| No. | Name of paper | Purpose | Advantage | Limitations | Applied Field | Future Work Possible | Dataset used |
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| **1.** | Text Recognition using Image Processing | A shallow representation of the low-resolution captured document images is proposed. | • Extremely efficient to extract all kinds of bimodal images including blur and illumination.<br>• Solves the problem of offline character recognition. | • Most OCR software packages - difficult to recognize the text.<br>• Due to very low-resolution, it is hard to extract the complete layout structure (logical or physical) of the documents and apply OCR systems. | • Support Vector Machines (SVM) based method with the<br>• multilayer perceptron (MLP) | • Text extraction from web images can also help in filtering of images with offensive language.<br>• It is also helpful in conversion of web page to voice.<br>• voice coding for blinds, intelligent transport system, Image tagging, robot vision and scene analysis, etc. | Not provided |
| **2.** | Object Detection with Deep Learning: A Review | A review on deep learning based object detection frameworks. Survey several specific tasks, including salient object detection, face detection and pedestrian detection. | • Improved detection performance.<br>• Deeper architectures with the capacity to learn more complex features (semantic, high-level, deeper) than shallow ones.<br>• No need to design features manually. | • Localization accuracy on small objects is low<br>• Small object detection is not up to the mark in face detection.<br>• Huge burden on manual labor in accomplishing real-time object detection. | • Deep Learning and its tool (CNN) Convolutional Neural Network.<br>• Deep Neural Networks (DNNs)<br>• Fast R-CNN-optimizes classification and bounding box regression tasks.<br>• Faster R-CNN-additional subnetwork to generate region proposals.<br>• YOLO-object detection via a fixed-grid regression | • Small object detection in face detection task.<br>• Decrease manual labor and accomplish real-time object detection.<br>• To extend typical methods for 2D object detection to adapt 3D object detection and video object detection, with the requirements from autonomous driving, intelligent transportation and intelligent surveillance. | Microsoft COCO dataset<br><br>PASCAL VOC 2007(R-FCN)<br><br>PASCAL VOC 2012<br><br>ILSVRC, a very large auxiliary dataset (R-CNN) |
| **3.** | Image Matters: Scalable Detection of Offensive and Non-compliant Content / Logo in Product Images | Present a computer vision driven offensive and non-compliant image detection system for extremely large image datasets. | • Fast and reliable processing of hundreds of thousands of images every day.<br>• Solved by using **two-stage inference**. | • Running every image of the catalog through an array of deep learning models is prohibitively slow and costly. | • Deep learning-Inception-v3 based deep learning model<br>• FAISS or an Elastic Search (for approx. nearest neighbor search)<br>• Logistic Regression & Random Forest for shallow classifier.<br>• Faster R-CNN and YOLO. | • Combining image and textual signals from products to build a more effective model.<br>• Allow the system to detect unforeseen types of non-compliant cases with minimal amount of retraining and fine tuning of existing parameters. | ImageNet Dataset. |
| **4.** | Skin Sheriff: A Machine Learning Solution for Detecting Explicit Images | Present an adaptable solution for detecting nudity or pornography in color images. We combine a novel skin detection | It can be aligned to reflect individual subjective views, or, in the case of law enforcement, legal boundaries. | • Objects that have the same color as skin and therefore produce false positives in the detected skin areas.<br>• Not work for skin | • Support Vector Machine (SVM)-based machine learning approach | • To enhance the overall performance of our approach. To improve skin and shape detection, other frames of the same video could be used. | Compaq dataset |

