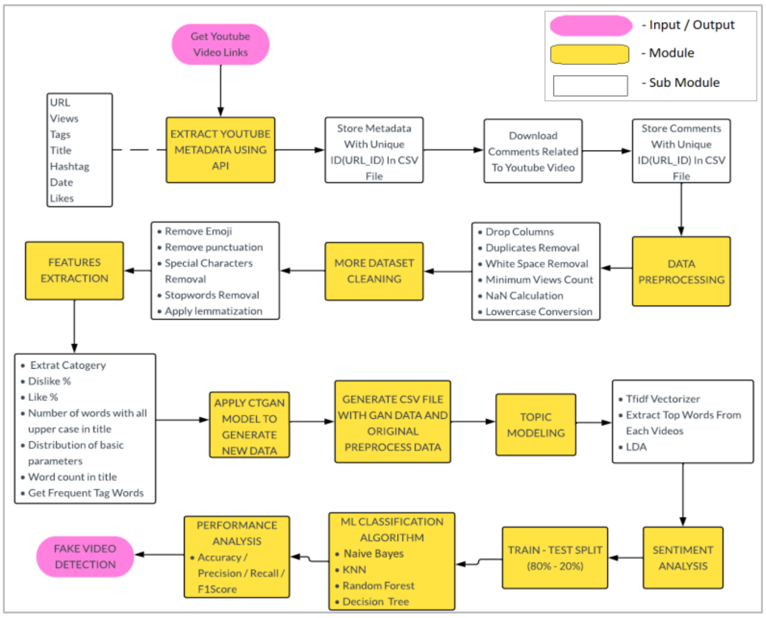

Figure 6: Proposed system architecture diagram

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4.2.2 Data Preprocessing

In order to prepare a dataset relating to comments on YouTube videos, data preparation is necessary. In order to maintain data cleanliness, this entails reducing superfluous columns, removing duplicate comments, removing white spaces for consistency, establishing a minimum views count threshold for relevancy, treating NaN values appropriately, and changing text to lowercase for analytical uniformity. Through these preprocessing methods, the dataset is improved and made more appropriate for modelling and analysis tasks involving comments on YouTube videos. The pre-process data and related metadata sample is shown in Figure 7.

	video_id	trending_date	title	channel_title	category_id	tags	views	likes
0	2kyS6SvSYSE	17.14.11	WE WANT TO TALK ABOUT OUR MARRIAGE	CaseyNeistat	22	SHANtell martin	748374	57527
1	1ZAPwfrtAFY	17.14.11	The Trump Presidency: Last Week Tonight with J...	LastWeekTonight	24	last week tonight trump presidency|"last week ...	2418783	97185
2	5qpjK5DgCt4	17.14.11	Racist Superman | Rudy Mancuso, King Bach & Le...	Rudy Mancuso	23	racist superman|"rudy"|"mancuso"|"king"|"bach"...	3191434	146033
3	puqaWrEC7tY	17.14.11	Nickelback Lyrics: Real or Fake?	Good Mythical Morning	24	rhett and link|"gmm"|"good mythical morning"|"...	343168	10172

Figure 7: Pre-process dataset

Review cleaning: To maintain text uniformity and readability, emoticons, punctuation, and special characters are eliminated during reviews cleaning process from YouTube video reviews. Stopwords are also removed, and lemmatization is also applied on the text. This process will reduce variances and improve the quality of the dataset for further analysis, like topic modelling and sentiment analysis. By doing these actions, the dataset is improved and becomes more useful for problems involving natural language processing. The clean review sample of Self-created YouTube video review dataset is shown in Figure 8.

```
['nice movi forev',
 'great',
 'movi jersi',
 'krti ka kuj btay hi ni',
 'movi name sahi dal diya kro',
 'movi name sahi dal diya kro',
 'jursi movi',
 'ye jarsi h',
 'yr movi ka name kuch v de diy',
 'master piec',
 'itna hi upload karn ka shauk h toa real name dallo na movi ka',
```

Figure 8: Clean Reviews of Self-created YouTube Video Review Dataset.

