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Clickbait's Detection Using Deep Learning

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Abstract: *Clickbait's, in social media, are exaggerated headlines whose main motive is to mislead the reader to "click" on them. They create a nuisance in the online experience by creating a lure towards poor content. Online content creators are utilizing more of them to get increased page views and thereby more ad revenue without providing the backing content. This paper proposes a model for detection of click bait by utilizing Artificial neural networks and presents a compiled click bait corpus. We create a corpus using multiple social media platforms and utilize deep learning for learning features rather than undergoing the long and complex process of feature engineering. Our model achieves high performance in identification of clickbait's.*

Keywords: *Clickbaits, Exaggerated headlines, Artificial Neural Networks, Clickbait corpus*.

I. INTRODUCTION

The prevalence of click bait, which is nothing more than deceptive online content created with the sole purpose of drawing viewers to their website, is a current popular trend in online content. Poor quality, low-value content is a hallmark of click bait, and the agencies that use it heavily rely on ad revenue to make money.

In order to generate cash, they therefore construct titles that are visually appealing and entice people to click on them. These articles prey on human psychology and frequently promise a valuable experience or a crucial revelation; however, the user frequently does not receive the caliber of content they were hoping for. This frustrates the user. As can be seen, the headlines

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seem to promise some extremely unique or illuminating stuff, but when we click and visit the
page, we find virtually little worthwhile information. Since a few years ago, click bait has increased dramatically on social media to the point where some news publishers are now using these strategies.
There are a variety of explanations on why click bait has grown to be so popular. Around 69,
000 headlines from four worldwide media outlets were examined. They examined the polarity of these headlines' sentiments and discovered that extremes in sentiment led to an increase in popularity.
Even though click bait detection research is still in its early stages, click bait has received a lot of attention. Since click bait has become so prevalent in online news and media, there has been a considerable backlash against the social media sites where it is published. According to El-Arin and Tang, Facebook decided to take action against click bait, but the site is still inundated with the type of content. To fight this, a number of Twitter handles that exist just to identify click bait have emerged and amassed sizable followings.To raise awareness of these accounts, handles like @SavedYouAClick1 and @HuffPoSpoilers2 frequently update them feeds with click bait articles. The mechanism of their identification, however, is manual; the individuals who manage those Twitter accounts read the tweets and determine whether or not they are click bait for the advantage of other users.
Some of the research on this subject makes use of supervised learning and hand-crafted features. Our strategy, however, concentrates on deep learning for the detection. Recently, Deep Learning for Natural Language Processing (NLP) has drawn attention. Deep learning has now been shown to be quite successful for sentence categorization applications, despite initially being created for research on Computer Vision and Speech Recognition. According to a study published, sentence classification has been improved upon and has reached state-of-the-art levels using Artificial neural networks (ANN), a type of deep learning approach. We make publicly available a click bait corpus that has been taken from different social media sources. Currently no such corpus is available, and we utilize and evaluate the first deep learning model for click bait detection which achieves a high accuracy along with precision and recall. By utilizing a corpus derived from different social media sources, our model is able to learn generalized features and not features that are platform-specific. We also contribute by strengthening the support towards the evidence that

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pretraining of word vectors using unsupervised learning makes an important addition to deep learning methodologies for NLP.

MOTIVATION

There are a variety of explanations on why click bait has grown to be so popular. Around 69, 000 headlines from four worldwide media outlets were examined. They examined the polarity of these headlines' sentiments and discovered that extreme sentiments led to an increase in popularity. They discovered that headlines give readers their initial impression and can influence how they interpret news articles. A headline can change which prior knowledge is engaged in one's brain by highlighting specific aspects or facts. A headline's choice of words can affect one's attitude such that readers later remember facts that match what they anticipated, causing people to see the same content differently. The commonly referenced Loewenstein information gap theory is a notable alternative explanation. He wrote that these informational gaps cause the emotion of deprivation known as curiosity. To lessen or completely eliminate the feeling of deprivation, the curious person is motivated to learn the information that is missing. In other words, we feel uneasy when we don't know.