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| | | approach with machine learning techniques to alleviate manual image screening. | | which is too dark or bright.<br>• Suboptimal data structures used for storing images also increase the runtime.<br>• No clear definition between pornography, nudity and inoffensive images (vary from country and between individuals). | | • Logical evolution of image-based skin detection is video analysis. | |
| **8.** | ON LINE SOCIAL NETWORK CONTENT AND IMAGE FILTERING, CLASSIFICATIONS | | | | | | |
| **9** | A Framework for Cyberbullying Detection in Social Network | proposed an automated system to detect cyberbullying activities like abusive text messages or images on the social network. | a very few implementation has been done to detect the cyberbullying activities by analyzing the combination of text and image data.<br><br>Only the text analysis have gained the majority as a detection mechanism. We have proposed an automated system that can identify the abusive kinds of images and text messages. | | In image analysis, Bag of Visual Words (BoVW) concept has been used with the SVM classifier for classification of adult images.<br><br>For analysis of text messages, Bag of words (BoW) is incorporated with the Naïve Bayes classifier to classify the abusive text message.<br><br>Finally, Boolean system categorize the bullying content by considering the analysis results obtained by the text & image classification modules. | can implement cyber bullying detection techniques for audio and video messages.<br><br>In the text analysis also, can include sentiment or context related knowledge to enhance the detection of bullying text contents. | |
| **10** | Detection of Cyberbullying Incidents on the Instagram Social Network | The main goal of this paper is to investigate fundamentally new approaches to understand and automatically detect incidents of cyberbullying over images in Instagram. | Major Contributions- an appropriate definition of cyberbullying that incorporates both frequency of negativity and imbalance powe is applied in large-scale labeling, and is differentiated from cyberaggression; cyberbullying is studied in the context of a media-based social network, incorporating both images and comments | A limitation of the current classifier is that it is designed only for highly negative media sessions. A more general classifier that can apply to all media sessions is needed.<br><br>This will also require to enlarge our labeled data set substantially. Incorporating image features needs to be automated by applying image recognition algorithms. | Employed a multi-modal feature obtained from text, meta data and images as input into a Naïve Bayes and linear SVM classifier, | Possibility to improve the performance of the classifier by adding more input features, such as new image features, temporal behavior of commenting, mobile sensor data,<br><br>plan to consider designing classifiers for cyberaggression in addition to cyberbullying, and to investigate those media sessions that represent the former but not the latter behavior.<br><br>To obtain greater detail | collected a sample Instagram data set consisting of images and their associated comments. |

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| | | | in the labeling; | | | from the labeling surveys. | |
| **11** | Prediction of Cyberbullying Incidents on the Instagram Social Network | The main goal of this paper is to investigate fundamentally new approaches to understand and automatically detect and predict incidents of cyberbullying in Instagram. | | A limitation of current classifier is that it is designed only for media sessions that have at least one profanity word.<br><br>Only considered the image content and image and user metadata for prediction of cyberbullying. | | New algorithms should be considered, such as deep learning and neural networks.<br><br>More input features should be evaluated, such as new image features, mobile sensor data, etc.<br><br>Considering the commenting history of users in previously shared media can prove to be useful.<br><br>to obtain greater detail from the labeling surveys. | Instagram Dataset. |
| **12** | Content-Driven Detection of Cyberbullying on the Instagram Social Network | Investigate use of posted images and captions for improved detection of bullying in response to shared content. | | | CNN<br>SVM | This work is a foundational step toward developing software tools for social networks to monitor cyberbullying. | Instagram dataset |
| **13** | A Web Pornography Patrol System by Content-based<br><br>Analysis: In Particular Text and Image | In this paper, a content-based analysis technique is examined to filter the pornographic web sites.<br>The system consists of two primary content-based filtering techniques such as text and image. | The empirical results show that the analysis methods of text and image are more effective for pornographic web filtering. | | For text analysis, the Support Vector Machine (SVM) algorithm and N-gram model based on Bayes' theorem is applied and experimented to filter pornographic text for both Thai and English language web sites. | | Use URLs of various websites. |
| **14** | Adult Image Content Filtering: A Statistical Method Based on Multi-Color Skin Modeling | In this paper, a simple statistical framework for recognizing adult images based on an MCSM (Multi-Color Skin Model) is described. | Quantitative evaluation shows that the method compares favorably with the state-of-the-art methods in terms of detection rate and false alarm, while reducing the computational complexity by a factor of 1/6 with respect to the Forsyth's method. | | MCSM (Multi-Color Skin Model) | The future work will be along two major axes.<br><br>The first will be the further improvement of the method by using more elaborated feature sets; for example, by adding texture features, while the second will be to examine the robustness of the method by performing more experiments on real-word video data. | Own images database. The database has 562 test adult images and 1580 assorted control images, containing some images of people but none of adult images. |
| **15** | An adult image identification system employing | In this paper, an adult image identification approach is proposed based | The proposed method is superior to Others based on various performance metrics. | | Based on the MPEG-7's SCD, EHD, and the proposed CD feature, | | |

