**PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA**

**MINISTERY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH**

**UNIVERSITY OF MOHAMED BOUDIAF - M'SILA**

**FACULTY: Mathematics and Computer Science**

**DEPARTMENT: Computer Science**

**N° : ……**

**DOMAIN: Mathematics and Computer Science**

**FIELD: Computer Science**

**OPTION: Artificial Intelligence**

**A Dissertation Submitted in Partial Fulfilment of the Requirements for the Degree of Professional Master**

**By**:

BENZAOUI Ismail

BENZAOUI Aya

## SUBJECT

# A Text Extraction and Machine Learning based-solution for Multimedia Filtering and Classification

**Board of Examiners:**

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| Pr. Mustapha BOURAHLA | University of M'sila | President |
| Dr. Mahmoud BRAHIMI | University of M'sila | Supervisor |
| Dr. Rahima BENTRCIA | University of M'sila | Examiner |

**Academic Year: 2022 / 2023**

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# DEDICATIONS

*This thesis is dedicated to our wonderful family, who have provided us with inspiration, support, and encouragement along our journey. Your faith in our talents, as well as your ongoing drive, have been vital in assisting us in reaching this milestone. We will be eternally grateful for your love and sacrifices for us.*

*We would also like to thank our incredible friends and mentors for their assistance, intelligent discussions, and constant inspiration. Your trust in us and constant support have been critical in accomplishing this task as well as in our formation and progress. Thank you all one more time.*

*Ismail & Aya*

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# GENERAL INTRODUCTION

The Internet is currently being widely used by people all over the world. As a result, the Multimedia content presents certain risks that users may face. The inappropriate content such as pornography, violence, hate speech, criminal activities (terrorism), fraud, etc. may be offensive, harmful or inappropriate, especially for children and sensitive people.

Faced with these risks, the filtering and classification of multimedia content on the Internet have become essential measures. Filtering and classification help protect users, especially children, from inappropriate or dangerous content. This helps to create a safer and more suitable online environment for all users.

Therefore, in recent years, multimedia filtering and classification tasks have achieved great success. In particular, the topic has received attention following the emergence of machine learning and deep learning models as successful tools for automatically classifying multimedia. There are several review articles and survey reports on multimedia classification in the scientific literature. Multimedia filtering and classification systems have many practical uses, including content moderation, video search and recommendation, and targeted advertising. It can also be used in areas such as security and surveillance, where automatic detection of suspicious or illegal content is critical.

In this perspective, the goal of this project is to develop an automated system that can filter and classify multimedia (videos, audios and documents) based on their content using machine learning and computer vision techniques. The system will be able to identify and categorize videos, audios and documents based on their content, allowing users to easily find subjects that match their preferences. The work is done with the technique pf text extracting from multimedia content and then classifying the extracted text through a Naive -Bayes classification model. The latter was created by training multiple datasets. The work is implemented under Python environment given the richness of its machine learning oriented libraries.

To achieve this goal, we divided this dissertation in three chapters:

In the chapter one, we will present the concept of artificial intelligence, Machine learning and Multimedia filtering and classification which represent the fundamental concepts used to accomplish this work.

Chapter two is dedicated to explaining the development steps of our solution. It explains the (Video-Audio) and (Audio--Text) conversion phases with text extraction and classification techniques using a Naive-Bayes model trained through multiple datasets.

In the last chapter we will present the implementation of this work with the set of technical tools used in this phase. Our practical work will be reserved for the development of a multimedia filter and classifier using Python environment.

.

Finally, we will conclude this dissertation by a general conclusion and some suggestions to improve this work in the future.

# CHAPTER I

# AI & Multimedia filtering and classification: An overview

## 1. Introduction

The objectives of this chapter are to highlight the most important concepts used in our solution. Therefore, we will focus on the field of artificial intelligence and more precisely on the machine learning discipline. In addition, we will also introduce the field of text mining which plays an important role in this solution by defining the nature of documents and texts extracted from videos and audios. Finally, this chapter will be terminated by a section consecrated to the filtering and classification of the multimedia content.

## 2. Introduction to Artificial Intelligence (AI)

Basically, Artificial Intelligence (AI) is a field of computer science that focuses on creating intelligent machines capable of performing tasks that would typically require human intelligence. The goal of AI is to develop systems that can perceive, reason, learn, and make decisions, ultimately simulating human-like intelligence.

We can define AI from different sides. The table below summarizes the fourth categories of artificial intelligence definitions proposed by Russell and Norvig (2010).

| **Thinking Humanly**<br>Machines that think intelligently like humans | **Thinking Rationally**<br>Machines that think rationally |
|---|---|
| **Acting Humanly**<br>Machines that perform activities that human consider intelligent | **Acting Rationally**<br>Machines that act rationally |

*Table 1.1. Four Categories of AI Definitions (Russell and Norvig, 2010)*

In the first category of the definition, AI aims to build computing machines (models) that possess thinking mechanisms (processes) similar to those of humans. These mechanisms include language, knowledge representation (and memory) and reasoning and learning.

In the second category, machines are simply required to act like humans. They don't need to possess a human-like mechanism.
In the third category, the focus is on machines that think rationally based on mathematical logic.

Finally, the fourth category concerns machines that take optimal (rational) actions but may not be based on logical reasoning. Examples include optimal responses based on reflexes.

AI has witnessed significant advancements in recent years, thanks to breakthroughs in computing power, availability of large datasets, and innovative algorithms. These advancements have opened up new possibilities and applications across various domains, including healthcare, finance, transportation, and more.
To clarify the differences between artificial intelligence and traditional programming, in the following we explain the most important differences between the two schools.

### 2.1. Differences between Traditional Programming and AI

Traditional programming, also known as "old-school" programming, follows a rule-based approach where programmers explicitly code a set of instructions for a computer to follow. These instructions are created using programming languages and are designed to achieve specific tasks or solve particular problems. In traditional programming, the outcomes are deterministic, meaning that given the same inputs, the program will always produce the same outputs.
On the other hand, AI takes a different approach. Instead of explicitly programming every step, AI systems learn from data and experiences to make predictions or decisions. Machine Learning (ML) and Deep Learning (a subset of ML) are key components of AI. ML algorithms learn patterns from data and make predictions or take actions based on those patterns. Deep Learning, in particular, uses neural networks with multiple layers to extract complex representations from data.
The key difference between traditional programming and AI lies in their flexibility and adaptability. Traditional programs are designed for specific tasks and often require manual modifications when faced with new or changing situations. In contrast, AI systems can learn and adapt by continuously updating their models based on new data, allowing them to handle complex, dynamic scenarios more effectively.
AI systems excel in tasks such as image and speech recognition, natural language processing, recommendation systems, and autonomous decision-making. They can learn

from vast amounts of data, identify patterns that may not be apparent to humans, and make accurate predictions or perform actions with minimal human intervention.

As AI continues to advance, it is transforming various industries and reshaping the way we interact with technology. However, challenges such as ethical considerations, transparency, and accountability in AI systems need to be addressed to ensure responsible and beneficial deployment.

By harnessing the power of AI, we can unlock new capabilities and possibilities that were once only imaginable, paving the way for intelligent machines that can augment human capabilities and drive innovation across diverse domains.

## 2.2. Branches of Artificial Intelligence

Artificial Intelligence can be used to solve real-world problems by implementing the following processes/ techniques shown in figure 1.1.:

- Machine Learning
- Deep Learning
- Natural Language Processing
- Robotics
- Expert Systems
- Fuzzy Logic


*Figure 1.1. AI Branches (Tyagi, n.d.)*

Perhaps the most important and widely used field of AI mentioned above is that of machine learning, which we have used in our work. In the following, we will introduce this field and will be accompanied by further explanations about the classification subclass that was exploited in our solution.

## 3. Machine Learning

Machine learning is a subfield of artificial intelligence (AI) that focuses on developing algorithms and models that enable computers to learn from and make predictions or decisions based on data. It is based on the idea that machines can learn and improve from experience without being explicitly programmed (What Is Machine Learning? | IBM, n.d.). In traditional programming, we provide specific instructions to computers to perform tasks. However, in machine learning, instead of explicit instructions, we provide the computer with a large amount of data and algorithms that can learn patterns and relationships within that data. The computer then uses this learned information to make predictions or decisions on new, unseen data.

### 3.1. Machine-learning typology

There are various types of machine learning algorithms, but the two most common types are:

#### *3.1.1. Supervised Learning*

Supervised learning entails learning a mapping between a set of input variables X and an output variable Y and applying this mapping to predict the outputs for unseen data. Supervised learning is the most important methodology in machine learning and it also has a central importance in the processing of multimedia data which means the algorithm is trained on a labelled dataset, where each data point is associated with a known target or outcome. The algorithm learns to map input features to the correct output by finding patterns in the data

#### *3.1.2. Unsupervised Learning*

Unsupervised learning studies how systems can learn to represent particular input patterns in a way that reflects the statistical structure of the overall collection of input patterns which means the algorithm is given an unlabelled dataset and aims to find hidden patterns or structures within the data. It explores the data and clusters similar data points together based on their features or identifies other patterns. Unsupervised

learning is useful for tasks like clustering, anomaly detection, and dimensionality reduction

### *3.1.3. Reinforcement learning (RL)*

Reinforcement learning is a machine learning training method based on rewarding desired behaviours and/or punishing undesired ones. In general, a reinforcement learning agent is able to perceive and interpret its environment, take actions and learn through trial and error.

the figure below shows the fields of application for the three types of machine learning.

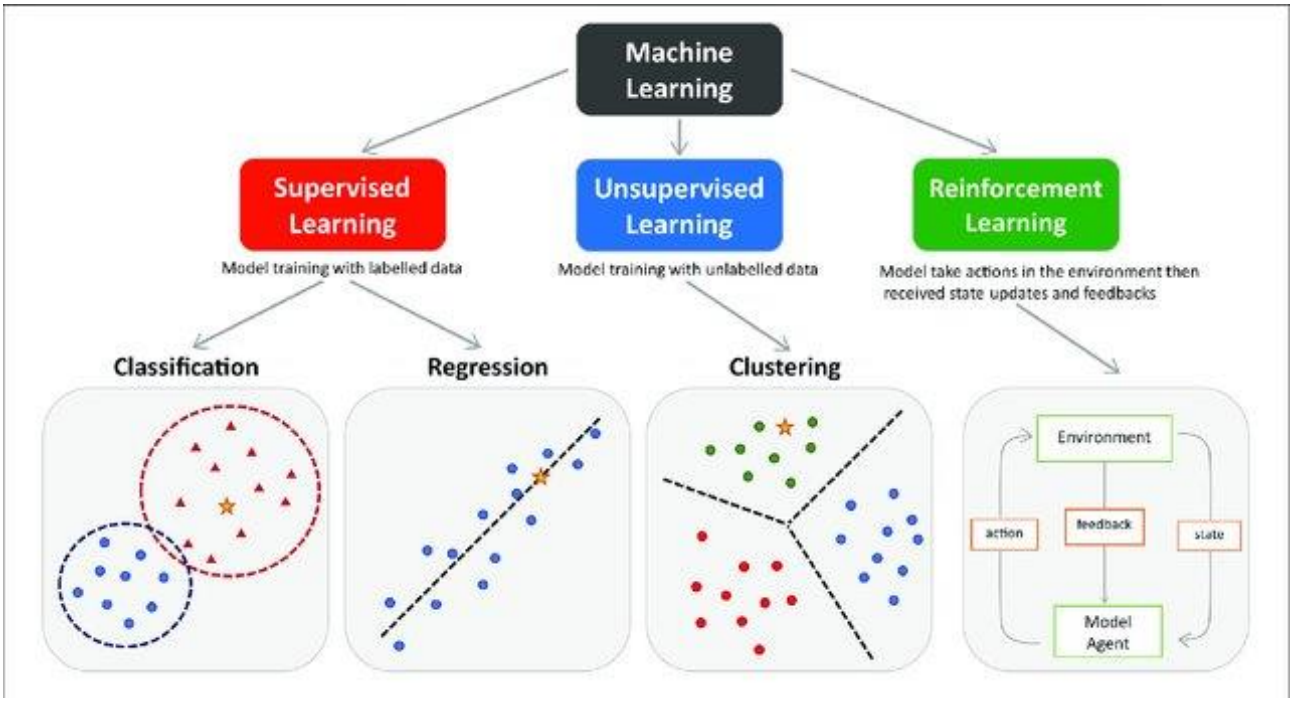


*Figure 1.2. The main types de machine Learning (Peng et al, 2021)*

In what follows, we give more clarification on the notion of classification which constitutes the core of our proposed solution.