4.2.3 GAN model

Preparing data, choosing a model, training, and evaluating the model are all part of using GANs. A CTGAN architecture is selected and trained to provide synthetic data that mimics the original dataset once the dataset has been cleaned and prepared. The generator creates synthetic samples for a variety of tasks once it has been trained. By evaluating the created data, the original dataset's quality and similarity are guaranteed. The detail explanation of CTGAN model working is shown in Algorithm section. Figure 9 shows the sample counts before and after applying GAN model on USVIDEO dataset.

```
Sentiment_Type
1    14258
2     7168
0     3525
Name: count, dtype: int64
```

```
Sentiment_Type
1    14258
0    14258
2    14258
Name: count, dtype: int64
```

Figure 9: (a) Before GAN Model Label Count, (b) After GAN Model Dataset Count of USVIDEO dataset.

4.2.4 Feature Extraction

A variety of properties, including category, dislike percentage, like percentage, the amount of words in the title that are all capital letters, the distribution of fundamental parameters, the number of words in the title, and frequently occurring tag phrases, are extracted for features from the YouTube video reviews. These attributes enable deeper analysis and comprehension of audience preferences and trends within the dataset by offering insightful information about the content and engagement of YouTube videos and helps to provide information like video is fake or not.

More Feature Extraction (Topic Modelling): In order to represent the text data in a numerical representation, topic modelling approaches such as TF-IDF [30] vectorization can be utilized for further feature extraction for the YouTube video comments dataset. This makes it possible to use TF-IDF scores to extract the most important words and phrases from all of the comments. Further insights into the content and audience involvement can be obtained by identifying the recurring themes or subjects covered in each video by taking the top words out of the comments.

4.2.5 Sentiment Analysis

Sentiment analysis evaluates the emotional content of reviews left on YouTube videos within a given dataset. Sentiment analysis uses natural language processing techniques to classify comments as neutral, negative, or positive. Figure 10 shows the sentiment analysis of USVIDEO Dataset. This allows for the classification of comments and gives important information about the thoughts and feelings of viewers regarding the material. In order to increase engagement and happiness, content creators and researchers uses this study to better understand audience sentiment, spot patterns, and make data-driven decisions.

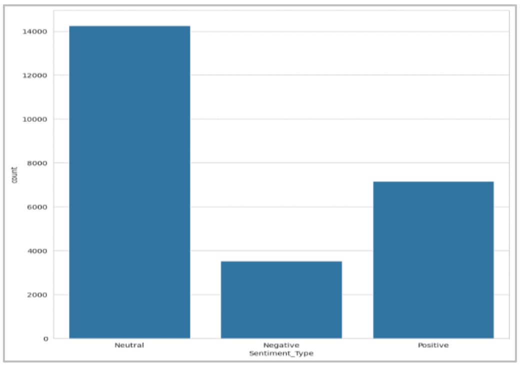

Figure 10: Sentiment Analysis (USVIDEO Dataset)

4.2.6 Fake Video Detection

Latent Dirichlet Allocation (LDA) [31] serves as a versatile tool for analyzing YouTube video reviews by simultaneously performing topic modeling and sentiment score calculation. In the context of topic modeling, LDA identifies latent topics within the corpus of reviews. Each topic represents a distribution of words that frequently co-occur across reviews, thereby revealing underlying themes or subjects discussed by reviewers. For example, topics could range from video quality and content relevance to viewer engagement and production values. By extracting these topics, LDA provides content creators and analysts with a structured understanding of the main discussion points and recurring themes within the reviews.

Moreover, LDA can extend its utility to sentiment analysis within the topic modeling framework. Sentiment analysis involves assessing the emotional polarity expressed towards specific topics or aspects of the videos. Post LDA topic modeling, sentiment scores are calculated by associating sentiment lexicons with each identified topic. This approach allows for nuanced insights into whether reviewers express positive, negative, or neutral sentiments towards various elements of the videos, such as content, presentation, or overall viewer experience along with these the fake reviews are identified based on title relevance with reviews and most used keywords. LDA remains a powerful method for uncovering actionable insights from textual data, empowering stakeholders to make informed decisions based on comprehensive analyses of user feedback and sentiment trends in YouTube video reviews. Figure 11 shows the sentiment score of YOUTUBE video dataset which represent the input has negative sentiment and the video is fake.

