### CSC4211 - PROJECT WORK

## ANALYSIS OF CLICKBAIT IN YOUTUBE VIDEOS USING ENSEMBLE MODELS

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### WHAT IS CLICKBAIT?

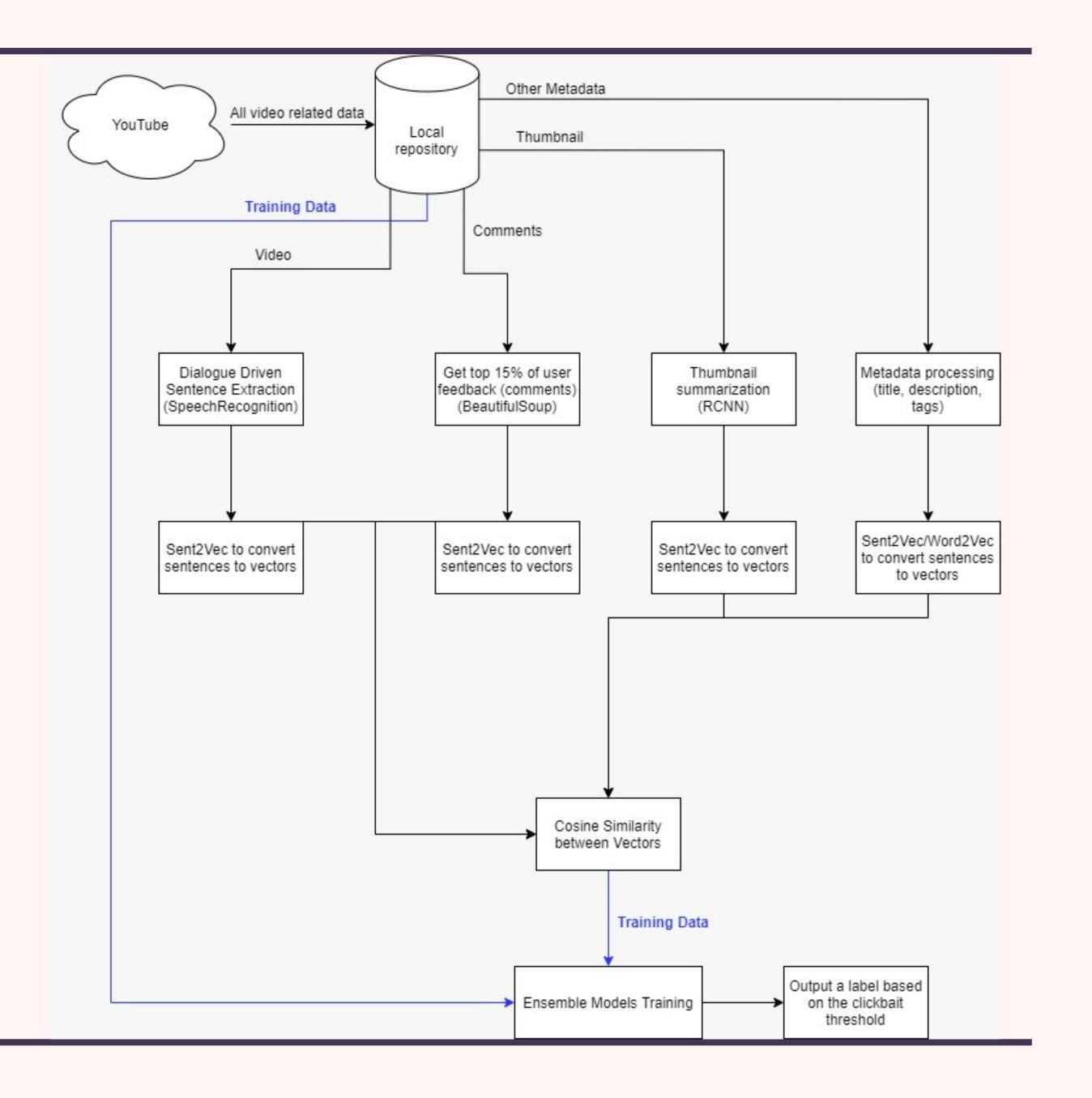
- \*Clickbait is a marketing device (such as a headline) designed to make readers want to click on a hyperlink especially when the link leads to content of dubious value or interest.
- \*Clickbait is ever prevalent in the recent world of sensationalist media at the cost of journalistic integrity.
- \*It has plagued the most popular video services provider on the internet YouTube.
- \*Our project's aim is to analyze and, eventually, create a model that helps detect clickbait, not only in currently uploaded videos, but also in any future video uploaded on the platform.

