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ENRICHING CYBER BULLYING DETECTION TECHNIQUES USING NEO4J

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Abstract:-

It is no exaggeration to say that bullying is a serious issue in communities all across the globe. Lawmakers were therefore urged to implement both political and social legislation and methods to address the epidemic of bullying. Multiple issues, including those associated with mental health, anxiety, distress, violent conduct, and sometimes even suicide ideation, have arisen as a direct result of bullying. These patterns have previously been seen in conventional forms of bullying. But with the introduction of the internet and online social networks platforms, cyberbullying has also been a problem. The technological revolution has resulted in about a dramatic improvement in the working conditions of individuals. Therefore, there is a need for an effective and useful mechanism for the purpose of achieving the detection of cyberbullying on online social networks. For this end, this article utilizes an online social network dataset for cyberbullying detection through the use of Neo4j graph database, Term Weight, Shannon information gain along with ECLAT algorithm and Fuzzy classification. To ascertain the performance of the approach in-depth experimentation has been performed that has produced highly accurate outcomes.

Keywords: Cyberbullying detection, Term Weight, Shannon Information Gain, Fuzzy Classification.

INTRODUCTION

The digital revolution plays an important role in civilization, and with nearly than 4 billion people around the world, it has become an integral part of daily life. The youngsters of today are fully immersed in the electronic world of the worldwide web. It is safe to say that modern society has been fundamentally altered by the proliferation of digital means of collaboration and intelligence. Cyberbullying is just one of numerous issues that have arisen as a result of the exponential development of information and communication technologies. The internet's ability to make their lives easier in many ways has also made it with the double blade. Cyberbullying, a kind of bullying communicated online, is only one of many negative trends that the web has facilitated.

Online use has skyrocketed in tandem with the rise of other forms of digital technology, making it an important primary means of interaction for people of all ages and backgrounds. Youngster’s at all educational levels of the Younger generation are heavy consumers of information and frequently serve as early adopters of cutting-edge tools. As a result of their increased access to technology, they may be more vulnerable to a wide range of potentially harmful influences, such as propaganda, political propaganda, pornographic material, narcotics, aggression, and cyberbullying. The vast proportion of internet consumers are under the age of 30, according to a recent poll. There are significantly more people in this age demographic who use the World Wide Web compared to any other. There is a correlation between adolescent vulnerability to cyberbullying and their increased use of information and communication technologies.

Bullying is characterized by a power differential between the abuser and the bullied, and is characterized by confrontational, purposeful, intentional, undesired, ethically questionable, inappropriate, corrupt, unrecognized, and disrespectful conduct. It does not matter whether the power differential is actual or imagined. Similar actions often repeat themselves. Solitary bullies and groups among like consumers both exist. Instances of physical aggression and abusive language, as well as the dissemination of false information, insults, blackmail, rumors, eavesdropping, social isolation, and other forms of harassment, all fall under the umbrella of bullying. Cyberbullying, defined as "the use of communication and information technology to enable purposeful, repetitive, and aggressive conduct by an individual or an organization with the intent to damage or slander another," has replaced conventional forms of bullying owing to technological advancements. Simply put, cyberbullying is a sort of peer intimidation that takes place online.

Conventional bullying versus cyberbullying have distinct outcomes and consequences. Survivors of both forms of bullying experience anxiety, despair, alienation, psychosocial issues, and sleep disturbances, but these repercussions are essentially identical.

Both cyberbullying and traditional bullying are committed with the explicit goal of causing the victim distress. Nonetheless, as time has progressed and the World Wide Web has expanded, bullying has become more sophisticated. Although the aggressor may remain anonymous online, cyberbullying is seen as more hazardous than conventional forms of bullying. This is the most noticeable distinction since modern tools like the internet may shield an offender from detection even farther. Because of this, cyberbullies have a faster time harassing their victims than ever before.

Waleed Mugahed Al-Rahmi [1] looked at what influences college pupils to participate in stalking and harassment or online bullying. In conclusion, the data show that being exposed to cyberbullying and online harassment via platforms for social media increases the likelihood of experiencing such behaviors. This research also highlights the expanding role of social media and other Internet-based resources in the daily lives of people of all ages throughout the globe. Additionally, the research emphasizes the importance of social networking in the worldwide phenomena of collaborative effort and accessible education. This may be because these resources help students learn more effectively, work together, and share knowledge.