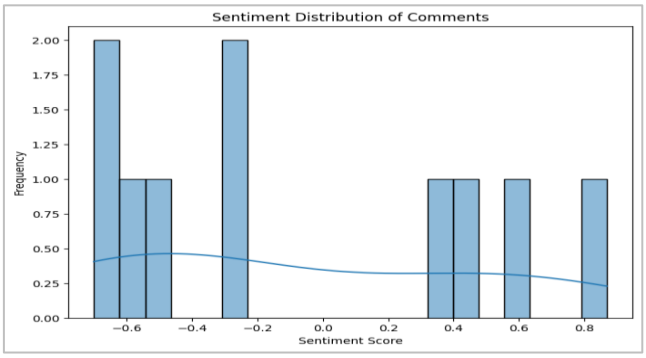

Figure 11. Sentiment Score (YouTube VIDEO Dataset)

4.3 Algorithms

This section elaborates on various algorithms used in fake video detection, including machine learning models such as Random forest, Naive Bayes, KNN, Decision Tree, LDA and Generative Adversarial Networks (GAN), with a focus on addressing data balance issues.

Algorithm 1: CTGAN

A generative adversarial network (GAN) has two parts:

- The generator learns to generate plausible data. The generated instances become negative training examples for the discriminator.
- The discriminator learns to distinguish the generator's fake data from real data. The discriminator penalizes the generator for producing implausible results.

When training begins, the generator produces fake data, and the discriminator quickly learns to tell that it's fake. For generating fake data, Generative Adversarial Networks (GANs) with Conditional Transformation (CT) models are employed. GANs consist of two neural networks, a generator and a discriminator, engaged in a competitive training process where the generator creates synthetic data samples and the discriminator evaluates their authenticity.

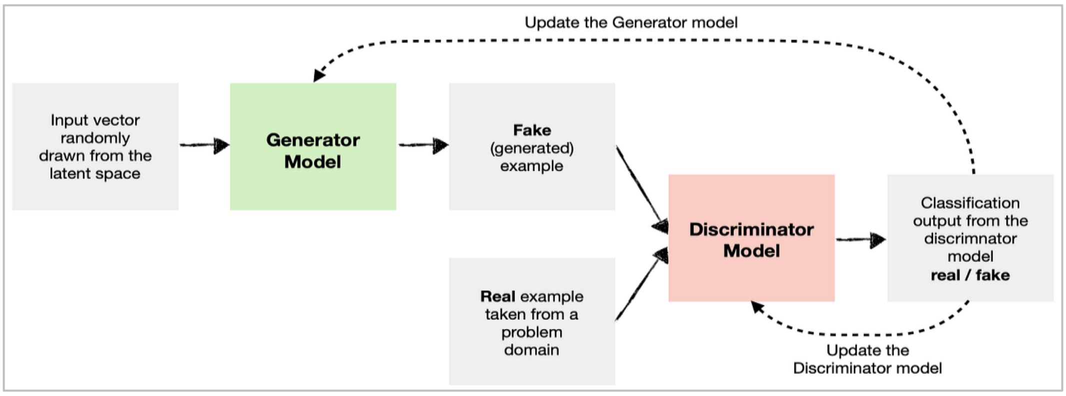

Figure 12: GAN model

The CT model enhances GANs by introducing conditional information, such as specific characteristics or attributes, to control the generated samples' properties. This approach enables the creation of highly realistic fake data that closely resembles the characteristics of the original dataset, offering valuable applications in data augmentation, privacy preservation, and synthetic data generation for training machine learning models. Figure 12 shows and overview of GAN model The functionality of CTGAN is explained step by step as follows:

1. The original dataset by cleaning, normalizing, and selecting features is pass to the Model.
2. Generated samples are produced by a generator, evaluated by the discriminative network against true data distribution.
3. Training progresses to increase network reliability, fooling the discriminator with synthetic candidates that closely match real data.
4. The initial training dataset serves as a benchmark for the discriminator.
5. Training continues until desired accuracy is achieved with dataset samples.
6. The generator learns to produce convincing candidates that deceive the discriminator when given random inputs.
7. Both generator and discriminator undergo backpropagation: the generator improves image quality, while the discriminator becomes adept at distinguishing real from synthetic images.
8. A de-convolutional neural network serves as the generative network, while a CNN acts as the discriminator.