## 3.2. Classification

Classification is a supervised machine learning method where the model tries to predict the correct label of a given input data (see figure 1.3). In classification, the model is fully trained using the training data, and then it is evaluated on test data before being used to perform prediction on new unseen data (Keita, 2022).

The algorithm which implements the classification on a dataset is known as a classifier. There are two types of Classifications (Classification Algorithm in Machine Learning - Javatpoint, n.d.):

### *3.2.1. Binary Classifier*

If the classification problem has only two possible outcomes, then it is called as Binary Classifier.

Examples: YES or NO, MALE or FEMALE, SPAM or NOT SPAM, CAT or DOG, etc.

### *3.2.2. Multi-class Classifier*

If a classification problem has more than two outcomes, then it is called as Multi-class Classifier.

Example: Classifications of types of crops, Classification of types of music.

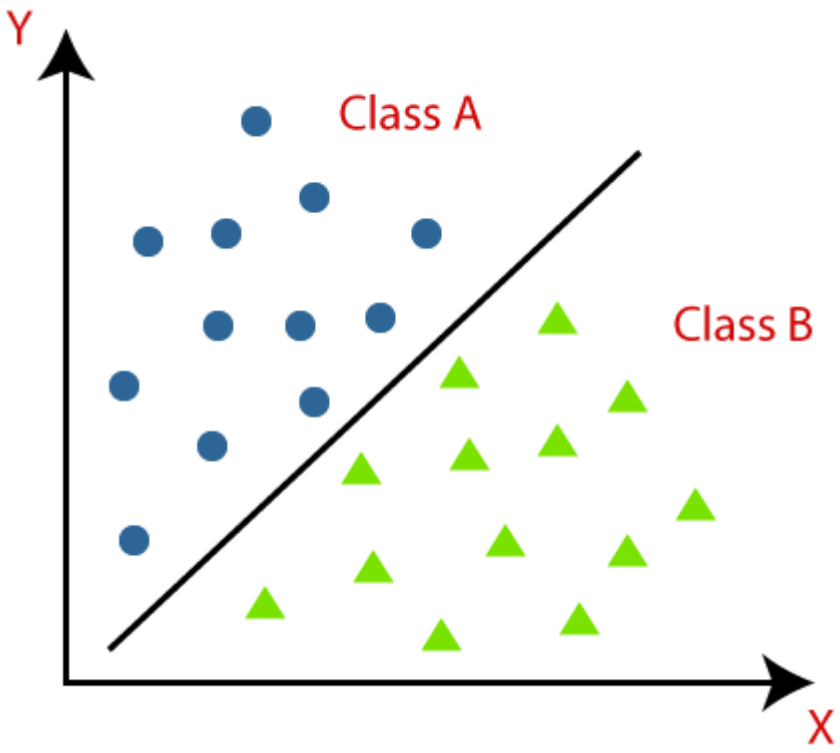


*Figure 1.3. Classification method*

Classification Algorithms can be further divided into the Mainly two category:

- **Linear Models**
    - Logistic Regression
    - Support Vector Machines
- **Non-linear Models**
    - K-Nearest Neighbours
    - Kernel SVM

- Naïve Bayes
- Decision Tree Classification
- Random Forest Classification

### 3.3. Machine learning applications

Machine learning to adapt to new circumstances and to detect and extrapolate patterns. Turing's test deliberately avoided direct physical interaction between the interrogator and the computer, because physical simulation of a person is unnecessary for intelligence.
Machine learning has numerous applications across various fields, including:
• natural language processing to enable it to communicate successfully
• knowledge representation to store what it knows or hears
• automated reasoning to use the stored information to answer questions and to draw new conclusions
• computer vision to perceive objects, and Robotics
• robotics to manipulate objects and move about
• Healthcare: Machine learning is applied in medical diagnosis, drug discovery, and personalized treatment recommendation systems.
• Finance: Machine learning is utilized for fraud detection, credit scoring, and stock market prediction.

## 4. Text Mining

Text mining is a new and exciting area of computer science research that tries to solve the crisis of information overload by combining techniques from data mining, machine learning, natural language processing, information retrieval, and knowledge management.
It can be described as the process of extracting essential data from standard language text. All the data that we generate via text messages, documents, emails, files are written in common language text. Text mining is primarily used to draw useful insights or patterns from such data (Text Data Mining - Javatpoint, n.d.).

Text mining can be broadly defined as a knowledge-intensive process in which a user interacts with a document collection over time by using a suite of analysis tools. Ina manner analogous to data mining, text mining seeks to extract useful information from data sources through the identification and exploration of interesting patterns. In the case of text mining, however, the data sources are document collections, and interesting patterns are found not

among formalized database records but in the unstructured textual data in the documents in these collection

## 4.1. Areas of text mining in data mining

In text mining, these are the following area:

### *4.1.1. Information Extraction*

The automatic extraction of structured data such as entities, entities relationships, and attributes describing entities from an unstructured source is called information extraction.

### *4.1.2. Natural Language Processing*

NLP stands for Natural language processing. Computer software can understand human language as same as it is spoken. NLP is primarily a component of artificial intelligence (AI). The development of the NLP application is difficult because computers generally expect humans to "Speak" to them in a programming language that is accurate, clear, and exceptionally structured. Human speech is usually not authentic so that it can depend on many complex variables, including slang, social context, and regional dialects.

### *4.1.3. Data Mining*

Data mining refers to the extraction of useful data, hidden patterns from large data sets. Data mining tools can predict behaviours and future trends that allow businesses to make a better data-driven decision. Data mining tools can be used to resolve many business problems that have traditionally been too time-consuming.

### *4.1.4. Information Retrieval*

Information retrieval deals with retrieving useful data from data that is stored in our systems. Alternately, as an analogy, we can view search engines that happen on websites such as e-commerce sites or any other sites as part of information retrieval.

In the following, we focus on natural language processing that interest us and enter into the mechanism of the solution used in our work.

### 4.2. Natural Language Processing (NLP)

Natural Language Processing is the analysis of linguistic data, most commonly in the form of textual data such as documents or publications, using computational methods (Verspoor & Cohen, 2013).

Natural Language Processing (NLP) allows machines to break down and interpret human language. It's at the core of tools we use every day – from translation software, chatbots, spam filters, and search engines, to grammar correction software, voice assistants, and social media monitoring tools.

According to Desai & Dabhi (2022), Natural Language processing system contain generally seven main component which are:

- Preprocessing
- Morph Analyzer
- Lexical Analyzer
- Syntax Analyzer
- Semantic Analyzer
- Discourse Analyzer
- Pragmatic Analyzer

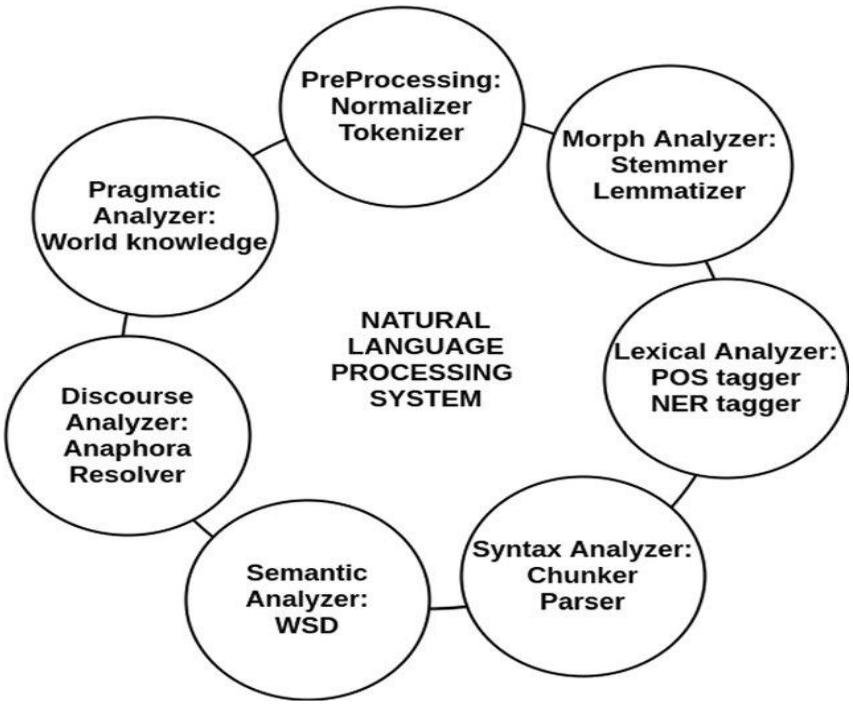


*Figure 1.4. NLP processing system*

## 5. Multimedia filtering and classification

Multimedia filtering and classification are processing that sort and organize multimedia contents such as images, videos, audios or documents according to their characteristics or content. These techniques often use machine learning and data analysis methods to extract relevant information and perform classification.

### 5.1.Video filtering and classification

Video filtering consists of analysing the content of a video to extract certain characteristics or to identify specific elements. For example, filtering can be used to detect faces, objects, violent or inappropriate scenes, brand logos, etc. Video filtering techniques can be based on computer vision, machine learning, or a combination of both (Yousaf & Nawaz, 2022).

On the other hand, video classification is the process of automatically categorizing videos based on their content. This may involve creating machine learning models that learn to recognize predefined categories such as sports, action movies, comedies, documentaries, etc. These models often use visual and temporal descriptors to extract features from videos and associate them with specific categories.

Video filtering and classification is often used to achieve the following goals:

- Detection of dangerous activities: identification of potentially dangerous or illegal activities in a video.
- Inappropriate content filtering: detection of inappropriate or offensive content in a video, such as violence, nudity, etc.
- Video categorization: classification of videos according to their genre (action, comedy, documentary, etc.) or their theme.
- Video indexing: extracting key information from videos, such as scenes, faces, objects, to facilitate search and navigation.

### 5.2. Audio Filtering and classification

Audio filtering involves the analysis and processing of audio content for different tasks such as removing noise, detecting specific sound events, or identifying acoustic characteristics. For example, audio filtering can be used to remove unwanted background noise from an audio recording or to detect specific keywords in an audio stream in real time.

On the other hand, audio classification: Audio classification involves assigning labels or categories to audio recordings based on their content. This can include speech recognition, music classification, detection of specific emotions or sound events, such as voice or musical instrument recognition. Audio classification techniques often use machine learning algorithms such as neural networks to extract audio features and associate them with predefined categories (Mesaros et al., 2018).

Audio filtering and classification is often used to achieve the following goals:

- Noise Filtering: Removal or reduction of unwanted background noise in an audio recording.
- Detection of inappropriate or offensive content in audio.
- Audio categorization like musical categorization of pieces of music according to their genre, style or mood.

### 5.3. Document filtering and classification

Document filtering and classification involves analysing the textual content of documents to extract information or organize them into specific categories (Korde & Mahender, 2012). This can include spam detection in emails, automatic categorization of documents based on their subject or tone, or searching for specific information in a large volume of documents. Commonly used techniques for filtering and classifying documents are based on automatic natural language processing (NLP) and machine learning. It is important to note that these filtering and classification tasks can be complex and often require advanced machine learning and signal processing techniques. Additionally, the accuracy of these tasks may vary depending on the quality of the input data and the complexity of the content to be analysed.

Document filtering and classification is often used to achieve the following goals:

- Spam detection: identification of unwanted or malicious emails or documents.
- Text classification: assigning categories or tags to documents based on their content, e.g., scientific papers, news, reviews, etc.

## 6. Conclusion

we have presented in this chapter some basic notions related to our work such as AI, machine learning, text mining and multimedia filtering and classification. In what follows we will present the conceptual phase of our solution which consists in filtering and classifying video, audio and documents by using all that we have presented in this first chapter.

# CHAPTER II

# Multimedia Filter and Classifier: The Development Process

## 1. Introduction

we will introduce in this chapter the development process of our proposed filter and classifier. the objective of this filter and classifier is to detect and filter unwanted content, especially for videos. In addition, it seeks to identify multimedia content (video, audio and document) in order to classify them into categories (politics, economy, sport, entertainment, etc.).

## 2. Overview of the proposed solution

The program utilizes a multi-step process to filter video based on its content.

First, it scans the video frame by frame to detect and identify adult content using advanced computer vision algorithms. Once adult content is identified, it is filtered out from the video.

Next, the program translates the video into audio by extracting the audio component. The audio is then converted into text using speech recognition techniques.

By leveraging Natural Language Processing (NLP) methods, the program employs text classification algorithms to analyse the extracted text and classify the content into different categories, such as explicit, violent, or educational. This technique is reinforced by Naive Bayes (NB) Algorithm which can provide accurate results without much training data. This comprehensive approach allows the program to effectively filter video content based on its content, providing a more accurate and robust content filtering system.

