Toxic Comment Identification using NLP

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***Abstract* — Toxic comments are the comments found in the online forums that are rude, offensive, or unfair and usually cause many users to exit the conversation. The prospect of cyberbullying and abuse restricts people's access to alternative opinions, preventing a free interchange of ideas. As per this survey of different papers the author conclude that among those papers, the techniques which were used are binary relevance, classifier chain and label power of machine learning algorithm. Among these, the binary relevance is found to give a bit higher accuracy as compared to other techniques which were used. Also, further experiment with more complex deep learning algorithms can be used to get high performance which will be beneficial for the future researchers to develop their systems more efficiently and precisely.**

Keywords— Toxic Comment, Natural Language Processing, Binary Relevance, Classifier Chain, and Label Power.

I. INTRODUCTION

One of the best inventions of the twenty-first century is that one person can connect with another person anywhere in the world using only a smartphone and the internet, thanks to the rapid growth of computer science and technology [1] .

Comments that are rude, disrespectful, or have a tendency to make users leave the discussion are referred to as toxic comments. If these toxic comment can be automatically identified, they could have safer discussions on various social networks, news portals, or online forums. Manual moderation of comments is costly, ineffective, and sometimes infeasible. Different machine learning techniques, primarily various deep neural network architectures, are used to automatically or semiautomatically detect toxic comments [9] .

Adults can manage social media abuse to some extent, but children and teens are susceptible to serious mental health issues. Some people abuse the freedom of speech and expression provided by social media platforms to flood these platforms with offensive content. Adults can control this abusive behaviour, but children and teenagers are even more vulnerable. There has been a 70% increase in bullying and hate speech among children and teenagers since the Covid-19 shutdown.

There has been a 70% increase in bullying and hate speech among children and teenagers since the Covid-19 shutdown. With regard to social and ethical issues, there has been an increase in interest in the communities of artificial intelligence and natural language processing as a result of the global commitment to combat toxic content. This harmful content is characterised by hate, offensiveness, abuse, cyberbullying, violence, and other forms of harassment online.

To limit toxic content, most social media platforms use content moderation. Thus, require unbiased and scalable systems to identify harmful content in real-time due to the enormous scope of online content. If these systems can pinpoint the section of text that qualifies the content as toxic, people will start to trust them. To encourage positive conversations among people, toxicfree social media platforms are required [8].

To identify toxic comments, variety of identification methods and machine learning algorithms can be use on the dataset.

II. RELATED WORK

Toxic comment identification has been extensively studied in recent years, especially in the context of social media, where researchers have used various machine learning algorithms to classify toxic comments found on social media forums into different toxic classes [1].

Determine the toxicity of a user's comment based on the comment itself. The objective is to develop a classifier model that can foretell whether input text is improper (toxic).

A. Machine Learning:

Artificial intelligence (AI) systems can automatically learn from their experiences and get better over time thanks to a technique called machine learning. The development of computer programmes that can access data and use it to learn for themselves is the focus of machine learning [23] .

The figure below (fig 1) describes the machine learning and its types which mainly consists of Supervised, Unsupervised, and reinforcement learning along with its applications.