### SCOPE OF THE PROJECT

The scope of this project extends to achieve the following 4 goals:

- Analyze the amount clickbait present in a sample set of YouTube videos.
- Detect factors that affect the viewer's perception of what constitutes "clickbait"
- Develop a learning model that studies the aforementioned factors to categorize videos as "clickbait" and "not clickbait"
- \* Test it on newly, non-encountered examples to measure its effectiveness and accuracy.

### PROPOSED ARCHITECTURE



### ALGORITHMS USED

There are various ML and DL algorithms that will be used in our training model.

- 1. RCNN (Ensemble) used to caption the thumbnails of videos
- 2. SBERT- used to create sentence and word embeddings (vectors)
- 3. Various Classification Models
  - Logistic Regression
  - Gaussian Naive Bayes
  - Decision Tree

- Random Forest Classifier
- K-Nearest Neighbors Classifier
- Support Vector Classifier

### FEATURES COLLECTED

Values	Data Type	Location
Creator Fed Values		
Video_ID	String	YouTube API v3
Title	String	YouTube API v3
Tags	String	YouTube API v3
Description	String	YouTube API v3
Thumbnail Caption (generated)	String	RCNN Ensemble Model
Video Rating	String	YouTube API v3
Video Category ID	String	YouTube API v3
Uploaded At	Timestamp	YouTube API v3
Audio Transcript	String	Audio to Speech Recognition
User Interaction Values		
Likes	Integer	YouTube API v3
Dislikes	Integer	YouTube API v3
Like-Dislike Ratio	Float	Calculated
Number of comments	Integer	YouTube API v3
Number of "Fake" Comments	Integer	Calculated
"Fake" Comment Ratio	Float	Calculated
Views	Integer	YouTube API v3
Content Creator's Data		
Channel Age	Integer	YouTube API v3
Channel Total Views	Integer	YouTube API v3
Channel Total Subscribers	Float	Calculated
Channel Made for kids	Integer	YouTube API v3
Channel number of videos	Integer	Calculated

## FEATURES COLLECTED (CONTD.)

- \* The data surrounding YouTube videos and clickbait is very less, almost non-existent
- \* Manual dataset creation using:
  - **♦** Google's own YouTube API
  - **♦** BeautifulSoup
  - Youtube-Transcript API
- \* Data collected across various categories.