The proposed solution is implemented under Python which constitute a very popular programming language for implementing filtering and classification techniques in multimedia applications view of its rich commonly used libraries and frameworks.

Figure 2.1 clearly shows the general architecture of the proposed solution with its various constituent steps, from dealing with the raw content to classifying it.

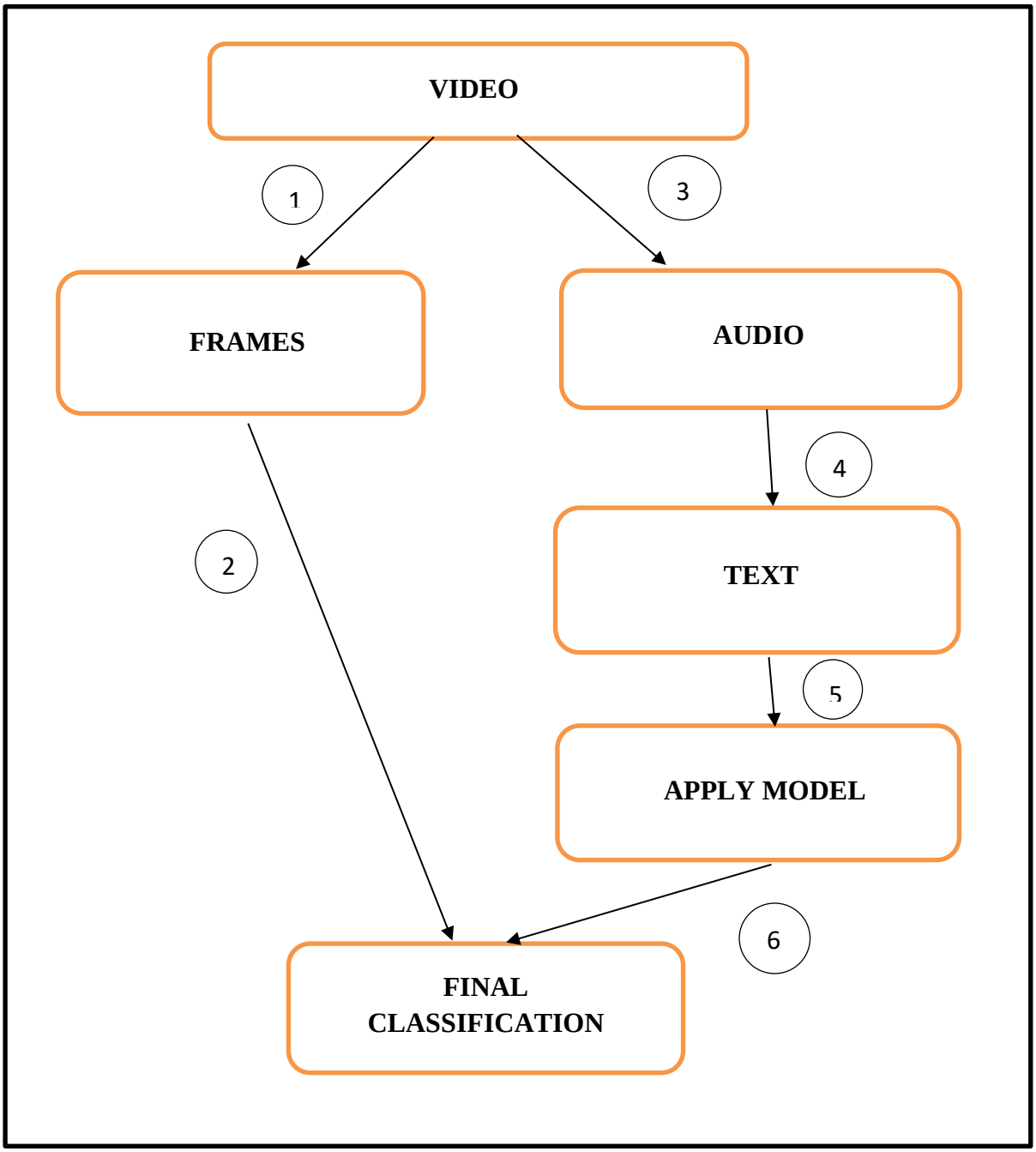


*Figure 2.1. Filtering and classification steps*

The steps followed by our solution are summarized as follows:

1- We use *Resnetv2* model to check if there is any adult content in the video
2- If there any adult content in the video we classify the video as non-unacceptable else we resume to audio-text step
3- We use *Moviepy* to extract the audio from the video
4- We use *speech recognize* to turn the audio to text
5- we use our prebuild model to classify the text

6- after we get the class of the video, we classify it as acceptable or unacceptable

In the following we will detail all these steps:

## 2.1. Video Content Filtering

In the first step, we perform video content filtering using the ResNetV2 model and computer vision techniques.

Here's a detailed explanation of the code:

A- The function “process_frame (frame)” takes an individual frame of the video as input and processes and making a prediction on the content within that frame using the ResNetV2 model. Here's a detailed explanation of the function:

- The function “frame ()” takes the input frame, which represents an individual frame of a video, as an argument.
- The frame is resized to a fixed size of 224x224 pixels using cv2.resize(frame, (224, 224)). This resizing ensures that the frame matches the input size expected by the ResNetV2 model.
- The resized frame is converted into a NumPy array using “tf.keras.preprocessing.image.img_to_array (resized_frame)”. This step converts the frame into a numerical representation suitable for further processing.
- The pixel values of the frame are pre-processed using “tf.keras.applications.resnet_v2.preprocess_input (img)”. This function applies specific preprocessing operations to the pixel values of the frame. It ensures that the pixel values are transformed to match the preprocessing requirements of the ResNetV2 model. This step helps improve the accuracy of the predictions.
- The pre-processed frame is then passed through the ResNetV2 model to make a prediction using “model.predict(tf.expand_dims(img, axis=0))”. The “tf.expand_dims()” function is used to add an extra dimension to the array, as the model expects a batch of images as input. The “model.predict()” function returns the predicted probabilities for each class.
- The label of the class with the highest predicted probability is extracted using “tf.keras.applications.resnet_v2.decode_predictions(predictions, top=1)[0][0][1]”. This function decodes the predicted probabilities and returns a list of predictions with class labels and their corresponding probabilities. The [0][0][1] indexing is used to extract the label of the highest predicted class
- Finally, the predicted class label is returned by the “process_frame()” function.

In summary, the “process_frame(frame)” function takes an input frame, resizes it to match the expected input size of the ResNetV2 model, preprocesses the pixel values, feeds it into the model for prediction, and returns the label of the highest predicted class for the given frame. This function can be called within a loop to process each frame of a video and make predictions on the content within the video.

B- The “cv2.VideoCapture()” function is a part of the OpenCV library and is used to open and access video files or capture video streams from cameras. It provides a way to read frames from a video source and retrieve video properties. Here's a detailed explanation of the “cv2.VideoCapture()” function

- Syntax: “cv2.VideoCapture(filename or index)”

➢ “filename”: This parameter represents the name of the video file to be opened. It can include the full path to the file.

➢ “Index”: This parameter represents the index of the camera or video capture device to be accessed. Usually, the index 0 corresponds to the default camera.

➢ The cv2.VideoCapture() function returns a VideoCapture object that allows us to interact with the video source.

- The “cv2.VideoCapture()” function returns a “VideoCapture” object that allows us to interact with the video source.
- Once the video capture object is created, we can use various methods and attributes to read frames and retrieve information about the video:

- "cap.read()": This method reads the next frame from the video source. It returns two values: "ret" (a Boolean value indicating whether a frame was successfully read) and "frame" (the actual frame data as a NumPy array
- "cap.isOpened()": This attribute returns a Boolean value indicating whether the video capture object is open and accessible.
- "cap.get(propID)": This method retrieves the value of a specific video property identified by "propID". Common properties include the width, height, frames per second (FPS), and codec used in the video.
- "cap.set(propID, value)": This method sets the value of a specific video property identified by "propID".
- "cap.release()": This method releases the video capture object and frees up any associated resources.

- To process a video frame by frame, we typically use a loop in conjunction with "cap.read()" to read frames until there are no more frames left in the video.

C- Next, the main code snippet performs video content filtering using the “process_frame()” and “cv2.VideoCapture()” functions :

- The variable "file_path" is used to prompt the user to select a video file (e.g., in .mp4 or .avi format) to be filtered.
- The video file is opened using "cv2.VideoCapture()" and assigned to the cap variable.
- A loop is executed to process each frame of the video. The loop continues until there are no more frames left to process.
- Inside the loop, a frame is read from the video using "cap.read()". The return value ret indicates if a frame was successfully read, while frame holds the actual frame data.
- The "process_frame()" function is called to process the frame and obtain the predicted class label.
- The loop continues to the next iteration until all frames have been processed.
- Finally, the video capture is released using "cap.release()" to free up system resources.

D- ResNetV2 (Residual Network V2) is a deep convolutional neural network (CNN) architecture that was introduced as an improvement over the original ResNet model. It was proposed by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their 2016 research paper titled "Identity Mappings in Deep Residual Networks." ResNetV2 aims to address the degradation problem observed in deeper networks by introducing residual connections and identity mappings.

Here are some key details about ResNetV2:

- Residual Learning:

- ResNetV2 utilizes residual learning, which is based on the idea that it is easier to learn the difference between the desired mapping and the current mapping, rather than learning the entire mapping from scratch.
- Residual connections, also known as skip connections, are added to the network to allow the gradient to flow directly through the network without vanishing or exploding.
- By using residual connections, the network can learn to model the residual mapping, which improves the optimization process and enables the training of very deep networks

- Architecture:

- ResNetV2 architecture consists of a series of residual blocks, where each block contains multiple convolutional layers.
- The basic building block of ResNetV2 is the residual unit, which consists of two main components: the identity mapping and the residual mapping.

- The identity mapping represents the input to the block, and the residual mapping represents the difference between the input and the output of the block.
- Each residual unit can have different variations, such as bottleneck structures or different numbers of convolutional layers.

- Pretrained Models:

- Pretrained ResNetV2 models are available for various applications, including image classification, object detection, and image segmentation.
- These pretrained models are trained on large-scale datasets, such as ImageNet, which enables them to learn rich representations of visual features.
- By utilizing transfer learning, these pretrained models can be fine-tuned on specific tasks with limited training data, improving performance and convergence.

- Implementation and Libraries:

- ResNetV2 can be implemented using deep learning frameworks, such as TensorFlow or PyTorch, which provide prebuilt implementations of the architecture.
- Libraries like "TensorFlow's tf.keras.applications" or PyTorch's "torchvision.models" provide easy access to pretrained ResNetV2 models for various tasks.
- These libraries often include helper functions for loading and preprocessing images according to the input requirements of the ResNetV2 models.

Overall, ResNetV2 addresses the challenges of training very deep neural networks by introducing residual connections and identity mappings. These architectural elements allow the gradients to flow effectively and enable the training of deeper models with improved accuracy. By utilizing pretrained ResNetV2 models, researchers and practitioners can leverage powerful image representations for various computer vision tasks and achieve state-of-the-art performance with less training data and computation.

## 2.2. Video to Audio Translation

a simple approach to perform video-to-audio translation using the MoviePy library. Video-to-audio translation involves extracting the audio component from a video file and saving it as a separate audio file. This can be useful in various scenarios, such as extracting the soundtrack from a video, analyzing the audio content, or performing audio-related tasks. The code utilizes MoviePy.

Here's a detailed explanation of the code:

A- The code begins by importing the necessary modules, including “moviepy.editor” from the MoviePy library

B- The variable “file_path” represents the path to the video file that we want to convert to audio. It is passed as an argument to “VideoFileClip()” from MoviePy, creating a “VideoFileClip” object called “video”.

C- The “VideoFileClip” object provides access to both the video and audio components of the file. In this case, the code retrieves the audio component using “video.audio” and assigns it to the variable “audio”.

D- A message is printed to indicate that the conversion process is starting.

E- The “write_audiofile()” function is called on the audio object to save the audio as a separate audio file. In this example, the audio file is saved as 'audio.wav'. The file format can be adjusted by specifying the desired file extension.

### 2.3. Audio to Text Conversion :

simple approach to perform audio-to-text conversion using the SpeechRecognition library. Audio-to-text conversion, also known as speech recognition or speech-to-text, involves transforming spoken language into written text. This process has various applications, including transcription services, voice-controlled systems, and natural language processing tasks. The code utilizes the SpeechRecognition library, which provides an easy-to-use interface for integrating speech recognition capabilities into Python applications.