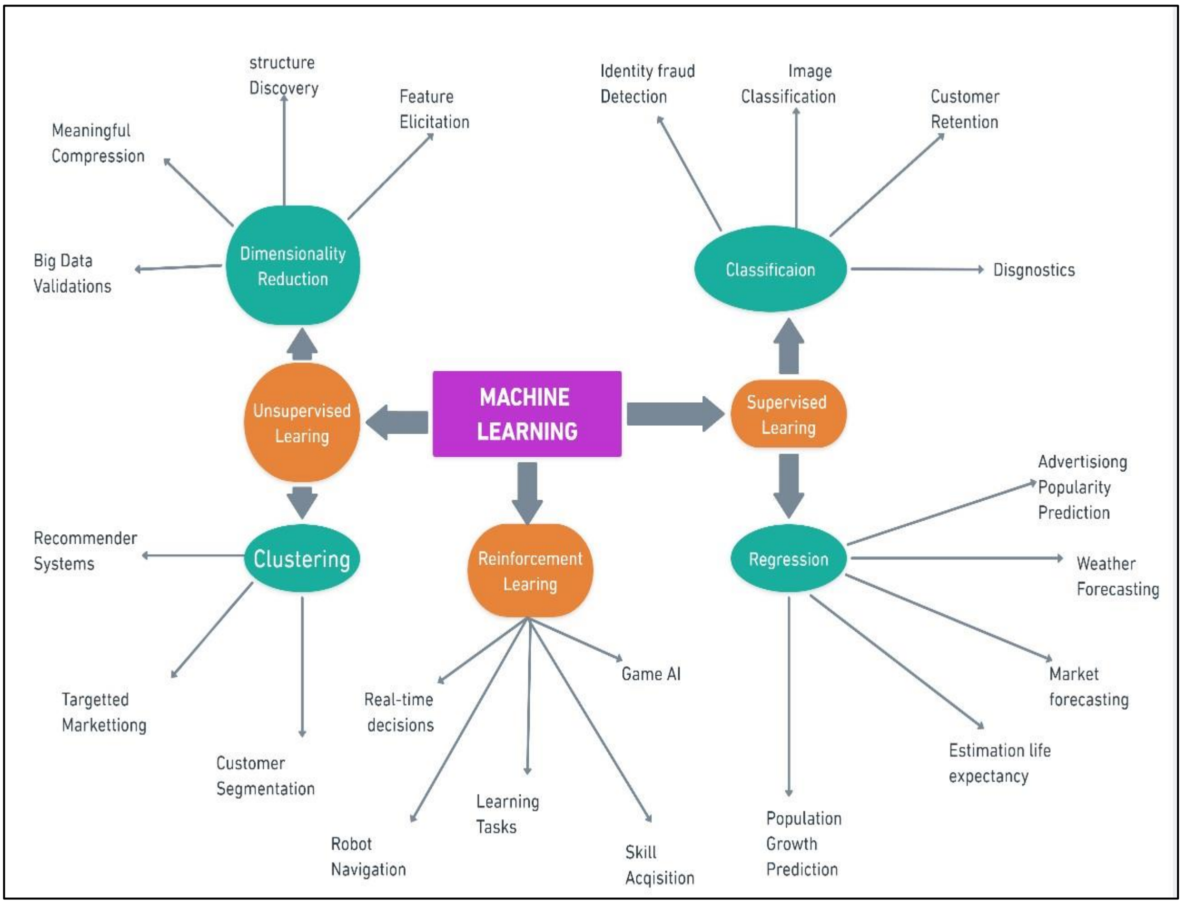

Fig 1 : Types of Machine Learning and its applications

A.1 Unsupervised Learning

Unsupervised learning is a machine learning technique in which models are not supervised using training dataset. Instead, models itself find the hidden patterns and insights from the given data. It can be compared to learning which takes place in the human brain while learning new things.

A.2 Supervised Learning

Supervised learning is the type of machine learning in which machines are trained using well "labelled" training data, and on basis of that data, machines predict the output.

A.3 Reinforcement Learning

Reinforcement Learning is a feedback-based Machine learning technique in which an agent learns to behave in an environment by performing the actions and seeing the results of actions. For each good action, the agent gets positive feedback, and for each bad action, the agent gets negative feedback or penalty.

B. Deep Learning:

Deep Learning is a specialized form of machine learning. A machine learning workflow starts with relevant feature being manually extracted from images, the features are then used to create a model that categorizes the object in the image [24] .

The figure below (fig 2) describes the hierarchy of Artificial Intelligence which consists of Machine Learning and Deep Learning as its sub parts.