Algorithm 2: Latent Dirichlet Allocation (LDA)

A probabilistic model called latent Dirichlet allocation (LDA) seeks to reveal hidden themes and patterns within a corpus of texts. According to the LDA hypothesis, every document has a variety of subjects, each of which represents a probability distribution across words. One important difficulty that arises in the huge universe of textual data is how to effectively categorize and comprehend the different topics that are present in our data collections. Let us introduce you to topic modelling, a statistical framework that can be used to uncover the underlying topics in a set of papers. LDA is a particularly useful technique in this field. LDA finds the subjects that most effectively represent a collection of texts by breaking down the presumptive procedure that produces documents. In the field of Natural Language Processing (NLP), LDA is highly influential. The growing amount of written content produced by the digital age—such as news stories and posts on social media—highlights the necessity of automating the classification and summarization of data. LDA assists in providing content recommendations, aiding in information retrieval, and understanding thematic structures in large data sets. Its independent nature, without the requirement for specific labels, makes it highly suitable for exploratory data analysis when the data's structure is unknown. LDA offers a structure for examining and grasping the fundamental thematic structure in extensive text collections, which is essential in the field of NLP.

$$P(z_i = j|\mathbf{z}_{-i}, w_i, d_i, \cdot) \propto \frac{C_{w_ij}^{WT} + \eta}{\sum_{w=1}^{W} C_{wj}^{WT} + W\eta} \frac{C_{d_ij}^{DT} + \alpha}{\sum_{t=1}^{T} C_{d_it}^{DT} + T\alpha} \tag{2}$$

Where,

- W is the length of vocabulary (i.e. number of unique words).
- T is the number of topics.
- α is a hyperparameter. A low alpha value places more weight on having each document composed of only a few dominant topics whereas a high value will return many more dominant topics.
- η is a hyperparameter. A low value for the η (i.e. eta) places more weight on having each topic composed of only a few dominant words.

Each of these algorithms contribute to the preprocessing, analysis, and categorization of YouTube video sentiment, enriching the dataset and providing valuable insights into audience engagement and content perception.

5. Results and Discussion

This section presents results and discussions on fake video detection using YouTube video reviews and metadata, alongside performance parameters, experimental setup, and analysis.

5.1 Experimental Setup

The experimental setup involved using Python 3.7 within Google Colab, leveraging various libraries to implement machine learning algorithms. Key libraries utilized included scikit-learn for implementing classifiers like Random Forest and Decision Tree for fake news classification. Natural Language Toolkit (NLTK) was employed for text preprocessing tasks such as tokenization and stopwords removal. The experimental pipeline included data preprocessing, model training, data balancing and machine learning classification and evaluation using metrics such as accuracy, precision, recall, and F1-score to assess model performance.

5.2 Performance Parameters

True Positives (TP) - Representing values correctly predicted as positive. True Negatives (TN) - Denoting values accurately predicted as negative. False Positives (FP) – Occurring when the actual class is no, but the predicted class is yes. False Negatives (FN) – Arising when the actual class is yes, but the predicted class is no.

$$Precision(Pre) = \frac{TP}{TP + FP} \tag{3}$$

$$Accuracy(Acc) = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$Recall(Rec) = \frac{TP}{TP + FN} \tag{5}$$

$$F1 - Score = 2 * \frac{Pre * Rec}{Pre + Rec} \tag{6}$$

5.3 Results

The result analysis step consists of comparing results of different machine learning techniques, such as K-Nearest Neighbours (KNN), Naive Bayes (NB), Decision Trees (DT), and Random Forest, to evaluate performance. The models were trained and assessed using both the publicly available USVIDEO dataset and a self-created YouTube video dataset to assess their effectiveness in review classification tasks. In addition, a Generative Adversarial Network (GAN) model was used to strengthen the dataset's resilience, leading to significant enhancements in accuracy, precision, and recall measurements. This study showcased the effectiveness of utilizing Generative Adversarial Networks (GANs) for creating artificial data to improve the performance of machine learning algorithms.