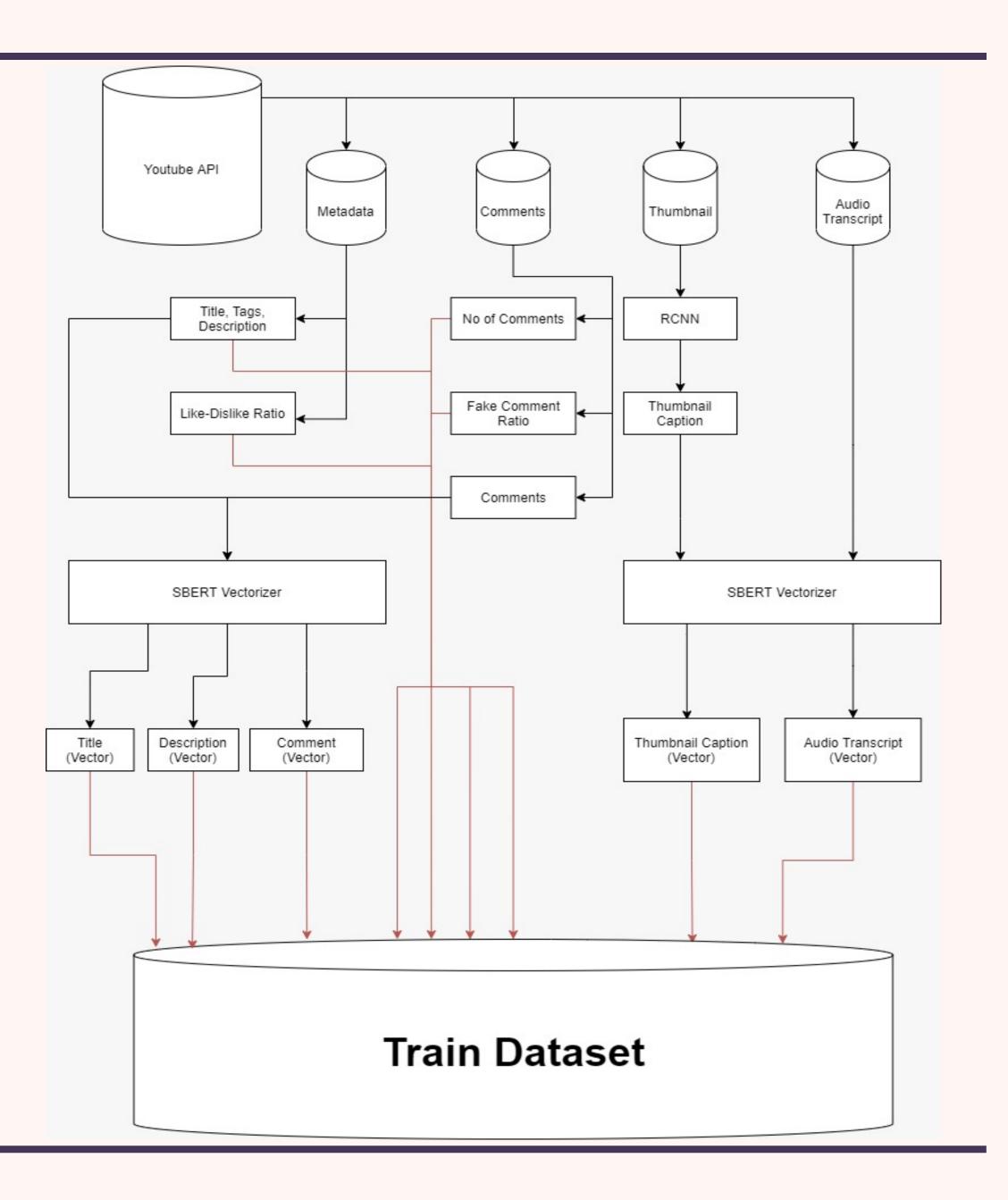
### SOFTWARE AND PACKAGES

### The primary tools, software, and websites used are as follows:

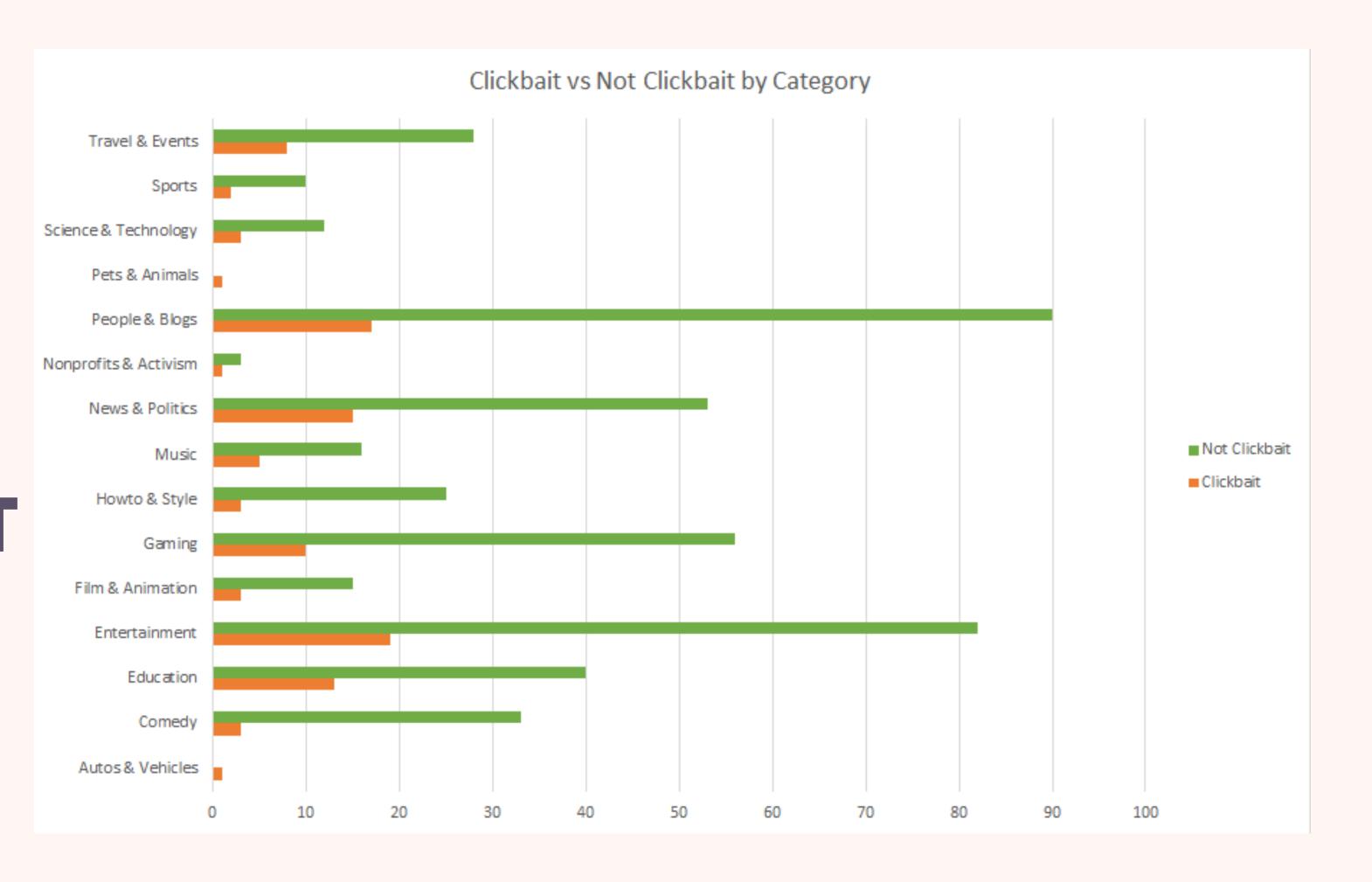
- Google Colaboratory
- Python 3
- YouTube API
- YouTube Transcript API
- Scikit-Learn