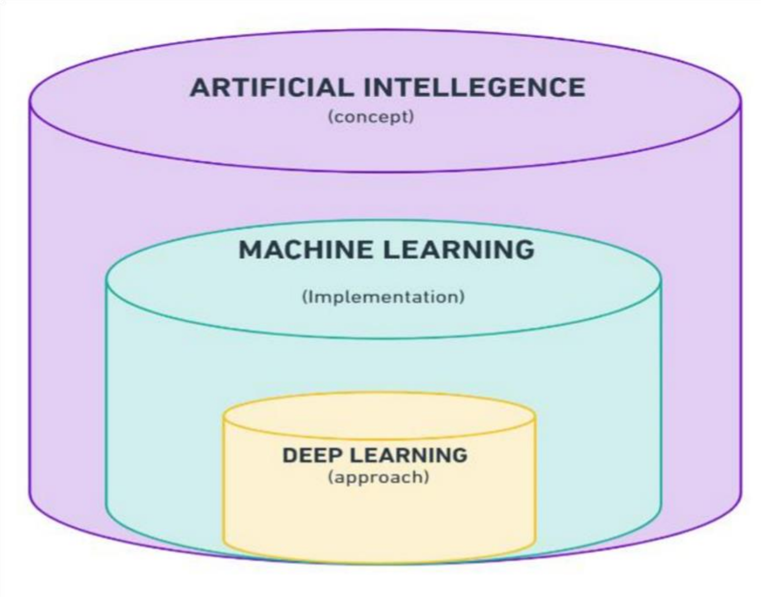

Fig 2: Layers of Artificial Intelligence

C. Sentiments Analysis:-

Sentiment analysis, also referred to as opinion mining, is a simple method for ascertaining the author's emotions in a text. What the author was trying to say when they wrote it. It use a range of text analysis and natural language processing (NLP) tools to determine what information might be subjective [25] .

The figure (fig 3) below describes the working process of Sentimental Analysis.

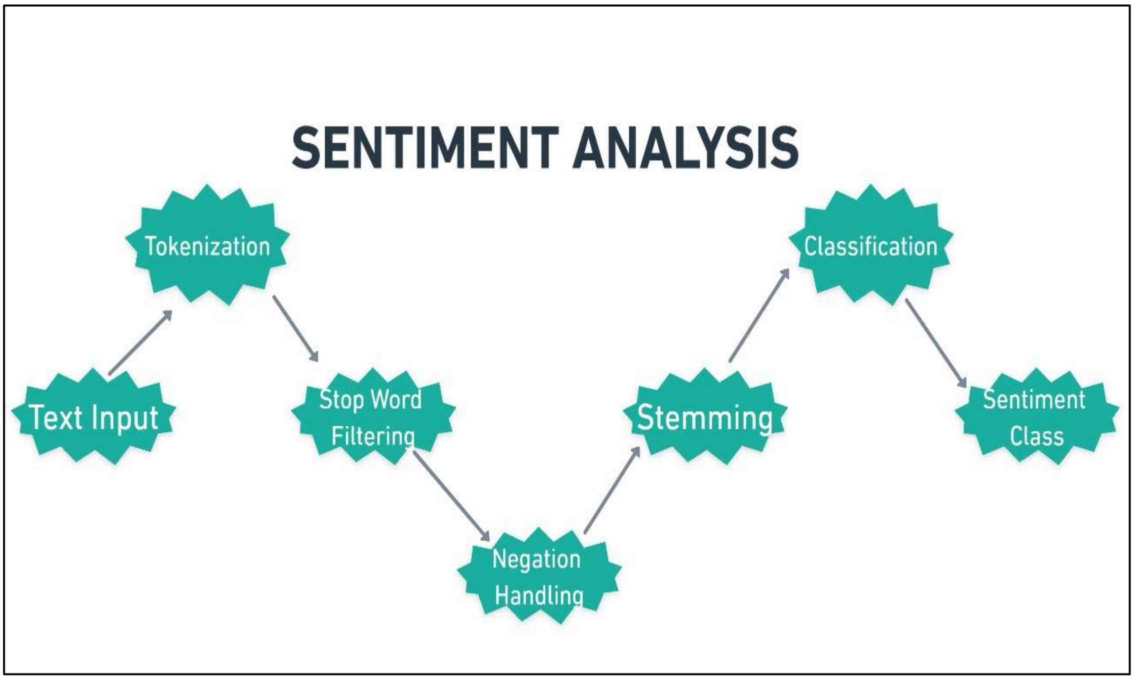

Fig 3: Working of Sentiment Analysis

D. NLP:

Natural Language Processing, or NLP for short, is a subfield of computer science, humanities, and artificial intelligence. Machines can comprehend, analyse, manipulate, and interpret human languages thanks to technology. It aids in the organisation of knowledge for tasks like topic segmentation, relationship extraction, named entity recognition (NER), speech recognition, automatic summarization, and translation [22] .