The result analysis is divided into two parts: experiments on the USVIDEO dataset and experiments on a self-created YouTube video dataset. The confusion matrix is an essential tool utilized for evaluating machine learning models, specifically in classification tasks like sentiment analysis of YouTube video comments. The summary provides a thorough overview of the model's performance by displaying the number of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. Within the aspect of sentiment analysis for YouTube video comments, the confusion matrix offers valuable information into the model's ability to accurately differentiate between positive, negative, and neutral remarks.

Dataset 1: USVIDEOS DATASET

Without GAN Model

Figure 13: (a), (b) shows the confusion matrix of USVIDEO Dataset using Random Forest and Decision Tree machine learning algorithms respectively,

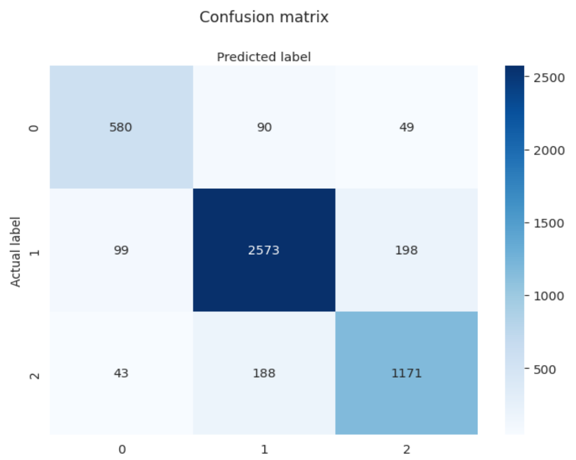

Figure 13: (a) RF Confusion Matrix

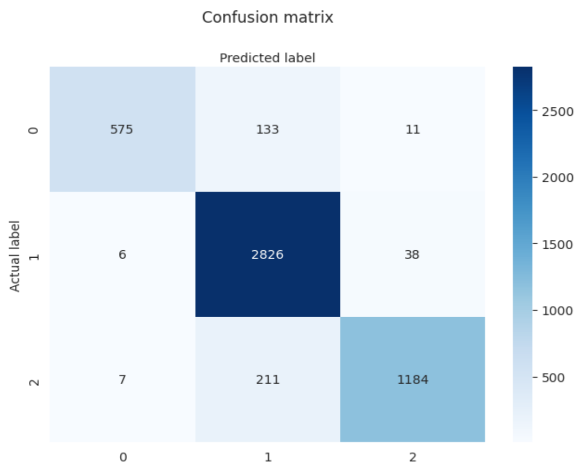

Figure 13: (b)DT Confusion Matrix

With GAN Model

Figure 14: (a), (b) shows the confusion matrix of USVIDEO Dataset with GAN model data balancing technique and using Random Forest and Decision Tree machine learning algorithms respectively.