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| | image<br><br>retrieval technique | on content-based image retrieval technique. | | | | | |
| **16** | Blocking Objectionable Images: Adult Images and Harmful Symbols* | The paper describes a practical objectionable image filtering system aimed at children's safer web<br>access. It includes two image filters: adult image filter and harmful symbol filter. | | | Skin detection with MaxEnt, Bethe tree approximation, parameter estimation of MaxEnt is eradicated.<br><br>BP algorithm<br><br>MLP<br>classifier, | To improve the performance of our filters, one can<br>use a face detector in adult image filter, and extract local features besides global features in symbol filter.<br><br>Combining with<br>text analysis could improve the performance of the image filters. | |
| **18.** | Characterization of the objectionable image content (pornography and nude images) of the Chilean web | Classification of the images in three classes: normal, porno and<br>nude | .<br>• 76% detection rate of objectionable images (porno + nude)<br>• Accurate results<br>• Content-based analysis of images for detecting offensive material.<br>• lists of adult web site addresses for filtering the access to these prohibited sites | • Images with size under 50x50 pixels are not considered.<br><br>• 11% false positive rates. | • Skin detection using skindiff algorithm which uses MoG skin model and local spatial context.<br>• Classification module, statistical classifier: a two-class cascade SVM | • The methodology can be employed for the automatic discovering of new pornographic sites.<br>• Characterization of pornographic contents can be important for determining user's behavior and user bandwidth requirement. | |
| **19.** | Neural Network based Adult Image Classification | classification system that can categorize input images into adult or<br>non-adult images. | Achieved 95% of the true rate whereas it reduces the false positive rate below 3%. | | • MPEG-7 reference software: the experimentation Model for feature extraction.<br>• Backpropagation algorithm to train the neural network. | Prototype system that can be used for the adult image classification. | 9000 images dult: 4500, non-adult: 4500) |
| **20.** | Automated Hate speech Detection and the problem of Offensive language | To label tweets into three categories: hate speech, offensive language or neither | Overall precision 0.91, recall of 0.90, and F1 score of 0.90. | 40% of hate speech is misclassified | • logistic regression with L2 regularization<br>• scikit-learn | Identify and correct the bias between hate speech and offensive language.<br><br>Better account for context and the heterogeneity in hate speech usage. | 35.4 million tweets from 33,458 Twitter users |
| **21.** | Abusive language detection in online user content | To develop a machine learning based method to detect hate speech on online | • accurate, automated methods to flag abusive language | • Avoids the problem of having to retrain embedding on each iteration. | • supervised classifycation method which uses NLP feature<br>• Vowpal Wabbit's | • To use this methodology for other languages than English.<br>• Another area of | comments postop on Yahoo!, Finance |

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| | | user comments from two domains which outperforms a state-of-the-art deep learning approach | | | regression model | future work includes using the context of the comment as additional features. | and news during October 2012 and January 2014 |
| **23.** | Detecting offensive language in Social Media to protect Adolescent Online safety | To detect offensive content and identify potential offensive users in social media | • High accuracy in subtle offensive message detection and it can reduce the false positive rate.<br>• achieves precision of 98.24% and recall of 94.34% in sentence offensive detection<br>• Processing speed is approx. 10msec per sentence | | Lexical Syntactic Feature-based (LSF) language model | This model will be helpful in online offensive language monitoring & building a safer online environment. | Dataset includes comments from 2,175,474 distinct users |
| **24.** | Detecting Offensive Language in Tweets Using Deep Learning | To develop a novel method that can improve the state-of-art approaches within hate-speech classification, in terms of classification performance / accuracy. | • Better performance in classifying short messages.<br>• a deep learning architecture that uses word frequency vectorization | | Neural Network solution composed of Multiple Long-Short-Term-Memory based classifiers. | To investigate other sources of information that can be utilized to detect hateful message | 16k short messages from Twitter |
| **25** | Detecting Offensive Tweets via Topical Feature Discovery over a Large Scale Twitter Corpus | Approach detects offensive tweets using highly expressive topical features as well as the reliable lexicon feature in a single machine learning framework. | 1.With a limited list of seed words, more novel offensive patterns are automatically captured<br>2. Approach is able to detect up to 5.4% more profane patterns without sacrificing the FP. | 1. Volume of raw training Corpus is huge.<br>2. Task of offensiveness detection is difficult sometimes.<br>3. Due to Limitation of space only LR results are proposed. | 1.ML Algorithms - Logistic Regression,SVM,RF,J48 Decision Trees<br>2.Artificial Intelligence-Natural Language Processing<br>3.Pattern Recognition | 1..In future the benefits of more complex features within the topic representation Can be considered<br>2.To adopt complex weighing algo like TF-IDF to capture occurrence of profane words | |
| **26** | Identifying and Categorizing Offensive Language in Social Media | A three-level hierarchical schema that considers (i) whether a message is offensive or not , (ii) what is the type of the offensive message and (iii) who is the target of the offensive | 1.Aggression identification<br>2.Bullying detection<br>3.Hate speech identification<br>4.Toxic comment Detection | 1. Small size of dataset used.<br>2. Issues of class Imbalance weren't solved. | 1.Machine Learning<br>2.Deep Learning | 1.To increase size of Dataset<br>2.Addressing issues such as class imbalance and the small size for the test partition, | |