The figure (fig 4) below shows the components of NLP.

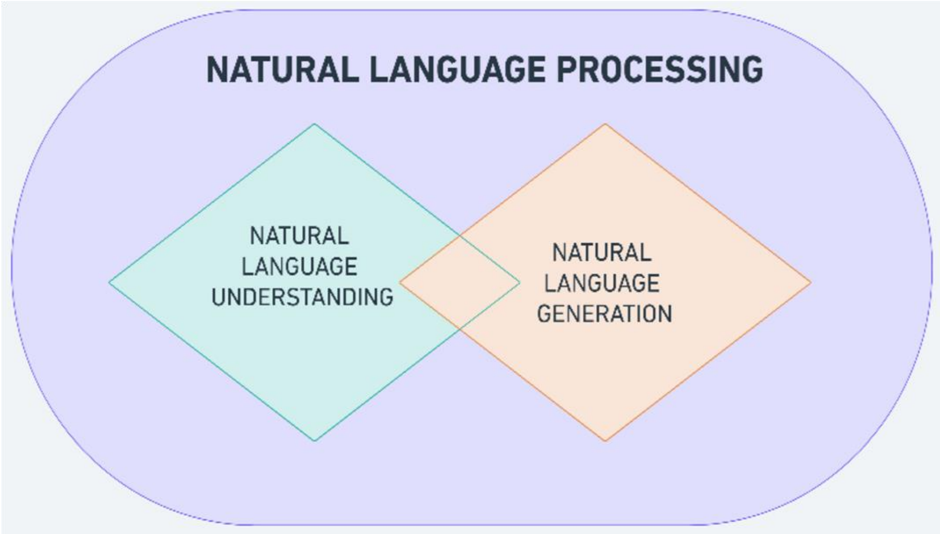

Fig 4: Components of Natural Language Processing

D.1 Natural Language Understanding (NLU)

Natural language understanding is a branch of artificial intelligence that uses computer software to understand input in the form of sentences using text or speech. NLU enables human-computer interaction.

D.2 Natural Language Generation (NLG)

Natural Language Generation, otherwise known as NLG, is a software process driven by artificial intelligence that produces natural written or spoken language from structured and unstructured data. It helps computers to feed back to users in human language that they can comprehend, rather than in a way a computer might.

III. LITERATURE SURVEY

The Purpose of this Survey is to detect any toxic statement/comment within a data set. Machine learning models that can detect toxicity in online conversations—which is defined as anything rude, disrespectful, or otherwise likely to cause someone to leave a discussion—are a major area of focus.

They build a model that recognizes toxicity and minimizes this type of unintended bias with respect to mentions of identities. You'll be optimising a metric created to measure unintended bias while working with a dataset that has been labelled for identity mentions. Create methods to lessen unintentional bias in machine learning models, and you'll aid the Conversation AI team and the sector as a whole in creating models that are effective for a variety of conversations.

Along with this, it also develops strategies to reduce unintended bias in machine learning models, and you will help the conversation AI team and the entire industry, build models that work well for a wide range of conversations [19].

In this [1] author described that they had classified the given dataset provided by Kaggle in six labels, i.e., toxic, obscene, identity hate, severe toxic, threat, or insult. The next step is to determine if the given comment belongs to one or more than one or none of the six labels mentioned. For example, the given comment can be toxic and insulting, hence falling into more than one label, but the comment can also be non-toxic and not fall into any of the six labels [1].

Although there have been a significant number of research papers published recently on the toxic comment identification problem, there has yet to be a systematic literature review of this research theme, making it difficult to assess the maturity, trends, and research gaps. In this work, our main aim was to overcome this by systematically listing, comparing and classifying the existing research on toxic comment identification to find promising research directions. The results of this systematic literature review are beneficial for researchers and natural language processing practitioners [9].