- Keras
- Inception V3
- NLTK
- Beautiful Soup
- SentenceTranformers

# DATA EXTRACTION AND DATA PRE-PROCESSING PIPELINE



## PRELIMINARY ANALYSIS ON COLLECTED DATASET

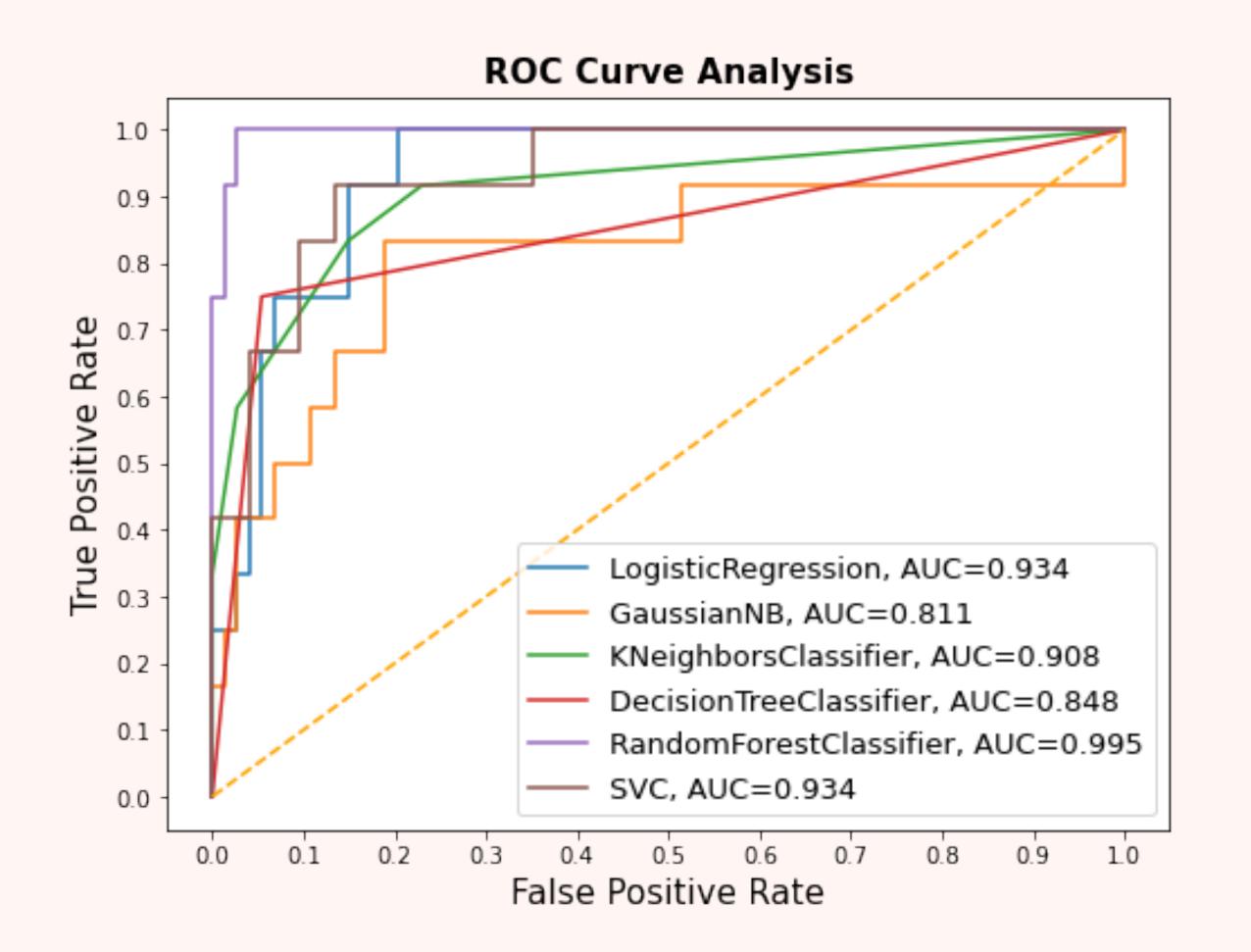