II. LITERATURE SURVEY

First impressions are lasting impressions: A primacy effect in memory for repetitions:

Object was presented to a subject five times, but either the first or fifth presentation was the mirror-reverse of the orientation that had been used on the previous four trials. Subjects reported seeing only the single mirror-reverse orientation more frequently if it was the first presentation than when it was the fifth presentation, and seeing only the standard orientation more frequently if it was presentations 1-4 than when it was presentations 2-5 when recognition was tested with both orientations at once. The results of a second experiment showed that the primacy effect applied to size changes as well. This pattern of outcomes supports the idea that top-down biases exist.

Effects of comprehension on retention of prose:

Two studies established the bias toward the characteristics of the first presentation in the encoding of a recurrent object. By presenting or omitting to offer a brief title that captures the passage's theme or major concept beforehand, metaphorical sections can be made to sound more understandable. By presenting the content in one of three ways—as random words, b as random phrases, or c as prose—we were able to independently change the word order. Both variable improved free recall performance

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in Experiment I, which involved 120 students, with no interactions. The identical input conditions were used in Exp. II with 240 undergraduates' students for a timed binary-recognition test. Only words that had already been determined to be thematically significant helped students who grasped the theme perform better, showing a true semantic effect and a method of matching test words to an internally maintained thematic database.

The Psychology of Curiosity: A Review and Reinterpretation:

There have been two phases of intense research on curiosity. The first, conducted in the 1960s, mainly examined the psychological roots of curiosity. The second, in the 1970s and 1980s, was distinguished by efforts to gauge curiosity's dimensions. The first wave is the focus of this article's review of their contributions. It is stated that the theoretical explanations of curiosity put out in the first period fell short in two ways: they did not provide a sufficient justification for why people actively pursue curiosity, and they did not identify the contextual factors that influence curiosity. Additionally, these accounts failed to mention or attempt to explain several important aspects of curiosity, such as its intensity, transience, connection to impulsivity, and propensity to disappoint when satiated. We present a fresh account of curiosity that makes an effort to correct these flaws. According to the new theory, curiosity is a type of cognitively induced deprivation that results from the perception of a knowledge or comprehension gap. All rights reserved (PsycINFO Database Record (c) 2012 APA).

Speech recognition with deep recurrent neural networks:

RNNs, or recurrent neural networks, are effective models for sequential data. When the input-output alignment is unknown, sequence labelling issues can be trained using end-to-end training techniques like Connectionist Temporal Classification. It has been especially successful to combine these techniques with the Long Short-term Memory RNN architecture, which has produced cutting-edge outcomes in the recognition of cursive handwriting. However, deep feedforward networks have produced greater outcomes than RNNs thus far in terms of speech recognition. This study explores deep recurrent neural networks, which combine flexible long-range context usage with several levels of representation that have been so successful in deep networks. We discover that deep Long Short-term Memory RNNs obtain superior performance when trained end-to-

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end with appropriate regularization. To our knowledge, the best result ever obtained on the TIMIT phoneme recognition benchmark was a test set error of 17.7%.

III. PROPOSED METHODOLOGY

We are utilizing a deep learning technique like LSTM in our suggested model. Deep learning

methods are more accurate and cause less loss than traditional algorithms, hence we utilized the LSTM algorithm. Long Short-Term Model (LSTM) in neural networks have proven to be one of the most effective methods for identifying strategies for prevention, early detection, and prediction This paper elaborates some of the methods for achieving the same and also

explains their results in this process

Click bait detection:

One of the most popular sources of information that people use today is online news portals. Its impact is caused by the occasionally questioned veracity of the news stories created by media actors. However, click bait is one of the issues with this information-gathering tool. This tactic seeks to entice readers to click on exaggerated headlines that often lead to disappointing reading. Therefore, this research was done to ascertain: 1) There is an existing dataset. 2) The process of data pre-processing, feature analysis, and classification employed in click bait detection. 3) Different procedures from the one used.

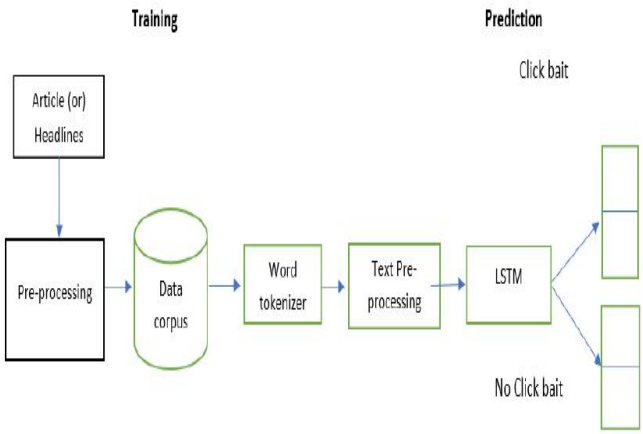

Fig.1 System architecture

IV. IMPLEMENTATION

Implementation is the stage where the theoretical design is turned into a working system. The