Today, many users leave numerous comments on different social networks, news portals, and forums. Some of the comments are toxic or abusive. Due to the large number of comments, it is unfeasible to manually moderate them, so most of the systems use some kind of automatic discovery of toxicity using machine learning models. In this work, they performed a systematic review of the state-of-the-art in toxic comment identification using machine learning methods.

Moreover, in further research, author uses algorithm adaptation methods that transform the algorithms to perform multi-label identification directly. Furthermore, they can also experiment with more complex deep learning algorithms like CNN (convolutional neural network), MLP (multilayer perceptron), and RNN (Recurrent neural networks) in the near future [1].

Also In this particular model, author intend to develop models using semantic embedding that take more delicate context and actors of text into account in order to handle the subtle differences in the usage of toxic keywords [8].

Supervised machine learning, and particularly supervised deep learning, is the current state-of-the-art for text categorization in general and toxic comment identification in particular. These classifiers' effectiveness is greatly influenced by the quantity and grade of training data, which is mostly utilized to hone general language models. The relatively small quantities of datasets with annotated harmful comments are a result of the significant expenses associated with acquiring labels of good quality as well as the task's extensive variability. Using a straightforward API, the software solution offer in this research enables quick access to a variety of distinct harmful comment datasets. The datasets can be filtered based on metadata and are all in the same data format. Researchers can integrate various datasets using our technology to provide specialized training and testing. It also promotes the study of harmful remarks and the creation of reliable systems with real-world applications [10].

Due to the widespread use of the internet in many spheres of life, there has been an increase in the number of people who actively participate and post comments in various online forums to express their concerns, views, and opinions. Although most of the time these comments help the creator explain the material that is being given to individuals, they occasionally have the potential to be abusive and foster animosity among the public. Therefore, it becomes the primary responsibility of the contentcreator (the host) to filter out these comments in order to stop the spread of negativity or hatred among people. These are openly available to the public and are viewed from various sections of the society, people in different age groups, different communities, and different socio-economic backgrounds. Toxic comment detection has been a major difficulty for all academics working in the field of research and development. This area has attracted a lot of interest not only because of the spread of hate but also because people are staying away from online forums, which has a variety of effects on all the creators/content-providers and hinders their ability to engage in productive public discourse that the general public can access without any hesitation. Many countries throughout the world have experienced an increase in cases related to cyberbullying that has resulted in the propagation of hatred and violence recently as a result of the growing threat of hate and negativity in online platforms, particularly social media [6] .

With numerous recently proposed approaches, the identification of toxic comments has developed into an active research area. While some of the challenges of the task are addressed by these methods, others remain unsolved, necessitating further research directions. To this end, they contrast various deep learning and shallow approaches on a fresh, sizable comment dataset and suggest an ensemble that outperforms all individual models. On a second dataset, they further validate our findings. The author carried out a thorough error analysis using the ensemble results, which reveals unsolved problems with current techniques and suggests areas for ongoing future research. Missing paradigmatic context and inconsistent dataset labels are examples of these difficulties. Platform providers have a critical responsibility to maintain inclusive, productive online discourse. The discussion can be kept productive by automatically classifying harmful comments like hate speech, threats, and insults. Additionally, new laws have been developed requiring the removal of illegal content in no more than 72 hours [5].

Constructing a multi-headed model that can recognize various forms of toxicity, such as threats, obscenities, insults, and hate motivated by a person's identity. It can be challenging to talk about topics you care about. Many people stop speaking their minds and give up on finding out other viewpoints due to the possibility of online abuse and harassment. Platforms find it difficult to efficiently enable dialogues, which forces many communities to restrict or disable user comments. The author provide a variety of publicly accessible models, including toxicity, through the perspective APIs. But the present models are still flawed, and they don't let users choose the kind of toxicity they're looking for [4].