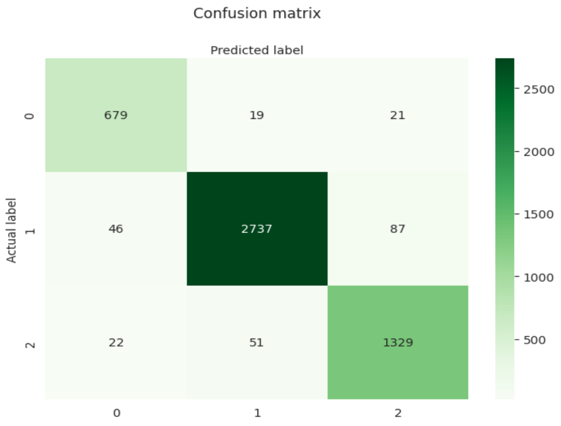

Figure 14: (a) DT Confusion Matrix

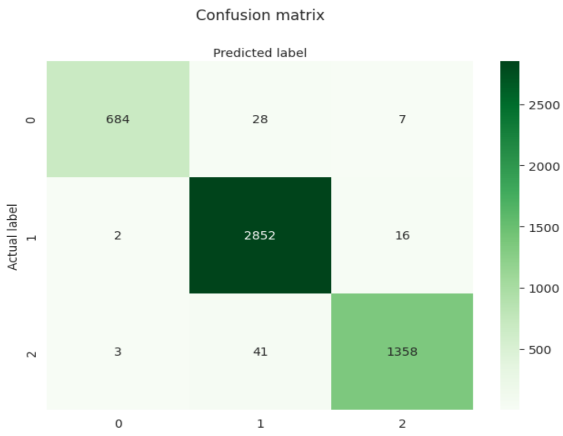

Figure 14: (b) RF Confusion Matrix

Dataset 2: YouTube Dataset

Without GAN Model

Figure 15: (a), (b) shows the confusion matrix of YouTube Video Dataset using Random Forest and Decision Tree machine learning algorithms respectively.

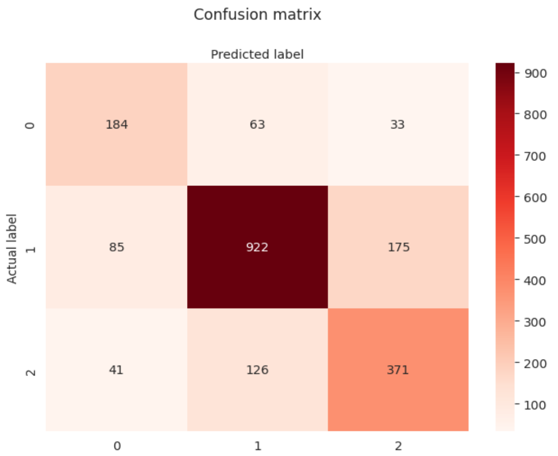

Figure 15: (a) RF Confusion Matrix

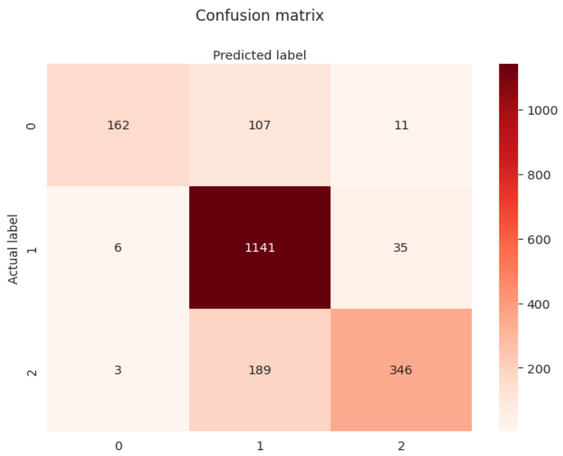

Figure 15: (b) DT Confusion Matrix

With GAN Model

Figure 16: (a), (b) shows the confusion matrix of YouTube Video Dataset with GAN model data balancing technique and using KNN, Naïve Bayes, Random Forest and Decision Tree machine learning algorithms respectively.