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| | | message | | | | | |
| **27** | Improving cyberbull ying detection with user context | The results of a study on the detection of cyberbullying in YouTube comments. | 1. It shows that detection performance improves when we add more bullying-specific features and that it improves further when context information is added. | As the data sets are different, it is not possible<br>to come up with a clear comparison of our results<br>2. Due to privacy issues Datasets used weren't accessible. | Supervised Learning | 1. Gender and the channels subscribed to could also be taken into account.<br>2. To employ predicting algorithms such as age prediction. | |
| **28** | Offensive Language Detection Using Multi-level Classificat ion | Detecting flames and abusive Language. | 1. The stability of the system after each level rose, and at the last level, the results on cross-validation and on the test set were quite similar.<br>2.The software can be used for message level or sentence level classification application in real-time applications.<br>3.Sensitive to Punctuation and Grammar mistakes | It does not consider the syntactical structure of the messages. | Statistical Models and Rule based Patterns | 1.add a synchronized adaptive weight modifier module to the IALD accessory,<br>2. Could apply second order co-occurrence features. | |
| **29** | Predicting the Type and Target of Offensive Posts in Social Media | Goal of the current research was to investigate the automatic detection of cyberbullying-related posts on social media. | Automatic detection of signals of Cyber Bullying on Social Media. | 1.claims intention to be inherent to traditional bullying, is much harder to ascertain in an online environment. | Similar to paper 26 | 1. To apply deep learning techniques to improve classifier performance.<br>2. Detection of fine-grained cyberbullying categories such as threats, curses and expressions of racism and hate.<br>3. false positives often include implicit cyberbullying or | |
| **30** | Automati c detection of cyberbull ying in social media text | | | | ML method based on SVM Classifier | | |
| **31** | Explicit Content Image Detection | Approach detects offensive tweets using highly expressive topical features as well as the reliable lexicon feature in a single machine learning framework. | We can rule out many objects using a simple filter, in this case we use skin detection to get only the areas of skin which are the most important for our objective. | To determine histogram of the HSV Model. | 1.Computer Vision Algorithms<br><br>2.Pattern Recognition<br><br>3.FTK software Explicit Image Detection. | ---------- | |

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| **32** | Scalable Detection of Offensive and Non-compliant Content / Logo in Product Images | It is a system that detects and removes offensive and non-compliant images from an e-commerce catalog containing hundreds of millions of items. | 1. Obtaining image locations at no Cost.<br>2.Technical challenges such as lack of training data, severe class imbalance, fine-grained class definitions were solved | 1.Lack of Usable Training Data<br><br>2.Scale and Variation in Catalog<br><br>3.Variety of Defining Examples<br><br>4.Custom and Fine-Grained Class<br><br>5.Definitions Constraints on using text | 1. Deep Learning<br>2. Detection framework used.<br>-Iterative Training<br>-Transfer Learning<br>-Multi Stage Inference. | 1. Combining image and textual signals from products to make an effective model.<br><br>2. To unforeseen types of non-compliant cases with minimal amount of re-training and fine tuning of existing parameters | |
| **33.** | Image Steganography and Global Terrorism | To identify terrorism acts using machine learning domain | Taken into account the data of all around the world | | | Improve efficiency and accuracy | |
| **34.** | Arbitrary Category Classification of Websites Based on Image Content | Classifying websites based on the content it shows to its user and identification of presence of inappropriate content on them. | | Low accuracy<br>Difficult to access datasets for the same | | | |
| **35.** | COMBATING TERRORISM WITH BIOMETRIC AUTHENTICATION USING FACE RECOGNITION | Using face recognition as biometric authentication to identify terrorism and opt measures to combat it. | | Low accuracy in face identification<br>Less security | Image processing – face recognition (CNN) | Improve the algorithm to make biometric authentication using face recognition more safe | |
| **36.** | Extracting text from image document and displaying its related information | To read text information from the image documents which are captured by camera, scanner | • gives good performance in text extraction by combining two algorithms, Edge Based and Connected Components<br>• The extracted text recognition done by OCR with better accuracy. | The paper does not include handwritten and complex font text. | • MATLAB code integrated with Simulink Support Package<br>• Optical Character Recognition (OCR) engine | To include handwritten and complex font texts. | - |
| **37.** | Text Extraction from images and Displaying its related information | To create a system that extracts text in images. | • Tilt text is detected.<br>• High accuracy in natural senses.<br>• Requires less extraction database.<br>• Most relevant and accurate data is retrieved from the web.. | Handwritten text cannot be accurately recognized. | • text extraction algorithm<br>• web context search algorithm<br>• web mining algorithm | • Analysis of documents can be easily done.<br>• Industrial automation. | - |

- Irrelevant (Or Outdated) - Important paper - Repeated

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