Here's a detailed explanation of the code:

A- The code begins by importing the necessary modules, including “speech_recognition” (renamed as “sr” for brevity) from the SpeechRecognition library.

B- The “Recognizer()” class from the SpeechRecognition library is instantiated and assigned to the variable “r”. This class provides the functionality to recognize speech from various audio sources.

C- A message is printed to indicate that the audio-to-text conversion process is starting.

D- The “AudioFile()” context manager is used to open the audio file ('audio.wav' in this example). This context manager ensures that the audio file is properly handled and automatically closed after use.

E- Within the context manager, the “record()” method of the “Recognizer” object (“r”) is called on the “source” object to capture the audio data from the file. The “record()” method reads the audio file and stores the audio data for further processing.

F- The “recognize_google()” function is called on the “Recognizer” object, passing the “audio_data” as the input. This function utilizes Google's Speech Recognition API to convert the audio data into text.

G- The recognized text is returned and assigned to the variable “text”.

## 2.4. Text NLP-based Content Classification

Text NLP-based content classification is a branch of natural language processing (NLP) that involves the automatic categorization and classification of text documents based on their content. It encompasses the use of NLP techniques and machine learning algorithms to analyse and extract features from textual data, enabling the classification of documents into predefined categories or classes. By leveraging methods such as text preprocessing, feature extraction, and supervised learning, NLP-based content classification systems can automatically assign labels or tags to text documents, facilitating tasks such as topic analysis, sentiment analysis, spam detection, and document organization. These systems are designed to handle large volumes of text data efficiently and accurately, aiding in information retrieval, content filtering, and decision-making processes across various domains such as news, social media, customer reviews, and document management.

We use NLP to classify Text into 5 classes “business”, “Tech”, “Politics”, “Sports”, “Entertainment”

Here's a detailed explanation of the code:

A- “text_data = data['Text']” and “class_labels = data['Category']” These lines extract the text data and corresponding class labels from a dataset. The text data represents the input text documents, and the class labels represent the categories or classes to which the documents belong.

B- “X_train, X_test, y_train, y_test = train_test_split(text_data, class_labels, test_size=0.2, random_state=42)”: This line splits the data into training and testing sets using the “train_test_split” function from the scikit-learn library. It takes the text data “(text_data)” and class labels “(class_labels)” as input, along with the “test_size” parameter which determines the proportion of the data that will be used for testing (20% in this case). The “random_state” parameter ensures reproducibility of the split.

C- “vectorizer = CountVectorizer()”: This line initializes the “CountVectorizer” object from the scikit-learn library. The “CountVectorizer” is used to convert the text data into

numerical feature vectors. Each document is transformed into a vector of term frequencies, where each term represents a unique word in the corpus.

D- "X_vectorized = vectorizer.fit_transform(text_data.tolist())": This line applies the "fit_transform" method of the vectorizer to the entire text data "(text_data)" after converting it to a list. It fits the vectorizer on the data and transforms the text into numerical feature vectors "(X_vectorized)".

E- "X_train_vectorized = vectorizer.fit_transform(X_train)": This line applies the "fit_transform" method to the training data "(X_train)". It fits the vectorizer on the training data and transforms it into numerical feature vectors "(X_train_vectorized)". Note that a separate fit transform is performed on the training data to ensure that the vectorizer learns the vocabulary from the training data only.

F- "X_test_vectorized = vectorizer.transform(X_test)": This line applies the "transform" method to the testing data ("X_test"). It transforms the testing data into numerical feature vectors ("X_test_vectorized") using the vocabulary learned from the training data. Here, we don't fit the vectorizer again, as we want to use the same vocabulary that was learned from the training data.

G- "classifier = MultinomialNB()": This line initializes the Naive Bayes classifier, specifically the "MultinomialNB" class, which is suitable for working with count-based features like the ones obtained from the "CountVectorizer".

H- "classifier.fit(X_train_vectorized, y_train)": This line trains the Naive Bayes classifier using the training data ("X_train_vectorized") and their corresponding class labels ("y_train"). The classifier learns the underlying patterns in the data and builds a model.

I- "predictions = classifier.predict(X_test_vectorized)": This line uses the trained classifier to make predictions on the testing data ("X_test_vectorized"). It assigns a predicted class label to each instance in the testing data based on the learned model.

J- "accuracy = metrics.accuracy_score(y_test, predictions), precision = metrics.precision_score(y_test, predictions, average='weighted'), recall = metrics.recall_score(y_test, predictions, average='weighted'), and f1_score = metrics.f1_score(y_test, predictions, average='weighted')": These lines calculate evaluation metrics to assess the performance of the classifier. The "accuracy_score", "precision_score", "recall_score", and "f1_score" functions from the "metrics" module of scikit-learn are used to compute these metrics. The "weighted" average is used to handle imbalanced class distributions.

K- Finally, the code prints the calculated metrics ("Accuracy", "Precision", "Recall", and "F1-Score") and saves the trained classifier and vectorizer using the "joblib.dump" function.

The classifier and vectorizer are saved as “naive_bayes_model.joblib” and “count_vectorizer.joblib”, respectively, for future use.

## 2.5. Multinomial Naïve Bayes classifier

In what follows, we explain how we exploit the naive-bayes classifier (1.9. Naive Bayes, n.d.) by presenting the dataset used for training the model as well as the results obtained.

### *2.5.1.* Training Dataset

The dataset used in the code (called Text_Data) it is a CSV file that contain text documents and their corresponding class labels. We have combined several datasets concerning news (BBC News Classification | Kaggle, n.d.) and documents (AG News Classification Dataset, 2020) (Avikumart, 2022) in order to have a credible dataset for our work.
The dataset serves as the foundation for training and evaluating the text classification model. It comprises two columns: 'Text' and 'Category'. The 'Text' column contains the textual content of the documents, which could be sentences, paragraphs, or any form of text data. The 'Category' column represents the class labels assigned to each document, indicating the category or class to which it belongs.

| | ArticleId | Category |
|---|---|---|
| **0** | 1018 | sport |
| **1** | 1319 | tech |
| **2** | 1138 | business |
| **3** | 459 | entertainment |
| **4** | 1020 | politics |
| **...** | ... | ... |
| **730** | 1923 | sport |
| **731** | 373 | tech |
| **732** | 1704 | business |
| **733** | 206 | entertainment |
| **734** | 471 | politics |

735 rows × 2 columns

*Table 2.1. Training Dataset*

The dataset plays a crucial role in building a robust and accurate text classification model by providing a diverse range of text samples across different categories, enabling the model to learn patterns and make predictions based on the textual content. The data contain 735 Article and it is divided in to 5 classes for classification.

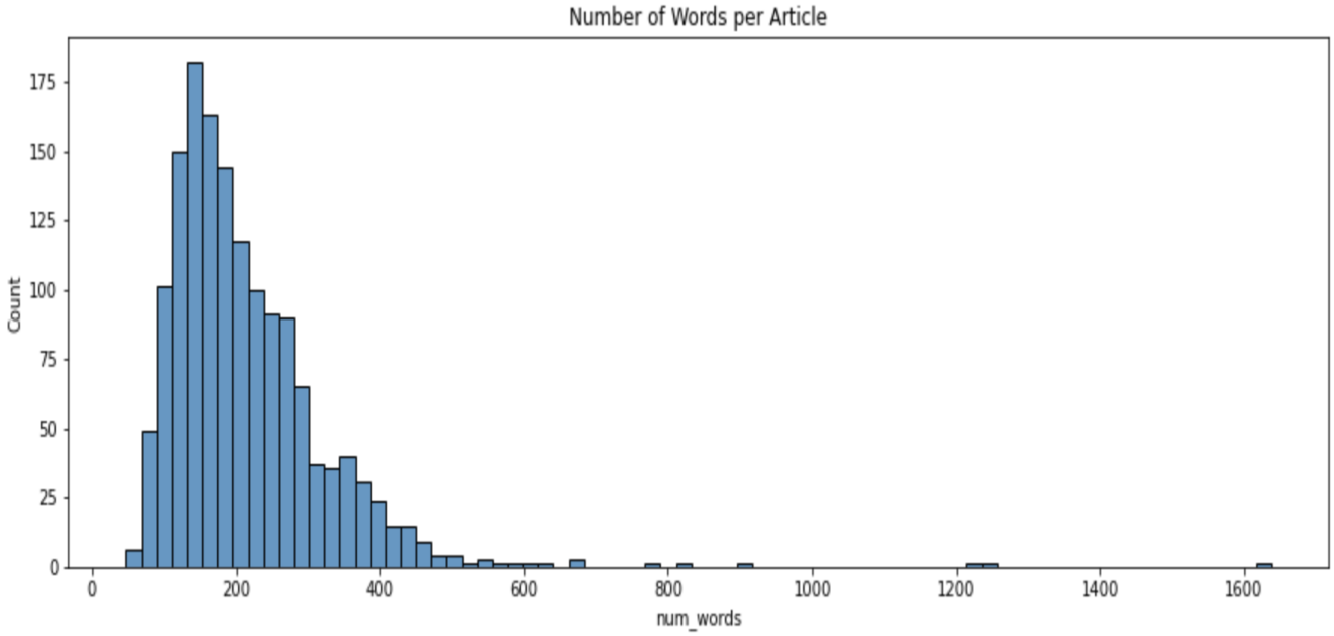


*Figure 2.2. Number of words per article in the used dataset*

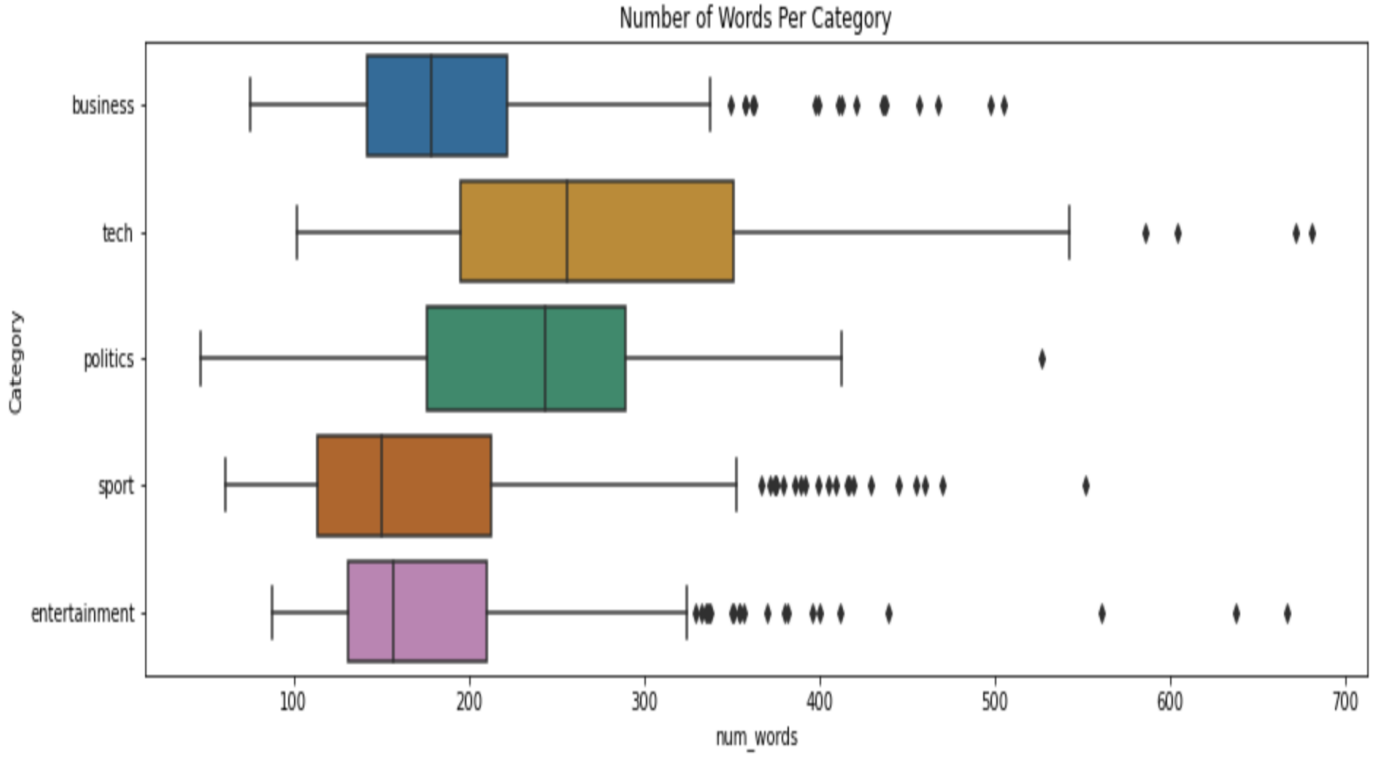


*Figure 2.3. Number of words per category in the used dataset*

### 2.5.2. Results

Before printing the results and accuracy, the code snippet performs the evaluation of the trained text classification model on the testing set. The model makes predictions on the feature vectors of the testing set using the 'predict' method, and the predicted class labels are stored in the 'predictions' variable. Then, several performance metrics are computed using the 'metrics' module from scikit-learn. The accuracy, precision, recall, and F1-score are calculated to assess the model's performance in terms of correct predictions, precision of positive predictions, coverage of positive instances, and the balance between precision and recall. These metrics provide a quantitative measure of how well the model performs in classifying the text documents into their respective categories. Finally, the accuracy and other performance metrics are printed to the console, giving an overview of the model's effectiveness in accurately classifying the text data.