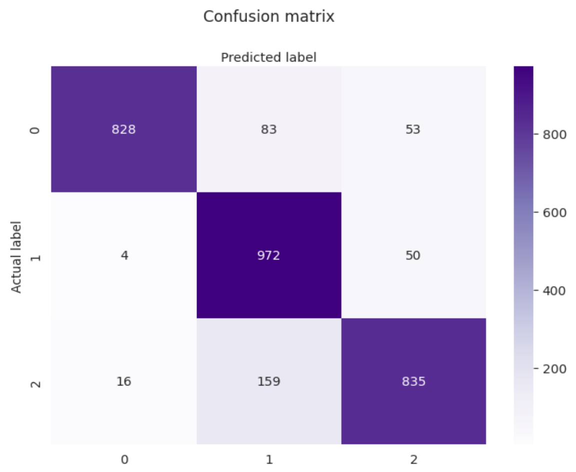

Figure 16: (a) RF Confusion Matrix

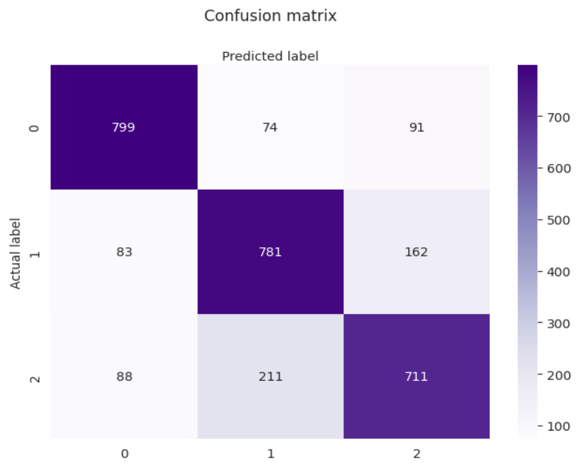

Figure 16: (b) DT Confusion Matrix

5.4 Comparative Analysis

In our study, we conducted a comprehensive evaluation of various machine learning algorithms, comparing their performance based on key metrics including accuracy, precision, recall, and F1 score. Additionally, we extended our analysis to include the results obtained from employing a Generative Adversarial Network (GAN) model. To facilitate this comparison, we utilized two distinct datasets: the USVIDEO dataset and a self-created YouTube dataset. Table 1 shows the comparative analysis table.

Table 1 Comparative Analysis of various machine learning models

	ACCURACY	PRECISION	RECALL	F1-SCORE
	USVIDEO DATASET (WITHOUT GAN MODEL)			
KNN	51	47	51	48
NB	35	46	35	35
DT	87	87	87	87
RF	92	92	92	92
	USVIDEO DATASET (WITH GAN MODEL)			
KNN	55	58	55	56
NB	29	45	29	18
DT	95	95	95	95
RF	**98**	**98**	**98**	**98**
	YOUTUBE_SELF_CREATED DATASET (WITHOUT GAN MODEL)			
KNN	50	36	35	34
NB	37	38	39	35
DT	74	69	71	70
RF	82	87	73	78
	YOUTUBE_SELF_CREATED DATASET (WITH GAN MODEL)			
KNN	47	47	47	47
NB	33	31	33	21
DT	76	76	76	76
RF	**88**	**89**	**88**	**88**

USVIDEO Dataset Comparative Analysis

Figure 16 shows the accuracy comparison of machine learning models with and without GAN model on USVIDEO dataset; from Figure 17 we can clearly see that with the use of GAN model except KNN model all machine learning algorithms shows ~5% increases in accuracy, which indicates GAN improves the overall performance of machine learning model and Random Forest outperform all other models with accuracy of 98%.

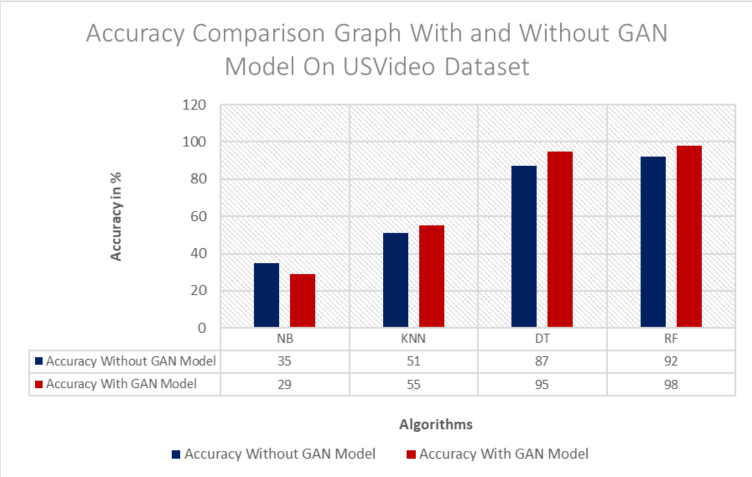

Figure 17. Accuracy Comparison Graph without and with GAN Model On USVIDEO Dataset

b. YOUTUBE SELF CREATED DATASET COMPARATIVE ANALYSIS

Figure 17 shows the accuracy comparison of machine learning models with and without GAN model on YouTube Video dataset; from Figure 17 we can clearly see that with the use of GAN model except KNN model all machine learning algorithms shows ~5% increases in accuracy, which indicates GAN improves the overall performance of machine learning model and Random Forest outperform all other models with accuracy of 88%.