### OUTPUT AND METRICS

Output - Probability percentage of the video being clickbait Metrics used to compare classification models:

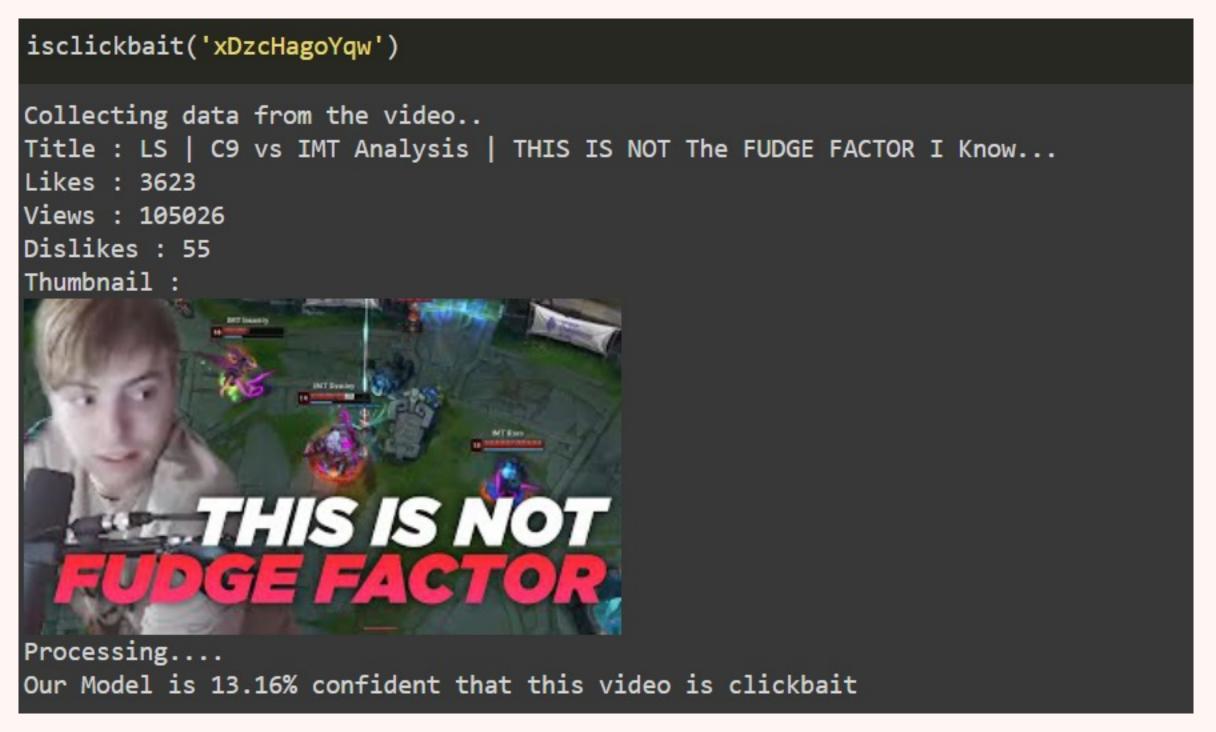
- 1. Precision
- 2. Recall
- 3. F1 Score
- 4. Accuracy
- 5. ROC-AUC