The Final Results are:

- Accuracy: 0.9765100671140939
- Precision: 0.9766937686759525
- Recall: 0.9765100671140939
- F1-Score: 0.9765452996043319

And the Evolution of results changes is as it shown:

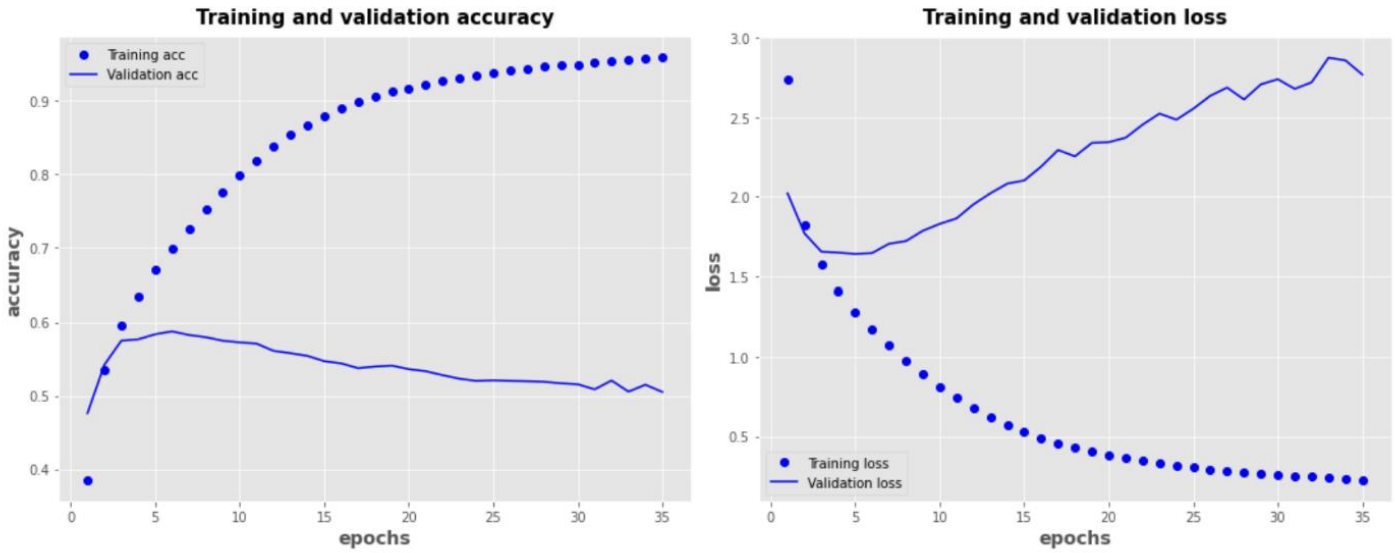


*Figure 2.4. Evolution of results changes*

## 3. Summary of the filtering and classification process

Here's a summary of the program:

A- The program begins by loading the dataset, assuming it contains text documents and their corresponding class labels. The text data and class labels are stored in separate variables. Next, the data is split into training and testing sets using the 'train_test_split' function from scikit-learn, with 80% of the data allocated for training and 20% for testing. The text data is then converted into numerical feature vectors using the 'CountVectorizer' class, which transforms the text into a matrix representation based on word frequencies. Separate feature vectors are created for the training and testing sets

B- The program proceeds by training a Naive Bayes classifier on the training data using the 'MultinomialNB' class from scikit-learn. The classifier learns patterns from the feature vectors and their corresponding class labels, enabling it to make predictions on unseen text data. The trained classifier is then used to make predictions on the feature vectors of the testing set. These predictions are stored in the 'predictions' variable.

C- To evaluate the performance of the classifier, several metrics are computed using the 'metrics' module from scikit-learn. The 'accuracy_score', 'precision_score', 'recall_score', and 'f1_score' functions are called, providing measures of accuracy, precision, recall, and F1-score, respectively. These metrics assess the model's performance in terms of correct predictions, precision of positive predictions, coverage of positive instances, and the balance between precision and recall. The computed metrics are printed to the console, providing an overview of the classifier's effectiveness in classifying the text data

D- Finally, the trained classifier and the vectorizer used to convert the text data into feature vectors are saved using the 'joblib.dump' function from the joblib library. This allows for future reuse of the classifier and vectorizer for predicting on new text data. Saving the models ensures that they can be loaded and used without having to retrain the classifier or recreate the vectorizer from scratch.

## 4. Conclusion

we have presented in this chapter the development process of our filter and classifier using the technique of text extraction coupled with the naive-bayes classifier which gave very satisfactory results. we will present in the next chapter more technical detail on the solution using the Python environment.

# CHAPTER III

# Implementation and Exploitation

## 1. Introduction

In this chapter we will focus on the implementation environment of our solution. Therefore, we will present Jupyter Notebook with the essential used libraries. Detailed explanations are provided on how each library was leveraged to perform specific tasks, such as data manipulation, visualization, machine learning algorithms, and natural language processing. Code examples and snippets are showcased to illustrate the practical usage of these libraries and highlight their contribution to the project's objectives.

## 2. Jupyter Notebook

Python is a highly versatile programming language that can be written and executed on various platforms, catering to developers' preferences and requirements. One popular platform is the Python IDLE (Integrated Development and Learning Environment), which provides a basic and user-friendly interface for writing and executing Python code. Another widely used platform is Jupyter Notebook, a web-based environment that allows interactive coding, data exploration, and documentation. Additionally, developers can utilize Integrated Development Environments (IDEs) such as PyCharm, Visual Studio Code, and Spyder, which offer advanced features like code autocompletion, debugging, and project management. Python code can also be written in plain text editors like Sublime Text and Atom, providing flexibility and simplicity. Moreover, online platforms like Replit and Google Colab enable writing and running Python code directly from the browser, making it accessible from any device. Overall, Python's versatility extends to multiple platforms, allowing developers to choose the one that suits their workflow and preferences.

Jupyter Notebook offer several advantages for development, data exploration and the communication of results. Here are some of the key benefits:

- Interactivity: Jupyter Notebook allow interactive execution of code. We can run individual code cells and see the results immediately, making the process of developing, testing, and debugging easier.
- Embedded Documentation: Jupyter Notebooks make it easy to embed explanatory text, images, and mathematical formulas in the same document as the code. This facilitates

the creation of interactive and descriptive documentation, which makes the results more understandable and reproducible.

- Data Visualization: Jupyter Notebooks is well suited for data visualization. We can embed graphs, charts, and tables directly into the Notebook, making it easier to explore and understand data.
- Multi-language support: Jupyter Notebook supports many programming languages, including Python, R, Julia, and others. This allows us to use a single environment to work with different languages and exploit the advantages specific to each language.
- Sharing and Collaboration: Jupyter Notebooks can be easily shared with others. We can export our notebooks to HTML, PDF or even as a Python script. Additionally, Jupyter Notebooks are compatible with online notebook sharing platforms, making it easy to collaborate and share results with other users. Flexibility and Extensibility: Jupyter Notebook is highly customizable and extensible. We can add extensions to improve functionality, use interactive widgets to interact with code, and even run system commands directly from the Notebook.
- Learning and teaching: Jupyter Notebook is widely used in teaching and learning because they allow an interactive and visual approach to exploring concepts and programming.

These benefits make Jupyter Notebook a popular tool for data scientists, researchers, developers, and educators. They promote experimentation, communication of results and interactive analysis of data.

# 3. Tools and Libraries

Libraries play a pivotal role in software development by providing pre-written code and functionality that can be leveraged to streamline programming tasks, enhance productivity, and extend the capabilities of programming languages.

In this chapter, we explore the significance and utility of libraries in the context of our project so we name the most important libraries:

## 4.1. Numpy

“NumPy”, short for "Numerical Python," is a fundamental library in Python for numerical computing. It provides efficient operations for handling large arrays and matrices, along

with an extensive collection of mathematical functions. NumPy serves as a foundational library for numerous scientific and data analysis tasks.

"Numpy" key Features and Functionalities are multiple such us (NumPy Reference — NumPy v1.24 Manual, n.d.):

- ndarray: The core data structure in NumPy is the ndarray (N-dimensional array), which is a homogeneous, multi-dimensional container for storing elements of the same data type. ndarrays offer efficient storage, indexing, and manipulation of numerical data, making them suitable for large-scale computations.
- Mathematical Functions: NumPy provides a comprehensive set of mathematical functions for array operations. These include basic mathematical operations (addition, subtraction, multiplication, division), trigonometric functions, exponential and logarithmic functions, statistical functions, linear algebra operations, and more. These functions are optimized for performance and can operate on entire arrays or specific elements.
- Broadcasting: NumPy enables broadcasting, which is a mechanism for performing element-wise operations between arrays of different shapes. Broadcasting allows for implicit expansion of arrays, avoiding the need for explicit looping and enabling more concise and efficient code.
- Array Manipulation: NumPy offers a variety of functions for manipulating arrays, including reshaping, slicing, joining, splitting, and indexing operations. These operations provide flexibility in rearranging and extracting data from arrays based on specific requirements.
- Integration with other Libraries: NumPy seamlessly integrates with other scientific computing libraries, such as SciPy, Matplotlib, and scikit-learn, forming a powerful ecosystem for data analysis, scientific computing, and machine learning tasks. This integration allows for easy sharing and interoperability of data and computations across different libraries.

"Numpy" offer several advantages for development such us:

- Performance: NumPy is designed to provide fast and efficient numerical computations by leveraging optimized C and Fortran code. It utilizes vectorized operations and avoids unnecessary loops, leading to significant performance improvements compared to traditional Python lists.

- Memory Efficiency: NumPy's ndarray consumes less memory compared to Python lists, as it stores data in a contiguous block of memory. This contiguous storage improves cache utilization and minimizes memory overhead, making NumPy suitable for handling large datasets.
- Ecosystem and Community: NumPy is part of a vibrant scientific computing ecosystem in Python. It enjoys widespread adoption and has a large community of developers and contributors. This community actively maintains and supports the library, ensuring regular updates, bug fixes, and the availability of extensive documentation and resources.
- Interoperability: NumPy arrays can be seamlessly integrated with code written in other languages, such as C, C++, and Fortran, through appropriate wrappers and interfaces. This interoperability allows for efficient utilization of existing codebases and libraries in different programming languages.

In summary, NumPy provides essential functionalities for numerical computing in Python, including efficient array operations, mathematical functions, and array manipulation. Its performance, memory efficiency, and integration with other libraries make it a fundamental tool for scientific computing, data analysis, and machine learning tasks

### 4.2. Pandas

Pandas is a powerful and widely used library in Python for data manipulation and analysis. It provides data structures and functions to efficiently handle structured data, such as tabular data, time series, and heterogeneous datasets. Pandas is built on top of NumPy and offers additional functionalities specifically tailored for data analysis tasks (API Reference — Pandas 2.0.2 Documentation, n.d.).

“Pandas” key Features and Functionality:

- DataFrame: The DataFrame is the central data structure in Pandas, resembling a table or spreadsheet. It consists of rows and columns, allowing for easy storage and manipulation of structured data. DataFrames can handle different data types and offer flexible indexing, slicing, and filtering operations.
- Data Manipulation: Pandas provides a wide range of operations for manipulating data, including merging, joining, reshaping, and pivoting. These operations enable efficient data cleaning, transformation, and restructuring, facilitating the preparation of data for analysis.
- Data Input and Output: Pandas supports various file formats for reading and writing data, including CSV, Excel, SQL databases, JSON, and more. It simplifies the process of

importing and exporting data from different sources, making it convenient for working with real-world datasets.