most crucial stage in achieving a new successful system with best accuracy and classifying the new images given by the user. The system can be implemented once after testing is done and found working according to the specification. It involves careful planning, investigation of the both current and existing system with implementation design of methods to achieve the change over an evaluation of change in method. Two major tasks are collecting the relevant data and training the model based on the data with model evaluation.

\Dataset information:

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This dataset contains headlines from various news sites such as 'WikiNews', 'New York Times', 'The Guardian', 'The Hindu', 'BuzzFeed', 'Upworthy', 'ViralNova', 'Thatscoop', 'Scoopwhoop' and 'ViralStories'. It has two columns first one contains headlines and the second one has numerical labels of clickbait in which 1 represents that it is clickbait and 0 represents that it is non-clickbait headline. The dataset contains 32000 rows of which 50% are clickbait and other 50% are non-clickbait.

- **Data Source:** Open Source
- **Data Collected From:** Kaggle
- **Data Source Link**: https://www.kaggle.com/datasets/amananandrai/clickbait-dataset

Text Pre-Processing:

Text data derived from natural language is unstructured and noisy. Text pre-processing involves transforming text into a clean and consistent format that can then be fed into a model for further analysis and learning. Text pre-processing techniques may be general so that they are applicable to many types of applications, or they can be specialized for a specific task. For example, the methods for processing scientific documents with equations and other mathematical symbols can be quite different from those for dealing with user comments on social media. However, some steps, such as sentence segmentation, tokenization, spelling corrections, and stemming, are common to both. Here's what you need to know about text pre-processing to improve your natural language processing (NLP).

The NLP Pre-processing Pipeline:

A natural language processing system for textual data reads, processes, analyzes, and interprets text. As a first step, the system preprocesses the text into a more structured format using several different stages. The output from one stage becomes an input for the next—hence the name "preprocessing pipeline." An NLP pipeline for document classification might include steps such as sentence segmentation, word tokenization, lowercasing, stemming or lemmatization, stop word removal, and spelling correction. Some or all of these commonly used text pre-processing stages are used in typical NLP systems, although the order can vary depending on the application.

Segmentation

Segmentation involves breaking up text into corresponding sentences. While this may seem like a trivial task, it has a few challenges. For example, in the English

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language, a period normally indicates the end of a sentence, but many abbreviations, including "Inc.," "Calif.," "Mr.," and "Ms.," and all fractional numbers contain periods and introduce uncertainty unless the end-of-sentence rules accommodate those exceptions.

Tokenization

The tokenization stage involves converting a sentence into a stream of words, also called "tokens." Tokens are the basic building blocks upon which analysis and other methods are

built. Many NLP toolkits allow users to input multiple criteria based on which word boundaries are determined. For example, you can use a whitespace or punctuation to determine if one word has ended and the next one has started. Again, in some instances, these rules might fail. For example, don't, it's, etc. are words themselves that contain punctuation marks and have to be dealt with separately.

Change Case

Changing the case involves converting all text to lowercase or uppercase so that all word strings follow a consistent format. Lowercasing is the more frequent choice in NLP software.

Stop-Words Removal

"Stop words" are frequently occurring words used to construct sentences. In the English language, stop words include *is*, *the*, *are*, *of*, *in,* and *and*. For some NLP applications, such as document categorization, sentiment analysis, and spam filtering, these words are redundant, and so are removed at the pre-processing stage.

Stemming

The term *word stem* is borrowed from linguistics and used to refer to the base or root form of a word. For example, *learn* is a base word for its variants such as *learn, learns, learning,* and *learned.* Stemming is the process of converting all words to their base form, or stem. Normally, a lookup table is used to find the word and its corresponding stem. Many search engines apply stemming for retrieving documents that match user queries. Stemming is also used at the pre-processing stage for applications such as emotion identification and text classification.