### COMPARISON OF CLASSIFIERS



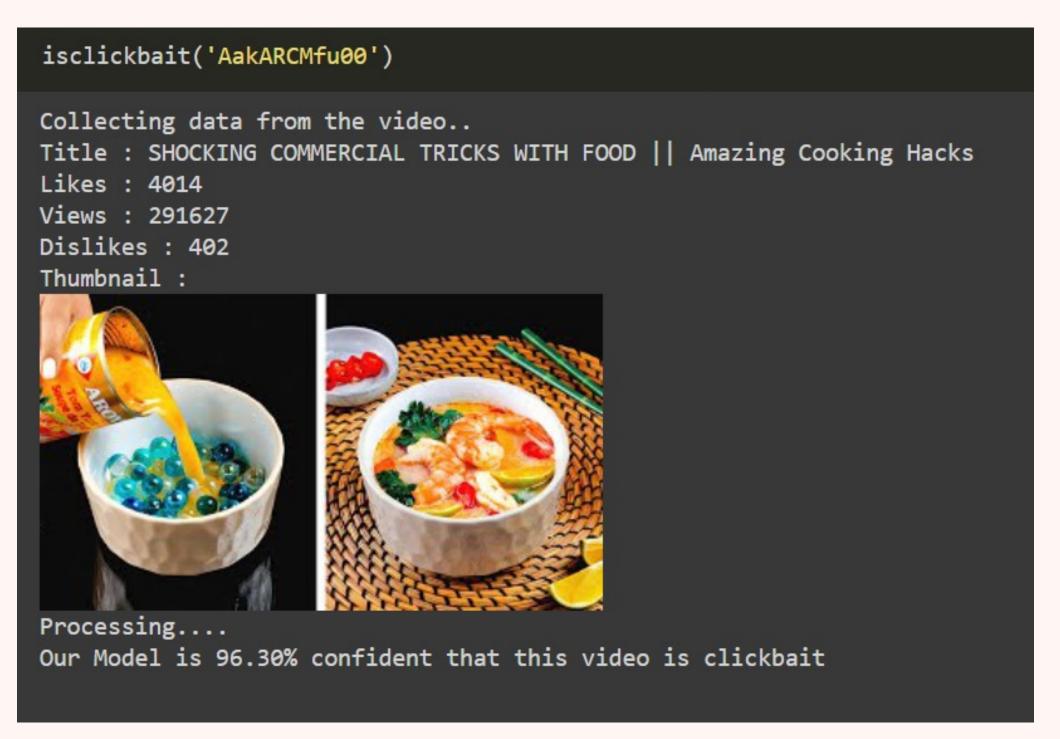
	Logistic Regression								
recall		0	1	accuracy	macro avg	weighted avg			
recall	:	:	:	:	:	:			
f1-score	precision	0.898734	0.571429	0.872093	0.735081	0.853064			
Support   74   12   0.872093   86   86   86	recall	0.959459	0.333333	0.872093	0.646396	0.872093			
Gaussian Naive Bayes	f1-score	0.928105	0.421053	0.872093	0.674579	0.857353			
0	support	74	12	0.872093	86	86			
precision   0.947368   0.164179   0.337209   0.555774   0.838086   recall   0.243243   0.916667   0.337209   0.579755   0.337209   f1-score   0.387097   0.278481   0.337209   0.332789   0.371941   support   74   12   0.337209   86   86   86	Gaussian Naive Bayes								
recall		0	1	accuracy	macro avg	weighted avg			
recall	:	:	:	:	:	:			
f1-score	precision	0.947368	0.164179	0.337209	0.555774	0.838086			
Support   74   12   0.337209   86   86	recall	0.243243	0.916667	0.337209	0.579955	0.337209			
KNN Classifier    0	f1-score	0.387097	0.278481	0.337209	0.332789	0.371941			
0	support	74	12	0.337209	86	86			
precision   0.935065   0.777778   0.918605   0.856421   0.913118   recall   0.972973   0.5833333   0.918605   0.778153   0.918605   f1-score   0.953642   0.666667   0.918605   0.810155   0.913599   support   74   12   0.918605   86   86   86	KNN Classifier								
		0	1	accuracy	macro avg	weighted avg			
recall	i:i	:	:	:	:	:			
recall	precision	0.935065	0.777778	0.918605	0.856421	0.913118			
f1-score									
Support   74   12   0.918605   86   86   86									
Decision Tree Classifier									
0	Jupport			0.510005	00	00			
	Decision Tree	Classifier							
recall		0	1	accuracy	macro avg	weighted avg			
recall	[:	:	:	:	:	:			
recall	precision	0.958904	0.692308	0.918605	0.825606	0.921705			
f1-score	10 m 20 m	0.945946	0.75	0.918605	0.847973	0.918605			
support   74   12   0.918605   86   86     Random Forest Classifier	f1-score	0.952381	0.72			0.919956			
Random Forest Classifier			12		86				
0   1   accuracy   macro avg   weighted avg					0.000				
precision   0.960526   0.9   0.953488   0.930263   0.952081   recall   0.986486   0.75   0.953488   0.868243   0.953488   f1-score   0.973333   0.818182   0.953488   0.895758   0.951684   support   74   12   0.953488   86   86     Support Vector Classifier	Random Forest	Classifier							
recall		0	1	accuracy	macro avg	weighted avg			
recall	:	:	:	:	:	:			
f1-score	precision	0.960526	0.9	0.953488	0.930263	0.952081			
support   74   12   0.953488   86   86	recall	0.986486	0.75	0.953488	0.868243	0.953488			
Support Vector Classifier    0   1   accuracy   macro avg   weighted avg    :	f1-score	0.973333	0.818182	0.953488	0.895758	0.951684			
0   1   accuracy   macro avg   weighted avg	support	74	12	0.953488	86	86			
0   1   accuracy   macro avg   weighted avg	Support Vector Classifier								
:		0	(2)	accuracy	macro avg	weighted avg			
recall   0.986486   0.416667   0.906977   0.701577   0.906977   f1-score   0.948052   0.555556   0.906977   0.751804   0.893285	:	:	:	:	:	:			
recall   0.986486   0.416667   0.906977   0.701577   0.906977   f1-score   0.948052   0.555556   0.906977   0.751804   0.893285	precision	0.9125	0.833333	0.906977	0.872917	0.901453			
f1-score   0.948052   0.555556   0.906977   0.751804   0.893285									
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### OUTPUT SCREENSHOTS