- Missing Data Handling: Pandas offers robust functionalities to handle missing data. It provides methods to identify, filter, fill, or drop missing values in a DataFrame, ensuring data integrity and consistency during analysis.
- Data Aggregation and Grouping: Pandas enables aggregation and grouping operations on data, allowing for calculations based on specific variables or categories. Functions like groupby, pivot_table, and resample facilitate summarizing and aggregating data, generating valuable insights from large datasets.
- Time Series Analysis: Pandas has dedicated tools for working with time series data. It provides functionality for date/time manipulation, resampling, shifting, and rolling window calculations, making it suitable for analyzing and modeling time-dependent data.

“Pandas” Benefits and Advantages are multiple such us:

- Data Handling Efficiency: Pandas is designed to efficiently handle large datasets. It provides optimized data structures and algorithms that minimize memory usage and improve computational performance. Pandas' vectorized operations and optimized functions contribute to faster data processing compared to traditional Python data structures.
- Data Exploration and Analysis: Pandas simplifies data exploration and analysis tasks by providing intuitive and expressive syntax. Its extensive set of built-in functions enables easy data manipulation, filtering, aggregation, and visualization, facilitating in-depth data exploration and generating valuable insights.
- Integration with Other Libraries: Pandas seamlessly integrates with other libraries in the data analysis ecosystem, such as NumPy, Matplotlib, and scikit-learn. This integration allows for smooth data exchange and interoperability, enabling a comprehensive and cohesive data analysis workflow.
- contributors. This community provides continuous support, regular updates, and extensive documentation. Additionally, the active development of Pandas ensures the availability of new features and enhancements to meet evolving data analysis needs.

In summary, Pandas is a versatile and efficient library for data manipulation and analysis in Python. Its DataFrame data structure, along with various functions for data manipulation, missing data handling, aggregation, and time series analysis, make it a powerful tool for working with structured data. Pandas' performance, ease of use, and integration with other libraries contribute to its popularity in the data analysis and scientific computing communities.

### 4.3. TensorFlow :

TensorFlow is a widely used open-source library for machine learning and deep learning tasks. Developed by Google, TensorFlow provides a flexible framework for building and deploying machine learning models, particularly neural networks. It offers a range of functionalities to efficiently handle large-scale numerical computations and supports both CPU and GPU acceleration (TensorFlow C++ API Reference | TensorFlow v2.12.0, n.d.)
Key Features and Functionality:

- Computational Graph: TensorFlow operates based on a computational graph paradigm. It allows users to define a computational graph that represents the flow of operations and data between nodes. This graph-based approach provides flexibility and enables efficient execution of complex computations on distributed systems.
- Neural Networks: TensorFlow provides comprehensive support for building and training neural networks. It offers a high-level API, known as Keras, which simplifies the process of designing and training deep learning models. TensorFlow also provides lower-level APIs for fine-grained control and customization of neural network architectures.
- Automatic Differentiation: TensorFlow incorporates automatic differentiation, which is crucial for training deep learning models. It can automatically compute gradients of the model's parameters with respect to a given loss function. This gradient information is then used to update the model's weights during the optimization process, such as gradient descent.
- GPU Support: TensorFlow leverages GPU acceleration to speed up computations, particularly for training large neural networks. By utilizing the computational power of GPUs, TensorFlow can perform parallel computations and process large batches of data more efficiently, leading to significant speed improvements in deep learning tasks.
- Model Deployment: TensorFlow provides tools and APIs for deploying trained models in production environments. It offers support for various deployment scenarios, including serving models as RESTful APIs, deploying models on mobile and embedded devices, and integrating models with cloud-based platforms.
- Ecosystem and Community: TensorFlow has a vibrant ecosystem with a wide range of libraries and tools built on top of it. These include TensorFlow Hub for pre-trained models, TensorFlow Extended (TFX) for building end-to-end machine learning pipelines, and

TensorFlow Serving for serving models in production. The TensorFlow community actively contributes to the development of new features, libraries, and extensions.

Benefits and Advantages of TensorFlow are multiple such us:

- Flexibility and Scalability: TensorFlow provides a flexible framework for building and experimenting with different machine learning models. Its computational graph abstraction allows for easy customization and scalability, enabling the development of complex models for various tasks.
- Distributed Computing: TensorFlow supports distributed computing, allowing users to distribute computations across multiple devices, machines, or clusters. This capability is crucial for training large-scale models and handling massive datasets efficiently.
- Integration with Other Libraries: TensorFlow integrates well with other popular libraries and frameworks in the Python ecosystem. It can be seamlessly combined with libraries like NumPy, Pandas, and Matplotlib, enabling smooth data preprocessing, analysis, and visualization workflows.
- Performance Optimization: TensorFlow optimizes performance by leveraging hardware acceleration and providing efficient implementations of mathematical operations. It supports optimizations such as parallel computation, memory management, and mixed-precision calculations, leading to faster execution and improved resource utilization.
- Support for Research and Production: TensorFlow is widely used in both research and production environments. Its versatility allows researchers to experiment with novel models and algorithms, while its deployment capabilities make it suitable for integrating machine learning models into real-world applications.

In summary, TensorFlow is a powerful and versatile library for machine learning and deep learning tasks. Its features, including computational graph abstraction, neural network support, GPU acceleration, model deployment options, and integration with other libraries, contribute to its popularity and widespread adoption in the machine learning community. TensorFlow empowers researchers and practitioners to develop and deploy sophisticated machine learning models efficiently.

### 4.4. OpenCV (Open Source Computer Vision)

is a popular open-source library for computer vision and image processing tasks. It provides a wide range of functions and algorithms for handling and manipulating images and videos.

OpenCV is written in C++ and offers interfaces for various programming languages, including Python through the cv2 module. The essential features and functionalities provided by Open are (OpenCV: OpenCV Modules, n.d.):

:

- Image and Video I/O: OpenCV allows reading, writing, and processing of images and videos in various formats. It provides functions to load images and videos from files, capture frames from cameras, and save processed output. OpenCV supports a wide range of image and video formats, making it versatile for handling different media sources.
- Image Processing: OpenCV offers numerous images processing functions, including filtering, transformations, geometric operations, and colour space conversions. These functions enable tasks such as image enhancement, denoising, edge detection, morphological operations, and geometric transformations like resizing, rotation, and cropping.
- Object Detection and Tracking: OpenCV provides pre-trained models and algorithms for object detection and tracking. It includes popular algorithms such as Haar cascades, which are effective for face detection, as well as more advanced techniques like deep learning-based object detection models (e.g., YOLO and SSD).
- Feature Extraction and Matching: OpenCV offers algorithms for feature extraction, such as SIFT (Scale-Invariant Feature Transform) and SURF (Speeded-Up Robust Features). These algorithms can identify distinctive features in images and match them across different images, enabling tasks like image stitching, image registration, and object recognition.
- Computer Vision Utilities: OpenCV provides various utilities for computer vision tasks. This includes functions for camera calibration, image alignment, optical flow estimation, stereo vision, and 3D reconstruction. These utilities are useful for tasks such as camera calibration, depth estimation, and creating 3D models from multiple images.
- Machine Learning Integration: OpenCV seamlessly integrates with other machine learning libraries and frameworks, such as TensorFlow and scikit-learn. This integration allows for the combination of computer vision algorithms with machine learning techniques, enabling tasks like image classification, object recognition, and semantic segmentation.
- Versatility: OpenCV is a versatile library with a wide range of functions and algorithms for various computer vision tasks. It covers both basic image processing operations and advanced computer vision techniques, making it suitable for a broad range of applications.

Therefore, the advantages of this library are:

- Performance Optimization: OpenCV is optimized for efficient execution and high-performance computing. It leverages hardware acceleration, parallel processing, and optimized algorithms to ensure fast and efficient image and video processing, even for large-scale datasets.
- Cross-Platform Compatibility: OpenCV is cross-platform and runs on various operating systems, including Windows, macOS, Linux, iOS, and Android. This compatibility allows for the development of computer vision applications on different platforms.
- Active Community and Documentation: OpenCV has a large and active community of developers and researchers. This community provides regular updates, bug fixes, and extensive documentation, making it easy to learn and use OpenCV for computer vision projects.
- Integration with Other Libraries: OpenCV integrates well with other popular libraries and frameworks in the Python ecosystem. It can be combined with libraries like NumPy, Matplotlib, and scikit-image, enabling seamless data exchange and integration into comprehensive computer vision pipelines.

In summary, OpenCV is a powerful and widely used library for computer vision and image processing tasks. Its rich set of functions, algorithms, and utilities make it a go-to choose for a wide range of computer vision applications. OpenCV's versatility, performance optimization, cross-platform compatibility, and active community support contribute to its popularity and effectiveness in the field of computer vision.

### 4.5. The scikit-learn library

The scikit-learn library, often referred to as sklearn, is a popular open-source machine learning library in Python. It provides a comprehensive set of tools for data preprocessing, feature selection, model building, model evaluation, and model deployment. Scikit-learn is built on top of NumPy, SciPy, and matplotlib, and it integrates well with other libraries in the Python ecosystem. “scikit-learn” Key features and functionalities are multiple such us (User Guide: Contents, n.d.):

- Data Preprocessing: Scikit-learn offers a wide range of functions for data preprocessing tasks. It includes methods for handling missing values, feature scaling, one-hot encoding, label encoding, and data normalization. These preprocessing techniques are crucial for preparing the data before feeding it into machine learning models.

- Feature Selection and Extraction: Scikit-learn provides methods for feature selection, allowing users to choose relevant features that contribute most to the predictive power of the models. It also offers feature extraction techniques, such as Principal Component Analysis (PCA) and Non-negative Matrix Factorization (NMF), which can transform high-dimensional data into a lower-dimensional space while retaining important information.
- Supervised Learning: Scikit-learn supports a variety of supervised learning algorithms, including classification, regression, and time series analysis. It includes popular algorithms like logistic regression, decision trees, random forests, support vector machines (SVM), and gradient boosting algorithms such as XGBoost and LightGBM. These algorithms can be easily trained, tuned, and evaluated using scikit-learn's unified API.
- Unsupervised Learning: Scikit-learn offers a wide range of unsupervised learning algorithms for tasks such as clustering, dimensionality reduction, and anomaly detection. It includes algorithms like K-means clustering, hierarchical clustering, DBSCAN, and Gaussian Mixture Models (GMM). These algorithms can help discover patterns, group similar data points, and reduce the dimensionality of the data.
- Model Evaluation and Validation: Scikit-learn provides various metrics and techniques for model evaluation and validation. It includes functions for calculating accuracy, precision, recall, F1 score, ROC curve, and area under the curve (AUC). Scikit-learn also offers methods for cross-validation, hyperparameter tuning, and model selection to ensure robust and reliable model performance.
- Model Deployment and Integration: Scikit-learn supports model serialization and deserialization, allowing trained models to be saved and reused in production environments. It also provides integration with other libraries and frameworks, such as TensorFlow and Keras, enabling seamless integration of scikit-learn models with deep learning architectures.

Therefore, the advantages of this library are:

- Easy-to-Use API: Scikit-learn provides a consistent and intuitive API for building machine learning models. Its well-documented functions and classes make it easy for both beginners and experienced practitioners to use and experiment with different algorithms and techniques.
- Comprehensive Documentation and Examples: Scikit-learn has extensive documentation and a wide range of examples and tutorials. This documentation covers the usage and

implementation details of various algorithms, making it easier for users to understand and apply machine learning techniques.

- Integration with the Python Ecosystem: Scikit-learn seamlessly integrates with other popular libraries in the Python ecosystem, such as NumPy, pandas, and matplotlib. This integration allows for efficient data manipulation, visualization, and integration with data science workflows.
- Robust and Efficient Implementations: Scikit-learn implements algorithms and techniques using optimized code, providing efficient and scalable solutions for machine learning tasks. It leverages NumPy and SciPy for high-performance numerical computations, ensuring fast execution even with large datasets.
- Active Development and Community Support: Scikit-learn has a large and active community of developers and contributors. The library is regularly updated with new features, bug fixes, and performance improvements. The community provides support through forums, mailing lists, and open-source contributions.

In summary, scikit-learn is a comprehensive and widely used machine learning library in Python. Its rich set of functionalities, ease of use, and integration with the Python ecosystem make it a powerful tool for data preprocessing, model building, and evaluation. Whether we are a beginner or an experienced practitioner, scikit-learn provides the tools and techniques necessary to develop and deploy machine learning models effectively.

### 4.6. Joblib

Joblib is a Python library that provides tools for efficient serialization and deserialization of Python objects. It is primarily used for storing and retrieving complex objects, such as trained machine learning models, to and from disk. Joblib is designed to be simple and efficient, with a focus on reducing memory usage and optimizing performance (Joblib, 2022).