Lemmatization

Lemmatization is a more advanced form of stemming and involves converting all words to their corresponding root form, called "lemma." While stemming reduces all words to their stem via a lookup table, it does not employ any knowledge of the parts of speech or the context of the word. This means stemming can't distinguish which meaning of the word *right* is intended in the sentences "Please turn right at the next light" and "She is always right." The stemmer would stem *right* to *right* in both sentences; the lemmatizer

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would treat *right* differently based upon its usage in the two phrases. A lemmatizer also converts different word forms or inflections to a standard form. For example, it would convert *less* too *little*, *wrote* to *write*, *slept* to *sleep*, etc. It works with more rules of the language and contextual information than does a stemmer. It also relies on a dictionary to look up matching words. Because of that, it requires more processing power and time than a stemmer to generate output. For these reasons, some NLP applications only use a stemmer and not a lemmatizer.

Text Normalization

Text normalization is the pre-processing stage that converts text to a canonical representation. A common application is the processing of social media posts, where input text is shortened or words are spelled in different ways. For example, hello might be written as hellooo or something might appear as smth, and different people might choose to write real time, real-time, or realtime. Text normalization cleans the text and ideally replaces all words with their corresponding canonical representation. In the last example, all three forms would be converted to real time. Many text normalization stages also replace emojis in text with a corresponding word. For example, :-) is replaced by a happy face.

MODEL INFORMATION

LSTM (Long Short-Term Memory)

There can be various LSTM network types but we can divide them roughly into three types.

- LSTM forward pass
- LSTM backwards pass
- Bidirectional LSTM or Bi-LSTM

As the name suggests the forward pass and backward pass LSTM are unidirectional LSTM

which process the information in one direction either on the forward side or on the backside

where the bidirectional LSTM processes the data on both sides to persist the information. All

the above-given LSTM types work on a basic structure. Updating the basic structure causes the difference between various LSTM. Next, in the article, we will see different components of a basic LSTM model architecture.

The Architecture of LSTM

A simple LSTM network consists of the following components.

- Forget gate
- Input gate.
- Output gate

Why do we use LSTM with text data?

When performing normal text modeling, most of the pre-processing task and

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modelling task focuses on creating data sequentially. Examples of such tasks can be POS tagging, stop words elimination, sequencing of the text. These are the methods that try to make data understood by a model with less effort according to the known pattern. It can give the results. Here applying LSTM networks can have its own special feature. Earlier in the article, we have discussed that LSTM has a feature through which it can memorize the sequence of the data. It has one more feature that it works on the elimination of unused information and as we know the text data always consists a lot of unused information which can be eliminated by the LSTM so that the calculation timing and cost can be reduced, so basically the feature of elimination of unused information and memorizing the sequence of the information makes the

LSTM a powerful tool for performing text classification or other text-based tasks. In the modeling, we are making a sequential model. The first layer of the model is the embedding layer which uses the 32-length vector, and the next layer is the LSTM layer which has 100 neurons which will work as the memory unit of the model. After LSTM, the dense layer which is an output layer with sigmoid function, helps in providing the labels.