The subject of modelling user behaviour to identify user segments to target and to whom send advertisements (behavioural targeting) is one that has been extensively researched in the literature. To find these segments, a variety of data sources, including user inquiries, are mined and modelled. Since users rephrase their requests for information about 50% of the time, they first demonstrate the requirement for a user segmentation system to leverage trustworthy user preferences. Then, author suggest a technique for extracting a vector representation of the words from the descriptions of the objects that users have given high ratings
(word embedding's). Given that users frequently select things from the same categories, our strategy is intended to prevent the so-called preference stability, which would link consumers to unimportant segments. Additionally, it guarantees that they created segments' interpretability is a feature made available to the marketers that will use them. By conducting several sets of experiments on a sizable real-world dataset, which supported our methodology and demonstrated its capacity to generate useful segments [3].

The majority of machine learning models are still black boxes despite their broad deployment. However, judging trust, which is essential if one expects to act on a forecast, or deciding whether to deploy a new model, requires an understanding of the motivations underlying predictions. A trustworthy model or forecast can be created using these insights into the model, which can also be utilized to change an unreliable model or prediction. Additionally, they provided a technique for explaining models that frames the task as a submodular optimization issue and involves presenting representative individual predictions and their non-redundant explanations. By describing various models for text and image identification, they define the adaptability of these techniques. Author use novel experiments—simulated and conducted with human participants—on a variety of trust-requiring situations to demonstrate the value of explanations. These scenarios include deciding whether to believe a prediction, selecting a model, enhancing an unreliable classifier, and determining why a classifier cannot be trusted [2].

There are numerous datasets, including Twitter, Wikipedia, HASOC (Hate Speech and Offensive Content), OLID(Offensive Language Identification Dataset), and Kaggle Jigsaw, which many students use to build and train the Toxic Comment Classifier model in order to achieve the best results.

Table 1 : Survey table on Toxic comment Identification

REFERENCE	OBJECTIVES	DATA SET	TECHNIQUE USED	FUTURE SCOPE
Agarwal A (2011) [1]	The use of sentimental analysis as well as execute queries .	An dictionary of emoticons and a dictionary of acronyms.	A dictionary of emoticons and a dictionary of acronyms are two new dataset and techniques.	Examination of more sophisticated linguistic analysis techniques, such as topic modelling, semantic analysis, and parsing.
Ribeiro M (2016) [2]	Explanation of various models for text and image classification	Two sentiment analysis datasets (books and DVDs, 2000 instances each)	LIME, a novel explanation technique	Investigation of a variety of potential directions for our future work and to see a comparison study on these with actual users.
Borate L (2016) [3]	user segmentation system to use accurate user preferences.	Neural Word Embedding's extraction Neural Item Embedding's extraction User Modeling	Extraction of Neural Word Embedding's Extraction of Neural Item Embeddings	Evaluation of the method's capacity to categorize user groups whose purchases are semantically related.
Pallam ravi (2019) [4]	Recognition of various forms of toxicity, such as threats, obscenity, insults, and hate.	Wikipedia corpus dataset hosted by Kaggle	Using scikit-learn OneVsRestClassier and a variety of estimators,	Deep Learning (DL) techniques must be used in the future for recognition of toxicity.
Betty van aken1 (2018) [5]	Making an ensemble that performs better than all individual models by combining different shallow and deep learning techniques.	Wikipedia Dataset for Talk Pages, Google Jigsaw for the Kaggle.	Logistic Regression, Recurrent Neural Networks, Convolutional Neural Networks, (Sub-)Word Embeddings, Ensemble Learning	Perform more research into embeddings as a way to describe world knowledge.
P.Vidyullatha1 (2021) [6]	An online interface that would allow us to rank sentences according to their level of toxicity.	CNN and RNN neural networks, word embedding techniques, and primary level neural network algorithms.	The ScikitMultilearn library.	Working on get the more precise result by using advance techniques.