“Joblib” key features and functionality can be resume us:

- Object Serialization: Joblib offers a set of functions for serializing Python objects, allowing them to be saved to disk and loaded back into memory. This is particularly useful for storing and reusing trained machine learning models, as it allows us to persist the model's state and parameters.

- Efficient Memory Usage: Joblib employs a smart caching mechanism that minimizes memory consumption when serializing large objects. It uses memory mapping techniques to avoid loading the entire object into memory at once, making it suitable for handling large datasets and models.
- Parallel Processing: Joblib provides built-in support for parallel processing, enabling the serialization and deserialization of objects in parallel. This can significantly speed up the process when dealing with a large number of objects or when working with computationally intensive tasks.
- Seamless Integration with scikit-learn: Joblib is widely used in conjunction with scikit-learn for serializing and deserializing machine learning models. It seamlessly integrates with scikit-learn's model training and evaluation workflows, allowing models to be easily saved and reloaded for future use.
- Support for Different Backends: Joblib supports different backends for serialization, including pickle and memmap. It provides flexibility in choosing the most suitable backend based on the requirements of the application. Pickle is the default backend and is suitable for most use cases, while memmap allows for efficient memory-mapped storage of large arrays.

“joblib” benefits and advantages are multiple such us:

- Simplified Model Persistence: Joblib simplifies the process of storing trained models, allowing us to save and load them with just a few lines of code. This makes it convenient for sharing models across different environments or deploying them in production systems.
- Reduced Memory Overhead: Joblib's memory mapping mechanism reduces the memory overhead associated with serializing and deserializing large objects. This is especially important when dealing with large datasets or complex machine learning models that consume a significant amount of memory.
- Parallel Processing Support: Joblib's built-in support for parallel processing allows for efficient serialization and deserialization of objects. This can greatly speed up the execution time, particularly when dealing with a large number of objects or computationally intensive tasks.
- Seamless Integration: Joblib integrates seamlessly with other libraries and frameworks, such as scikit-learn. This allows us to easily serialize and deserialize machine learning models trained using scikit-learn, enabling smooth integration with the broader data science ecosystem.

- Widely Used and Well-Documented: Joblib is a widely adopted library in the Python data science community and has extensive documentation and examples. This makes it easy to learn and utilize its functionalities, and also facilitates community support and troubleshooting.

In summary, Joblib is a powerful library for efficient serialization and deserialization of Python objects, with a particular emphasis on machine learning models. Its features, such as efficient memory usage, parallel processing support, and seamless integration with other libraries, make it a valuable tool for storing and retrieving complex objects in data science and machine learning applications.

### 4.7. Speech_recognition

The speech_recognition library in Python provides an easy-to-use interface for performing speech recognition tasks. It allows us to convert spoken language into written text by leveraging various speech recognition engines and APIs. The library supports multiple platforms and provides a unified API to work with different speech recognition systems (SpeechRecognition, 2023).

“speech_recognition” key Features and Functionality:

- Speech Recognition Engines: speech_recognition supports multiple speech recognition engines, including Google Speech Recognition, CMU Sphinx, Microsoft Azure Speech, IBM Watson, and many more. These engines utilize advanced algorithms and machine learning techniques to transcribe spoken words into text.
- Audio Source Support: The library offers flexible audio source support, allowing us to work with different types of audio inputs. It can directly process audio from a microphone, audio files in various formats (e.g., WAV, MP3), or even online audio streams.
- Easy Integration: speech_recognition provides a straightforward API to integrate speech recognition capabilities into our Python applications. It offers methods to capture audio, perform speech recognition, and retrieve the recognized text results.
- Multi-Language Support: The library supports recognition of speech in multiple languages. We can specify the language or let the engine automatically detect the language from the input audio.
- Audio Manipulation: speech_recognition includes functionality to manipulate audio, such as adjusting the sample rate, changing the audio volume, and trimming or splitting audio

files. These features enable us to preprocess the audio data for better speech recognition results.

- Error Handling and Confidence Scores: The library allows us to handle recognition errors and provides confidence scores for the recognized text. This information can be useful for quality assessment and further processing of the transcriptions.

"speech_recognition" Benefits and Advantages:

- Easy-to-Use Interface: speech_recognition provides a high-level API that abstracts the complexities of working with different speech recognition engines. It simplifies the process of capturing audio, performing recognition, and retrieving the results, making it accessible to users with varying levels of expertise.
- Platform Independence: The library is platform-independent and can be used on different operating systems, including Windows, macOS, and Linux. This allows for cross-platform development and deployment of speech recognition applications.
- Wide Range of Recognition Engines: speech_recognition supports multiple recognition engines, giving us the flexibility to choose the engine that best suits our needs. This enables us to experiment with different engines and select the one that provides the most accurate and reliable results for our specific use case.
- Integration with Other Libraries: The library seamlessly integrates with other Python libraries and frameworks, allowing us to combine speech recognition capabilities with other data processing, analysis, or machine learning tasks. For example, we can integrate speech recognition with natural language processing (NLP) libraries to perform further analysis on the transcribed text.
- Community Support and Documentation: speech_recognition has an active community of developers, which ensures ongoing support, frequent updates, and bug fixes. The library also provides comprehensive documentation and examples, making it easier for users to understand and utilize its features effectively.

In summary, the speech_recognition library in Python simplifies the process of performing speech recognition tasks. It provides an intuitive API to capture and process audio from various sources, supports multiple speech recognition engines, and offers platform independence. With its ease of use and flexibility, speech_recognition empowers developers to incorporate speech recognition capabilities into their applications, opening up possibilities for voice-controlled interfaces, transcription services, and more.

### 4.8. MoviePy

The MoviePy library is a Python module for video editing, which includes a sub-module called ‘moviepy.editor’. This sub-module provides a wide range of functionalities to create, edit, and manipulate videos programmatically. It is built on top of the powerful ‘FFmpeg’ library and offers a simple yet powerful interface for working with videos.

“MoviePy” Key Features and Functionality:

- Video Editing: MoviePy's moviepy.editor allows us to perform various video editing operations, such as cutting, concatenating, and splitting videos. We can extract specific segments from a video, merge multiple videos together, or split a video into smaller parts.
- Video Compositing: The library provides tools for compositing videos, allowing us to overlay images, texts, or other videos onto a base video. We can add watermarks, subtitles, captions, or custom graphics to enhance our videos.
- Video Effects and Transitions: MoviePy offers a wide range of built-in video effects and transitions. We can apply effects like blurring, color adjustments, rotations, scaling, and more to modify the appearance of videos. Transitions like fade-in, fade-out, crossfade, and wipes can be used to create smooth transitions between video clips.
- Video Generation: MoviePy allows us to generate videos programmatically by creating animations or synthesizing visual content. We can create animations using keyframes or by defining motion paths. Additionally, we can generate videos from sequences of images or arrays.
- Video Playback and Visualization: The library provides capabilities for playing back and visualizing videos directly in Jupyter notebooks. We can preview videos, display video frames as images, or create animated visualizations using the powerful integration with Matplotlib.
- Format Conversion and Encoding: MoviePy supports a wide range of video formats and codecs for both input and output. It allows us to convert videos from one format to another and encode videos with different compression settings. This makes it a versatile tool for handling video files in various formats.

‘MoviePy’ Benefits and Advantages:

- Simplicity and Ease of Use: MoviePy's moviepy.editor offers a simple and intuitive API for video editing tasks. The library follows a Pythonic syntax and provides a high-level abstraction, making it accessible to both beginners and experienced developers.
- Integration with the Python Ecosystem: MoviePy integrates seamlessly with other popular Python libraries and frameworks, such as NumPy and Matplotlib. This allows us to combine video editing capabilities with data processing, visualization, or machine learning tasks.
- Customizability and Extensibility: MoviePy is highly customizable and extensible. It provides a flexible framework for defining custom video effects, transitions, or animations. We can write our own functions or use existing ones to extend the library's functionalities.
- Documentation and Community Support: MoviePy has comprehensive documentation and a vibrant community of users and developers. The library is actively maintained, with frequent updates, bug fixes, and new features. The community provides support, tutorials, and examples to assist users in utilizing MoviePy effectively.
- Cross-Platform Compatibility: MoviePy is compatible with multiple platforms, including Windows, macOS, and Linux. This ensures that our video editing scripts can run seamlessly across different operating systems.

In summary, the moviepy.editor sub-module of MoviePy provides a powerful yet user-friendly interface for video editing and manipulation in Python. With its extensive features, including video editing operations, effects, transitions, compositing, and video generation, MoviePy allows us to create and modify videos programmatically. Its simplicity, integration with the Python ecosystem, and cross-platform compatibility make it a valuable tool for video editing tasks in various domains, such as multimedia production, data visualization, and content creation**.**

### 4.9. Tkinter

The tkinter.filedialog module is a part of the tkinter library in Python, which provides a set of dialogs for selecting and saving files and directories. It offers a user-friendly interface to interactively choose files or directories from the file system (Tkinter — Python Interface to Tcl/Tk, n.d.).

‘Tkinter’ Key Features and Functionality:

- File Dialogs: The tkinter.filedialog module includes various dialogs for file selection, such as askopenfilename and askopenfilenames. These dialogs open a file selection window,

allowing users to browse and select one or multiple files, respectively. They provide an intuitive interface to navigate through directories, view file details, and choose desired files.

- Directory Dialogs: The module also provides directory selection dialogs, such as askdirectory, which opens a dialog to select a directory. Users can browse through directories, choose a specific directory, and retrieve the path for further processing.
- File Types and Filters: The file selection dialogs allow us to specify file types and apply filters. We can define file extensions or patterns to filter the displayed files in the selection dialog. This feature simplifies the process of selecting specific file types and improves user experience by displaying only relevant files.
- Initial Directory and Default File: The dialogs support specifying an initial directory to open when the dialog is launched. This is useful for providing a starting point in the file system hierarchy. Additionally, we can set a default file name that will be preselected when the file selection dialog opens, making it convenient for users to save new files.
- Customization: The tkinter.filedialog module allows us to customize the appearance and behavior of the dialogs. We can set the title of the dialog window, customize button labels, control the dialog's size and position, and define additional options to tailor the user experience to our specific requirements.
- Cross-Platform Compatibility: The tkinter.filedialog module is part of the tkinter library, which is available on different platforms, including Windows, macOS, and Linux. This ensures cross-platform compatibility, allowing us to use the file dialogs consistently across different operating systems.

‘Tkinter’ Benefits and Advantages:

- Simplified File and Directory Selection: The tkinter.filedialog module provides a convenient and user-friendly way to select files and directories. It eliminates the need for manually typing or navigating through the file system hierarchy, making the selection process more efficient and less error-prone.
- Integration with GUI Applications: The module integrates seamlessly with tkinter, the standard Python GUI toolkit. It can be used to incorporate file selection functionality into our GUI applications, allowing users to choose files or directories easily.
- Flexibility and Customization: The file dialogs can be customized to fit the specific requirements of our application. We can configure options, set initial directories, apply filters, and modify dialog appearance to provide a tailored user experience.

- Versatility: The module supports various file selection scenarios, including single file selection, multiple file selection, and directory selection. This versatility allows us to handle different use cases and user requirements in our applications.
- Simplified File Input and Output: The file dialogs simplify the process of handling file input and output in our Python programs. They provide a standardized way to prompt users for file selections or to specify output file paths, saving our from manually implementing file selection logic.

In summary, the tkinter.filedialog module in Python's tkinter library offers a straightforward and user-friendly approach to file and directory selection. It provides dialogs for browsing and selecting files or directories, supports file type filtering, and allows customization to fit our application's needs. By leveraging the module, we can easily incorporate file selection capabilities into our GUI applications and streamline the process of working with files and directories.

### 4.10. NLTK

The Natural Language Toolkit (NLTK) is a powerful library in Python that provides various tools and resources for natural language processing (NLP). It offers a wide range of functionalities to process, analyze, and manipulate human language data.

‘NLTK” key Features and Functionality:

- Text Processing: NLTK provides numerous functions for basic text processing tasks, such as tokenization (splitting text into individual words or sentences), stemming (reducing words to their base or root form), and lemmatization (converting words to their base form based on their dictionary meaning).
- Part-of-Speech Tagging: NLTK includes pre-trained models and algorithms for part-of-speech tagging, which assigns grammatical tags (e.g., noun, verb, adjective) to each word in a sentence. This information is essential for various NLP tasks, such as information extraction, sentiment analysis, and text classification.
- Named Entity Recognition (NER): NLTK provides tools to identify and extract named entities from text, such as person names, locations, organizations, and dates. NER helps in information extraction and entity-based analysis.