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V. RESULTS

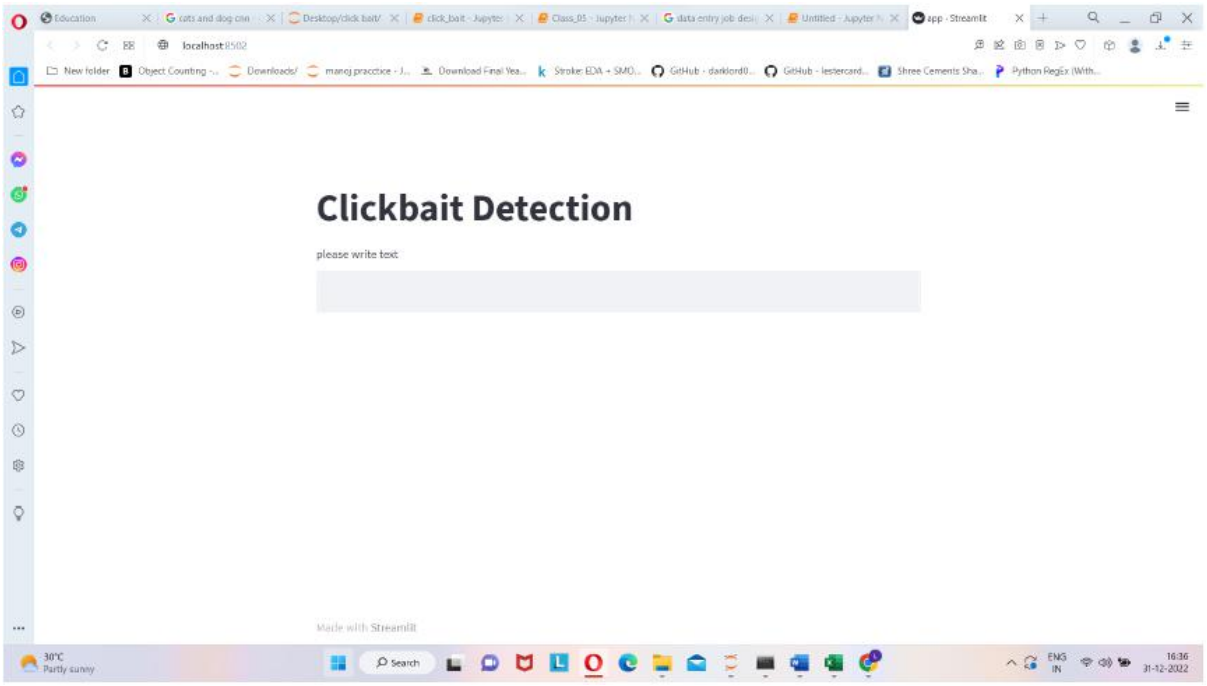

Fig.2 Clickbait detection first page

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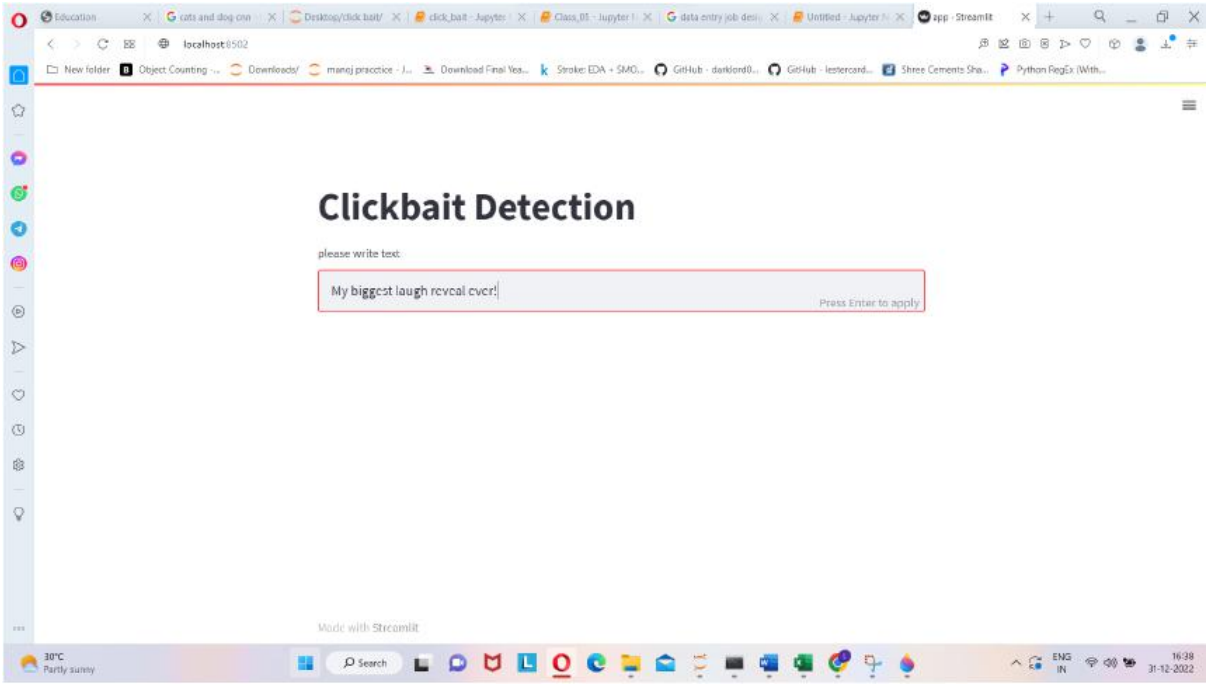