Abhishek Aggarwal (2021) [7]	To determine the toxicity as precisely as possible.	The dataset was provided by Kaggle.	1)Multinomial NaïveBayes 2)Random Forest Classifier 3)Bernoulli NaïveBayes 4)Nearest Centroid 5)Ridge Classifier	Accomplish multilabel classification directly using algorithm adaptation techniques also, experiment with more advanced deep learning algorithms.
Prof. Kiran Babu (2021) [8]	Identifying toxic spans or rationales and Toxic XLMR for bidirectional contextual embedding's.	*Kaggle-Jigsaw *TSD *Curated dataset	Multi-task neural network model, which jointly learns on the sequence classification and span prediction tasks.	To create models employing semantic embeddings that take more delicate context and text actors into consideration.
Prof. Darko Androcec (2020) [9]	Systematic review of toxic comment classification using machine learning methods.	Jigsaw's data collection, by Kaggle.	The systematic literature review (SLR) methodology was used.	Using transformers for the classification of harmful comments in future works.
Julian Risch (2021) [10]	Software solution that automatically downloads, processes, and shows a collection of more than forty datasets in a common data format.	Jigsaw's data collection by Kaggle.	GitHub repository1 and PyPI package2.	To promote the repeatability and reproducibility of toxic comment research.
Aditya Mahajan (2020) [11]	To eradicate "cyberbullying" and create a secure online environment.	*Jigsaw Toxic Comment Classification Challenge by Kaggle *Hate Speech Dataset by GitHub.	Model interpretability techniques (such LIME, etc.)	Additionally, model interpretability strategies can assist trust by explaining to end users and solutions including machine learning and deep learning.
Salvatore Carta (2019) [12]	utilizing several sets of word embedding's, our supervised technique outperforms stateof-the-art methods.	Jigsaw's data collection by Kaggle is used.	Apache Spark big data platform and various word embedding's.	To combine various contextual word embeddings, deep learning techniques, and an ensemble strategy to enhance the performance.
Akash G (2021) [14]	To compare standard deep learning methods like LSTMs and GRUs to categorize comments as per their toxicity.	The dataset from Kaggle was utilized to train the models. Wikipedia's CCSA-3.0.	Transformers, Bidirectional LSTMs with CNNs, GRUs, and Bidirectional LSTMs.	larger datasets containing comments from a variety of online forums can be used to construct newer and more inventive structures.

Lucjas Sterckx (2018) [16]	To automatically identify harmful comments and categorize them in accordance with the type of toxicity.	Jigsaw's data collection, by Kaggle is mostly used data set.	CNN Architectures, RNN Architectures, Pretrained Word Embeddings, Regularization	on regularization techniques and a variety of pretrained word embeddings in conjunction with CNN and RNN architectures.
kevin khieu (2019) [17]	To establish a safe atmosphere for people in without worrying about being targeted by trolls or abusers.	Wikipedia comments from the kaggle toxic comment classification challenge	SVM, LSTM, CNN AND MLP	Achieving higher performance using more complex models.
Shubhankar (2021) [18]	deals with the issue of subdividing harmful remarks to aid in online moderation.	Jigsaw's data collection, by Kaggle.	Multi-label classification techniques utilizing problem transformation techniques were used in this work.	on optimizing the algorithms and apply algorithm adaptation methods together with more complicated deep learning algorithms

CONCLUSION

The toxic comment identification helps to provide the way to tackle the problems related to increased hetaerism and toxicity on the current social media platforms. Because these things can imperil the way people participating in communication at social networks, blogs, forums, etc. The goal of this survey is to identify those harmful comments from various platforms.

Thus, the ultimate goal for this particular survey is to explore the scope of online abusive comments and categorize them into different labels to assess the toxicity as well as the accuracy, by using various machine learning algorithms combined with Natural Language Processing and compare their performance. This survey demonstrated a multi-task model that performs toxic comment identification while predicting the toxic spans as rationales. In many papers, researchers basically opted for three methods like "Binary Relevance, Classifier Chain, and Label Power "of machine learning algorithm in which Binary Relevance method gives the high accuracy. Thus, reducing the threat of bullying and abuse on the internet obstructs the free exchange of ideas by limiting people's opposing viewpoints. This identification is very helpful for reducing the toxicity from different comments from various social media handles does leading to free and toxic free exchange of comments between the people using the social Medias.

In the future, a more reliable algorithm might be approached by classifiers using the Grid Search Algorithm. Further, we can also do experiment with more complex deep learning algorithms to get high performance.

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