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A DEEP LEARNING-BASED APPROACH FOR DETECTING AND CLASSIFYING INAPPROPRIATE CONTENT IN YOUTUBE VIDEOS

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ABSTRACT_ There are now billions of videos on YouTube, with most of the viewers being young people. The growth in the quantity of videos has been exponential. To add insult to injury, some unscrupulous users post unsettling animated cartoon films and other material that parents should not allow their children to see. Therefore, social media sites should have a way to filter videos automatically in real time. In order to identify and categorize objectionable video material, this research proposes a new architecture based on deep learning. To do this, the suggested system employs a convolutional neural network (CNN) model named EfficientNet-B7 that has been pre-trained on ImageNet to extract video descriptors. A bidirectional long short-term memory (BiLSTM) network is trained to classify videos into many categories using these characteristics. In order to distribute attention probabilities throughout the network, an attention mechanism is also included after BiLSTM. We test these models using a dataset that has 111,156 cartoon clips tagged by humans from YouTube videos. The experimental findings showed that EfficientNet-BiLSTM achieved a higher accuracy (D=95.30%) than the EfficientNet-BiLSTM framework that was based on the attention mechanism. To continue, when compared to more conventional machine learning classifiers, deep learning ones outperform the pack. With an overall f1 score of D 0.9267, the combination of EfficientNet and BiLSTM, which includes 128 hidden units, achieved state-of-the-art performance. Furthermore, when stacked on top of CNN, BiLSTM outperforms state-of-the-art methods in detecting and classifying children-unsuitable video content because it better grasps the contextual information of video descriptors in network architecture.

1.INTRODUCTION

The amount of videos shared and seen on various social media sites has increased exponentially in recent years. There are a lot of videos on YouTube, which is why it's the most popular social networking site for sharing videos overall. Statistics show that over 500 hours of video material is posted every minute to YouTube, and that over 2 billion individuals throughout the globe have an account [1]. Video material, both general and customized, amounts to billions of hours that viewers of all ages may explore [2]. When thinking about such a huge crowdsourced database, it is quite tough to monitor and filter posted material in compliance with platform requirements. Harmful individuals are able to spam because they deceive audiences with misleadingly promoted material. This content might be video, audio, or text. The most upsetting thing that bad users do is expose young people to scary stuff, even if it's made to seem like it's safe for them. YouTube has solidified its position as a substitute for conventional screen media (like television) and accounts for the vast majority of children's internet time today [3, 4]. The press statement from YouTube [5] further revealed that the social media platform is quite popular among younger demographics compared to others. The lack of constraints is the reason for its appeal [6].

2.LITERATURESURVEY

2.1 An effective technique for detecting communities in social networks based on modularity, published in the IEEE.

A network identification approach is anticipated to detect clusters in an interpersonal organization (SN) where hubs within the group have significant connections to hubs outside the group. In the field of long-distance interpersonal communication, this approach poses one of the greatest challenges to large-scale data processing. Onscreen actors may be represented as hubs in a schematic information structure, while relationships between entertainers can be shown by edges. There are limitations to any form of computation that an SN may do when attempting to locate networks over a massive region. A robust quality-based network discovery computation is presented in this research. The suggested strategy was determined to be the most trustworthy and accurate when contrasted with other preexisting network identification techniques. The specificity and bunching coefficient are two examples of the many metrics used to measure the quality of a calculation's execution.

In a distributed setting, 2.2 Louvain algorithm is used for large-scale graph community detection.

For very large diagrams, we provide a novel network discovery calculation that utilizes the Louvain method. By using this approach, we can guarantee that the current work is finished and that the communication between the different processors is adjusted correctly. A different heuristic approach will be used to expedite the network building process within a suitable domain and guarantee that the circulating bunching computation will be integrated with the

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final network blueprint. Our enhanced test study proved that our method, when applied to designed chart datasets, is both flexible and accurate.