Fig.3 Clickbait detection search page

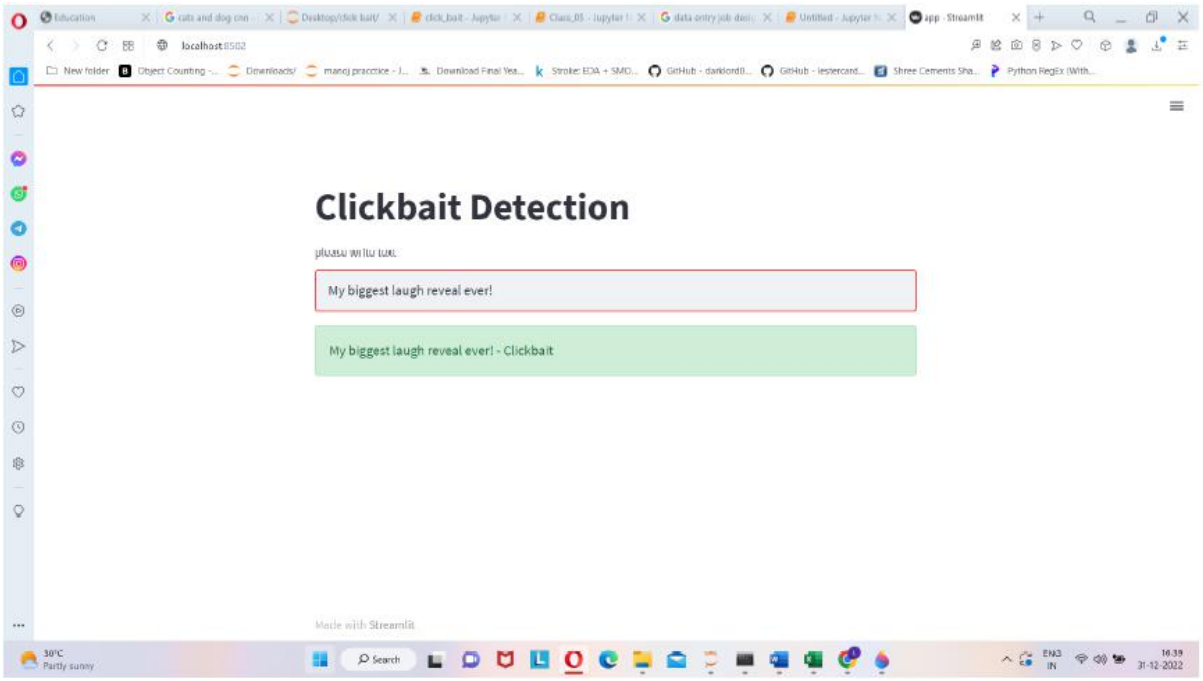

Fig.4 Result clickbait detection page

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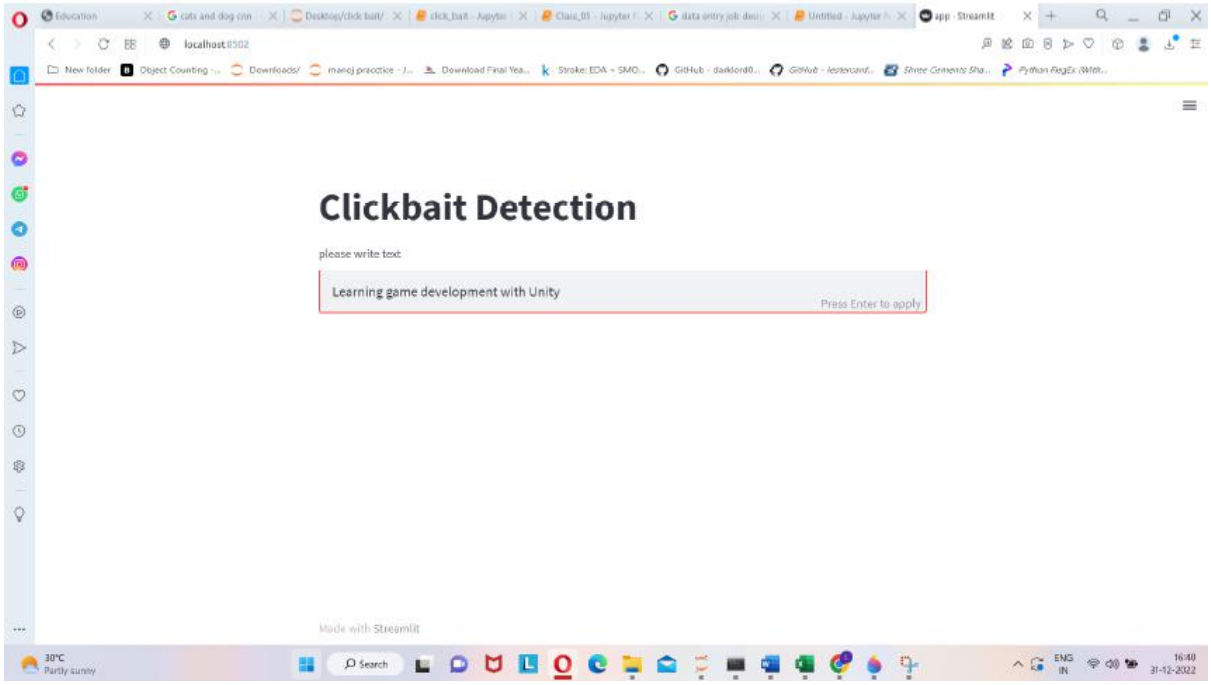