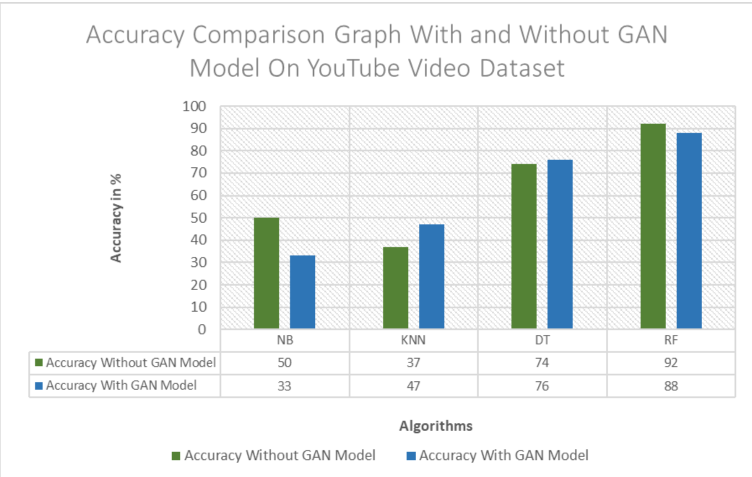

Figure 18. Accuracy Comparison Graph without and with GAN Model On YouTube Video Dataset

The evaluation findings showed significant disparities in the performance of several machine learning methods across the datasets. Algorithms such as K-Nearest Neighbours (KNN), Naive Bayes (NB), Decision Trees (DT), and Random Forest were evaluated based on their accuracy, precision, recall, and F1 score metrics. These measurements offered valuable insights into the algorithms' proficiency in accurately categorizing sentiment in YouTube video comments across both datasets. In addition, the integration of the GAN model added an extra level of analysis, resulting in enhanced accuracy, precision, recall, and F1 score metrics compared to the outcomes achieved only utilizing conventional machine learning algorithms. This improvement highlights the efficacy of utilizing GANs for expanding datasets and enhancing the performance of sentiment analysis jobs. In summary, our study emphasizes the significance of carefully choosing suitable machine learning algorithms and dataset augmentation strategies for conducting sentiment analysis on YouTube video comments. Through the comparison of outcomes from several algorithms and datasets, we have acquired useful knowledge about the advantages and constraints of each method. This will enable us to make more informed decisions in future sentiment analysis projects.

6. Conclusion

This research showcases significant advancements in sentiment analysis techniques tailored specifically for the extraction and annotation of metadata from a wide array of YouTube video categories. Through extensive experimental evaluations on a diverse dataset, our methodology has demonstrated substantial improvements in sentiment analysis performance, particularly with the integration of a Generative Adversarial Networks (GANs) model for effective data balancing. The incorporation of two datasets, comprising both a self-created dataset and the publicly available YouTube US video dataset, has further bolstered the robustness and versatility of our approach. Notably, the integration of the GAN model has led to notable enhancements in accuracy and F1-score metrics across all machine learning models, achieving an approximate increase of 5% to 6%. Of particular note is the Random Forest algorithm, which emerges as the top performer, obtaining an impressive accuracy of 98% on the USVIDEO dataset and 88% on the Self-Created YouTube Dataset. This highlights the effectiveness of our methodology in optimizing sentiment analysis outcomes across varied datasets. These findings underscore the considerable potential of advanced techniques like GANs in elevating sentiment analysis performance and offer valuable insights for enhancing the organization and recommendation of YouTube content, especially in scenarios characterized by limited user comments. Additionally, our methodology's ability to extract metadata and comments from YouTube videos and detect fake videos with limited reviews holds promise for expediting the detection of fraudulent content and sentiment analysis processes, ultimately contributing to more efficient decision-making in content moderation and recommendation tasks.

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