The recommendation representation using common attributes is discussed in section 2.3 of the book "What Videos Are Similar to Yours? ".Still, it's not easy to fix the cold start problem, discover how social traits and substance features are depicted in bad customer video communications, and modify their roles. Currently, there is a proposal for a technique called REDAR that uses lattice factorization to regularize dual-factor regression. At now, the shortage issue is being addressed by the expert combination of material attributes and traits. A progressive REDAR variant solves the cool-start problem. The suggested method for video recommendation application outperforms state-of-the-art pattern approaches by over 20% in terms of overall performance.

3.PROPOSED SYSTEM

1. A new convolutional neural network (CNN) called EfficientNet-B7 and a deep learning framework called BiLSTM are suggested by the system for the purpose of detecting and classifying improper video material.

2. The system provides a ground truth video dataset consisting of 1860 minutes (111,561 seconds) of cartoon films aimed at children under the age of 13. Annotations have been made by hand to these videos. We scoured YouTube for all of these videos featuring famous cartoon characters. An unsafe or safe class annotation is appended to every video clip. To determine if a video is hazardous, we look for examples of fantasy violence and pornographic material. We also want to share this dataset with academics for their use.

3. The system assesses our suggested CNN-BiLSTM architecture. At 95.66 percent, our multiclass video classifier passed the validation test. We also assess and contrast a number of different state-of-the-art deep learning and machine learning architectures for the purpose of improper video content detection.

3.1 IMPLEMENTTAION

Service Provider

A valid username and password are required for the Service Provider to access this module. Once he has successfully logged in, he will be able to do several actions, including: Data Sets for Training and Testing YouTube Content, Check out the Bar Chart for Trained and Tested Accuracy, Check Out the Results for Trained and Tested Accuracy,You may see the results of the YouTube content data sets ratio, download the data sets that are predicted to be there, and see the data sets that are available for viewing.See Who Is Remotely Connected.

View and Authorize Users

The admin can get a complete rundown of all registered users in this section. Here, the administrator may see the user's information (name, email, and address) and grant them access.

Remote User

All all, there are n users in this module. Registration is required prior to performing any operations. Details will be entered into the database after a user registers. He will need to log in using the permitted username and password when registration is completed. Users may do things like see their profiles, predict the kind of content that will be popular on YouTube, and register and log in after the login process is complete.

4 .CONCLUSION

This research presents a new framework for detecting and classifying children's unsuitable video material that is based on deep learning. Video feature extraction makes use of the EfficientNet-B7 architecture in conjunction with TL. In the BiLSTM network, the model learns the best ways to represent videos and does multiclass video classification using the extracted features. All of the test runs make use of the same dataset—111,156 YouTube video clips tagged with cartoons. Test models including Efficient Net-FC, Efficient Net-SVM, Efficient Net-KNN, Efficient Net-Random Forest, and Efficient Net-BiLSTM with attention mechanism-based models (with hidden units D 64, 128, 256, and 512) outperformed the suggested framework of Efficient Net-BiLSTM (with hidden units D 128) in terms of performance, with an accuracy of 95.66%. Furthermore, in the performance comparison, our BiLSTM-based framework outperformed other existing models and approaches with a recall score of 92.22%. The suggested technique for identifying child-oriented video material that relies on deep learning has many advantages, including the following:

1) It filters live-captured movies by processing them at a pace of 22 frames per second using a deep learning architecture based on Ef_cientNet-B7 and BiLSTM. This accounts for the current, actual circumstances.

2) It may assist any site that allows users to share videos blur or conceal disturbing frames or eliminate inappropriate recordings.

3) It may also help with the development of parental control systems for the Internet by giving users the option to install plugins or extensions that automatically filter out child-harming material.

Furthermore, our method for detecting kid-friendly YouTube videos does not rely on the video metadata, which may be readily manipulated by bad users to trick viewers. To improve the model's performance even further by understanding the global video representations, we want to merge the spatial RGB frame stream with the temporal optical low frame stream in the future. Also, we want to improve the categorization labels so that we can target specific YouTube videos that include explicit material that children shouldn't see.

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