#### Video 1

- Talking about a niche subject matter
- Very wordy title
- Good LD Ratio
- Model only 13.5% confident that it is clickbait
- (thus, not clickbait)

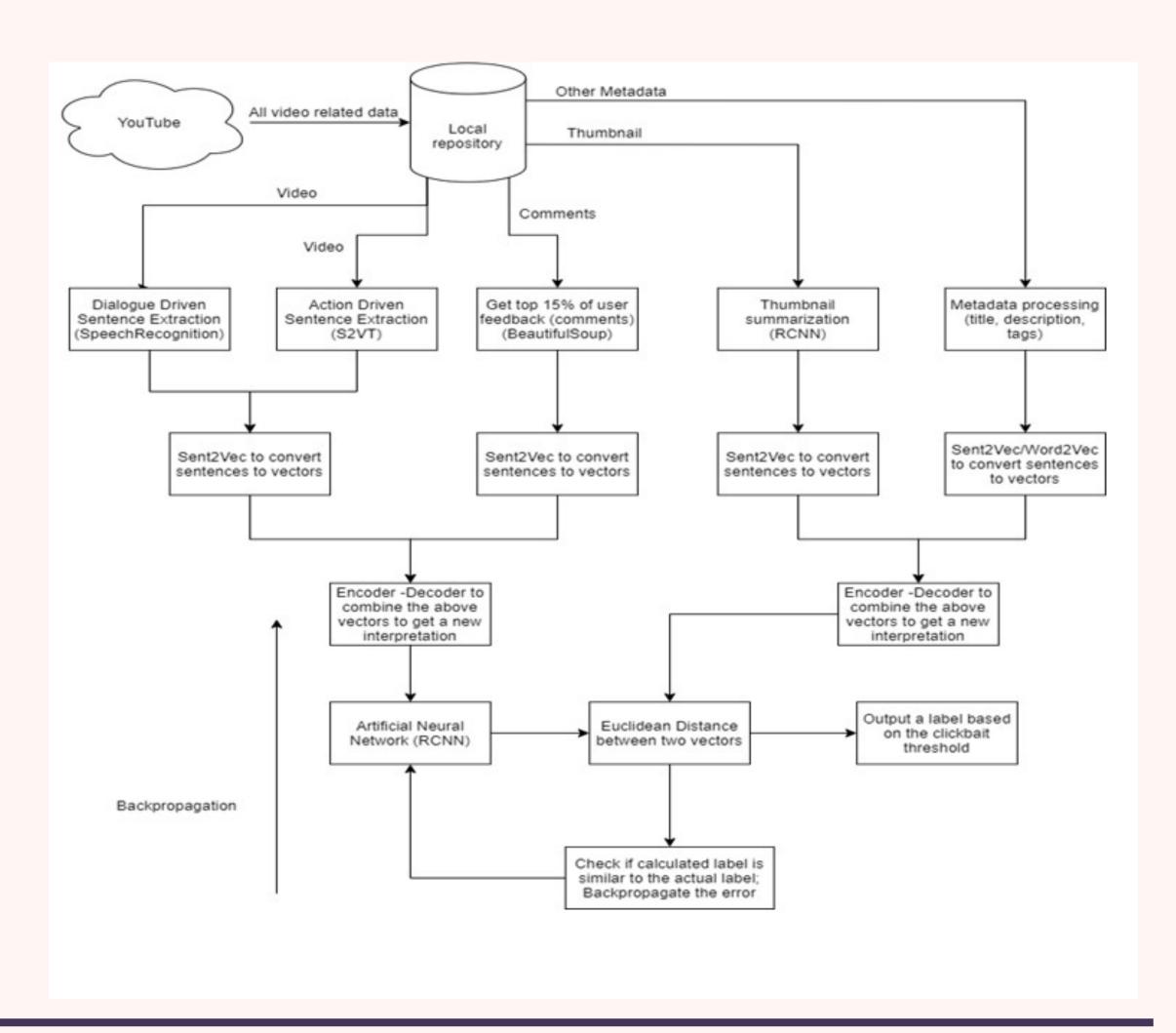


#### Video 2

- Very bright thumbnail
- Extremely catchy words
- Average LD Ratio
- Model 96.3% confident that it is clickbait
- (thus, clickbait)

### LIMITATIONS

- Biased to our opinion of what is clickbait and what is not
- Generic model for every YouTube video very difficult
- Lack of computational resources and quality data
- Unable to implement our initial vision for this project due to the above



### FUTURE ENHANCEMENTS

There are a number of enhancements that we can think of applying in the near future:

- \* Implementing video summarization and captioning to directly extract the essence of the video
- \* Building an extension that gets user feedback for the clickbait value and retrain periodically
- \* Consider uploader's track record of clickbait history once the model has enough data

### REFERENCES

- Sarjak Chawda, Aditi Patil, Abhishek Singh, Prof. Ashwini Save, A Novel Approach for Clickbait Detection' Proceedings of the Third International Conference on Trends in Electronics and Informatics (ICOEI 2019) IEEE Xplore Part Number: CFP19J32-ART; ISBN: 978-1-5386-9439-8
- E. Uzun, "A Novel Web Scraping Approach Using the Additional Information Obtained From Web Pages," in IEEE Access, vol. 8, pp. 61726-61740, 2020, doi: 10.1109/ACCESS.2020.2984503.
- Meng Wang, Richang Hong, Guangda Li, Zheng-Jun Zha, Shuicheng Yan, Tat-Seng Chua 'Event Driven Web Video Summarization by Tag Localization and Key-Shot Identification' in IEEE TRANSACTIONS ON MULTIMEDIA, VOL. 14, NO. 4, AUGUST 2012
- Andrej Karpathy, Li Fei-Fei 'Deep Visual-Semantic Alignments for Generating Image Descriptions' Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 3128-3137
- Jeff Donahue, Lisa Anne Hendricks, Marcus Rohrbach, Subhashini Venugopalan, Sergio Guadarrama, Kate Saenko, Trevor Darrell 'Long-term Recurrent Convolutional Networks for Visual Recognition and Description'
- Oriol Vinyals, Alexander Toshev, Samy Bengio, Dumitru Erhan 'Show and Tell: A Neural Image Caption Generator' Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 3156-3164
- Kelvin Xu, Jimmy Lei Ba, Ryan Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhutdinov, Richard S. Zemel, Yoshua Bengio 'Show, Attend and Tell: Neural Image Caption Generation with Visual Attention' Proceedings of the 32nd International Conference on Machine Learning, PMLR 37:2048-2057, 2015.
- Subhashini Venugopalan, Marcus Rohrbach, Jeff Donahue, Raymond Mooney, Trevor Darrell, Kate Saenko "Sequence to Sequence Video to Text" Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2015, pp. 4534-4542
- Abinash Pujahari and Dilip Singh Sisodia "Clickbait Detection using Multiple Categorization Techniques"
- Shu, Kai & Wang, Suhang & Lee, Dongwon & Liu, Huan. "(2020). Mining Disinformation and Fake News: Concepts, Methods, and Recent Advancements" 10.1007/978-3-030-42699-6\_1.

## THANKYOU