Fig.5 Enter text to search

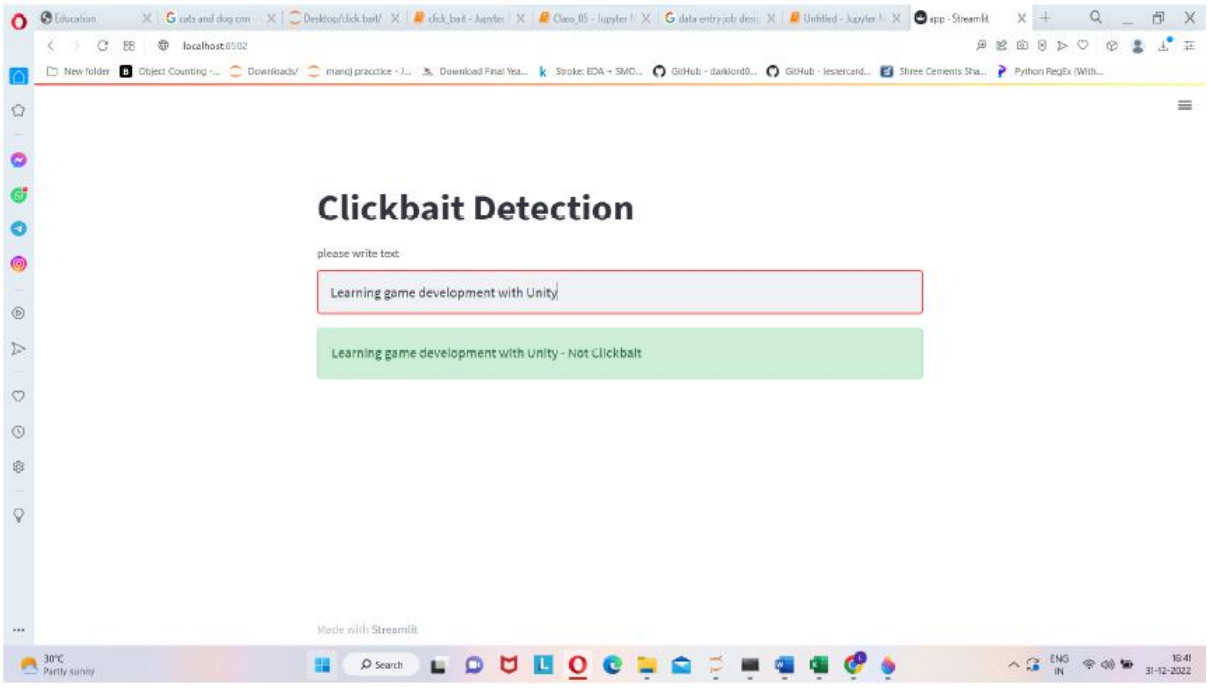

Fig. 6 Result not clickbait page

VI. CONCLUSION

We proposed several methods for predicting click bait detection. We created a corpus using multiple social media platforms and utilized deep learning for learning features rather than undergoing the long and complex process of feature engineering. Our model achieved high performance in identification of clickbait's. We intend to use a popular method ANN

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to reduce model size and improve runtime accuracy.

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