- Chunking and Parsing: NLTK offers capabilities for chunking and parsing sentences to identify phrases and sentence structures. It supports techniques like regular expressions, n-gram models, and probabilistic parsers to extract meaningful chunks and parse syntactic structures.
- Sentiment Analysis: NLTK includes sentiment analysis modules that allow us to determine the sentiment polarity (positive, negative, neutral) of text. It provides pre-trained sentiment classifiers and lexicons for sentiment analysis tasks.
- Language Models: NLTK enables the creation and training of language models using n-grams or probabilistic models. These models help in predicting the likelihood of words or sequences of words, and they are widely used in applications like machine translation, spell checking, and text generation.
- Corpus and Resources: NLTK provides access to a vast collection of corpora and lexical resources, including text collections, word lists, and lexicons. These resources cover a wide range of languages and domains, supporting various NLP research and development tasks.
- Text Classification and Machine Learning: NLTK integrates with machine learning libraries, such as scikit-learn, to perform text classification tasks. It supports algorithms like Naive Bayes, Maximum Entropy, and Decision Trees for training and evaluating text classifiers.

'NLTK' Benefits and Advantages:

- Comprehensive NLP Functionality: NLTK offers a comprehensive set of tools and functionalities for various NLP tasks, making it a one-stop solution for many natural language processing needs.
- Extensibility and Customizability: NLTK is highly extensible, allowing us to customize and adapt its functionalities to specific requirements. We can create and train our own models, define custom parsers or taggers, and incorporate external resources.
- Educational Resource: NLTK is widely used in academia and serves as an educational resource for learning NLP concepts and techniques. It provides extensive documentation, tutorials, and example code to facilitate NLP learning and experimentation.
- Active Community and Contributions: NLTK has a vibrant community of users and contributors. The library is actively maintained and updated with new features, bug fixes, and improvements. The community provides support, resources, and additional contributions, enriching the ecosystem around NLTK.
- Integration with Other Libraries: NLTK integrates well with other popular Python libraries and frameworks, such as scikit-learn, NumPy, and pandas. This allows us to combine NLP

functionalities with data manipulation, machine learning, and other data science tasks seamlessly.

In summary, NLTK is a comprehensive and widely-used library for natural language processing in Python. It offers a broad range of functionalities, including text processing, part-of-speech tagging, named entity recognition, sentiment analysis, language modeling, and text classification. With its extensive set of tools, resources, and community support, NLTK empowers developers and researchers to perform a wide range of NLP tasks effectively and efficiently.

### 4.11. WordCloud

The WordCloud library, along with the STOPWORDS collection, is a popular Python library used for generating word clouds from text data. Word clouds are visual representations of text data where the size of each word corresponds to its frequency or importance within the text. The WordCloud library provides a simple and effective way to create visually appealing word clouds (Wordcloud, 2023).

The key components of the WordCloud library are:

- WordCloud Generation: The library allows us to create a word cloud by passing text data as input. It analyzes the frequency of words in the text and generates a visual representation where the size of each word is proportional to its frequency.
- Customization Options: The WordCloud library provides various customization options to tailor the appearance and layout of the word cloud. We can control parameters such as the size, color, font, background color, and shape of the word cloud. These options enable us to create visually appealing and informative word clouds.
- Stopwords Removal: Stopwords are common words such as "and," "the," "is," etc., that do not carry much meaning and are often excluded from word clouds. The STOPWORDS collection in the WordCloud library contains a predefined set of stopwords that can be easily removed from the text data during word cloud generation. This helps to focus the visualization on more relevant and meaningful words.
- Word Frequency Customization: The library provides options to customize the handling of word frequencies. We can adjust the scaling of word frequencies to control how the size of the words is determined in the word cloud. This allows us to emphasize certain words or adjust the visual representation based on our specific requirements.

- Masking: The WordCloud library allows us to create word clouds in custom shapes by using masks. A mask is an image or shape that defines the outline of the word cloud. The word cloud is then fitted within the boundaries of the mask, creating a visually appealing representation that aligns with the chosen shape.
- The WordCloud library, along with the STOPWORDS collection, offers a convenient and effective way to generate word clouds from text data. It provides customization options, stopwords removal, and the ability to create word clouds in custom shapes. By leveraging these features, we can create visually appealing and informative word clouds that highlight the most important words in our text data.

## 5. Implementation keys

In what follows, we will present pieces of code which constitute the keys of our implementation work.

```
import numpy as np
import pandas as pd
import tensorflow as tf
import cv2
import csv
from sklearn import metrics
import joblib
import speech_recognition as sr
import moviepy.editor
from tkinter import filedialog as fd
from tkinter.filedialog import *
model = tf.keras.applications.ResNet50V2(weights="imagenet")
from keras.preprocessing.text import Tokenizer
import tkinter as tk
from tkinter import scrolledtext
import nltk
import pandas_profiling as pp
from markupsafe import escape
from wordcloud import WordCloud, STOPWORDS
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
from tensorflow import keras
from keras.callbacks import ModelCheckpoint
```

*Figure 3.1. Used libraries*

```
def process_frame(frame):
    # Resize the frame to a fixed size (224x224) for the model input
    resized_frame = cv2.resize(frame, (224, 224))

    # Convert the frame to a format expected by the model
    img = tf.keras.preprocessing.image.img_to_array(resized_frame)
    img = tf.keras.applications.resnet_v2.preprocess_input(img)

    # Use the model to make a prediction on the frame
    predictions = model.predict(tf.expand_dims(img, axis=0))

    # Get the label of the highest predicted class
    predicted_class = tf.keras.applications.resnet_v2.decode_predictions(predictions, top=1)[0][0][1]

    return predicted_class
text1 =("checking if there is any Adult content in the Video")
file_path = fd.askopenfilename(filetypes=[("Video Files", "*.mp4;*.avi")])
cap = cv2.VideoCapture(file_path)

while True:
    # Read a frame from the video
    ret, frame = cap.read()

    if not ret:
        break

    # Process the frame to get the predicted class
    predicted_class = process_frame(frame)
cap.release()
```

*Figure 3.2. Adult content filtering*

```
In [3]: video = moviepy.editor.VideoFileClip(file_path)
        audio = video.audio
        print("converting vedio to audio ...")
        audio.write_audiofile('audio.wav')
        r = sr.Recognizer()
        print("converting audio to Text ...")
        with sr.AudioFile('audio.wav') as source:
            audio_data = r.record(source)
            text = r.recognize_google(audio_data)

        converting vedio to audio ...
        MoviePy - Writing audio in audio.wav


        MoviePy - Done.
        converting audio to Text ...
        result2:
        {   'alternative': [   {   'confidence': 0.65385342,
                                   'transcript': 'show me how fast are p310. Is mine '
                                                 'is longer there we go'},
                               {   'transcript': 'show me how fast your PC turned on '
                                                 'his mine is longer there we go'},
                               {   'transcript': "show me how fast are p310. Here's "
                                                 'mine is longer there we go'},
                               {   'transcript': 'show me how fast your p310. Is mine '
                                                 'is longer there we go'},
                               {   'transcript': 'show me how fast your PC turned on '
                                                 'is mine is longer there we go'}],
            'final': True}
```

*Figure 3.3. Conversion video to audio*

```
video = moviepy.editor.VideoFileClip(file_path)
audio = video.audio
print("converting vedio to audio ...")
audio.write_audiofile('audio.wav')
r = sr.Recognizer()
print("converting audio to Text ...")
with sr.AudioFile('audio.wav') as source:
    audio_data = r.record(source)
    text = r.recognize_google(audio_data)
```

*Figure 3.4. Audio to text conversion*

```
In [2]: # Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(text_data, class_labels, test_size=0.2, random_state=42)

# Convert text to numerical feature vectors using CountVectorizer
vectorizer = CountVectorizer()
X_vectorized = vectorizer.fit_transform(text_data.tolist())  # Convert text_data to a list
X_train_vectorized = vectorizer.fit_transform(X_train)
X_test_vectorized = vectorizer.transform(X_test)



# Train the Naive Bayes classifier
classifier = MultinomialNB()
classifier.fit(X_train_vectorized, y_train)

# Make predictions on the test set
predictions = classifier.predict(X_test_vectorized)

# Evaluate the performance of the classifier
accuracy = metrics.accuracy_score(y_test, predictions)
precision = metrics.precision_score(y_test, predictions, average='weighted')
recall = metrics.recall_score(y_test, predictions, average='weighted')
f1_score = metrics.f1_score(y_test, predictions, average='weighted')

print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-Score:", f1_score)

joblib.dump(classifier, 'naive_bayes_model.joblib')
joblib.dump(vectorizer, 'count_vectorizer.joblib')

Accuracy: 0.9765100671140939
Precision: 0.9766937686759525
Recall: 0.9765100671140939
F1-Score: 0.9765452996043319

Out[2]: ['count_vectorizer.joblib']
```

*Figure 3.5. Naïve-Bayes model training*

## 6. Conclusion

We have presented in this chapter the technical tools of the Python environment used in the realization of this work with some source codes which constitute the keys of our implementation work.

# GENERAL CONCLUSION

In this dissertation, we have presented a solution for multimedia filtering and classification using AI and NLP techniques.

The implementation of this work demonstrates the potential of AI especially the Naïve-Bayes classifier and NLP in automating the content filtering and classification process, enhancing the efficiency of multimedia analysis, and ensuring safer content consumption. The use of computer vision techniques through OpenCV enables frame-by-frame analysis, while deep learning models like ResNetV2 aid in identifying adult content accurately. The translation of video to audio and subsequent audio-to-text conversion allows for further analysis and content classification using NLP techniques.

The program's effectiveness is evaluated through metrics such as accuracy, precision, recall, and F1-score, providing quantitative insights into the classification performance. The trained Naive Bayes classifier demonstrates reliable performance in categorizing the multimedia content based on the extracted text. In addition, the dissertation explores the importance of data preparation, feature extraction, and model training to achieve optimal results.

Throughout the implementation of this work, the Python programming language and its associated libraries have played a crucial role in enabling the implementation of the multimedia content filtering and classification program. The versatility and extensive functionalities offered by libraries such as numpy, pandas, scikit-learn, and joblib have facilitated data processing, machine learning, and model persistence. Besides, the program developed in Python showcases the integration of various technologies and libraries to achieve the desired outcome. The process involves scanning video frames for adult content, translating the video to audio, converting the audio to text, and utilizing NLP for content classification. The program leverages libraries such as OpenCV, TensorFlow, NLTK, and Moviepy.editor to perform the necessary tasks.

For future improvement, we believe that it is necessary to train the Naïve-Bayes model on more dataset and to enable the program to recognize more multiple and accurate categories like hate speech and cursing religions .

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## ملخص

الهدف من هذا العمل هو اقتراح مرشح ومصنف للتحكم في محتوى الوسائط المتعددة الذي قد يكون غير مناسب .يعمل المرشح والمصنف عن طريق استخراج النص من محتوى الوسائط المتعددة وتصنيفه لاحقًا باستخدام نموذج Naive-Bayes المدرب على مجموعة من البيانات المتعددة .تمت برمجة ذا العمل باستخدام بيئة Python نظرًا لمجموعتها الواسعة من المكتبات الموجهة للتعلم الآلي.



**الكلمات المفتاحية:**

تصفية الوسائط المتعددة، تصنيف الوسائط المتعددة، التعلم الآلي، استخراج النص، Naïve-Bayes، Python.


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## Abstract

The objective of this work is to propose a filter and classifier for controlling multimedia content that may be inappropriate. The filter and classifier operate by extracting text from multimedia content and subsequently classifying it using a Naive-Bayes model trained on multiple datasets. The implementation was carried out using the Python environment due to its extensive collection of machine learning-oriented libraries.



**Key words:**

Multimedia Filtering, Multimedia classification, Machine learning, Text extraction Naïve-Bayes, Python.


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## Résumé

L'objectif de ce travail est de proposer un filtre et un classifieur pour contrôler le contenu multimédia qui peut être inapproprié. Le produit réalisé fonctionne en extrayant le texte du contenu multimédia et en le classant ensuite à l'aide d'un modèle Naive-Bayes qui a été trainé sur plusieurs dataset. L'implémentation a été réalisée à l'aide de l'environnement Python en raison de sa vaste collection de bibliothèques orientées apprentissage automatique.



**Mots clés :**

Filtrage Multimédia, Classification Multimédia, Machine Learning, Extraction de texte, Naïve-Bayes, Python.