According to Waleed Mugahed Al-Rahmi [2], the field of cyberbullying exploration has developed significantly over through the past few years, with observations suggesting that, like traditional forms of bullying in universities and schools, involvement is linked to a wide range of variables that can be both personal and environmental. In regards to unique characteristics, studies show that both males and girls engage in cyberbullying, but also in distinct ways. Since numerous bad instances on cyber bullying, online harassment, and trolling were discovered, this study shows that notwithstanding the fact that such social networks are supposed to enrich human unique interactions, numerous adverse ones have been detected.

According to Belal Abdullah Hezam Murshed [3], with the growing popularity of using Tweets for language models, there is a pressing need to address the poor significance of social media analysis before analyzing it in order to get useful insights from these sources. To combat the poor level of social media content, this research presented a technique named Social Media information Purification Models. In addition, 6 prototypes (Latent Dirichlet Redistribution, Word-Network Involves A complete, Biterm Topic Model, Pseudo-document predicated Forecast The future, Worldwide and Regional word embedding-based Predictor Variables, and Fuzzy Predictor variables) were used to examine how information from social media purification models influenced the effectiveness of short message sentiment classification. Extensive tests with varying situations were run across two distinct social media data sources: Cyberbullying in the Modern Classroom, Twitter and Cyberbullying in the Real World, Cyberbullying in the Academic Community, Cyberbullying in the Use Mendeley to compare the performance of several short message subject model that describes in regards to data cleanliness, Mutual Awareness normalization, correctness, and topic integrity within every case study.

Section 2 of this research article presents an analysis of the relevant literature; Section 3 explains the research approach; Section 4 discusses the experimental assessments; and Section 5 closes with suggestions for further study in the future

RELETED WORKS

To combat the problem of identifying hateful speech on Twitter, Pradeep Kumar Roy [4] employs a deep cnn. Originally, the HS-related comments on Facebook were identified utilizing LR, RF, NB, SVM, DT, GB, and KNN, all of which are machine learning based classifiers. Since of the unbalanced collection, the algorithm is more likely to forecast NHS tweets because they have more occurrences, which may explain why HS tweets are predicted so poorly. Comparable performance can be shown with the constant segmented dataset using deep learning-based CNN, Support vector machines (svm, and their hybrid C-LSTM algorithms. Results from experiments using both classic machine intelligence as well as deep learning approaches showed that neither could effectively forecast HS messages using a constant train-test split.

In his article "Cyber-syndrome," Huansheng Ning [5] describes the physiological, cognitive, and interpersonal issues that may arise from excessive and constant exposure to the online world. Cyber-developmental syndrome's phases and a taxonomy of cyber-related problems are presented, with illustrative instances provided. Additionally, a multitude of preventative actions are listed to help users avoid the syndrome's negative impacts and use the internet safely. A large range of internet consumers may benefit from the rules and concerns that are identified and clarified in this study, which may help them avoid Cyber-syndrome.

An autonomous detection algorithm has indeed been published by Fatima Shannaq [6] to identify objectionable words in Arabic tweets. A two-step refining and probabilistic model was presented by us. Pre-trained word embedding algorithms were used after being fine-tuned during the initial step. After that, they applied genetically-based optimization techniques like eXtreme Gradient Booster and Support Vector Machine (GA). They put the suggested method to the test on a Twitter-based Arabic cyberbullying dataset. The study's authors tried out three different word embedding frameworks, AraVec N-gram, as well as AraVec Unigram—to see which performed best. In order to enhance the quantity of vocabularies, the models were fine-tuned by receiving additional phases of training examples from the Arabic Cyberbullying Database.

Farhan Bashir Shaikh [7] produced a significant participation by determining the variables actively participating university students in and out of cyberbullying 3 behavior, and by providing a comprehensive perspective on the variables attributed to cyberbullying behavior, as opposed to the conventional methodology of concentrating solely on a single and perhaps even two considerations. The cyberbullying variables that were discovered may be used as a roadmap to facilitate the forecasting of cyberbullying actions. There is a serious problem with cyberbullying within today's children. Youngsters have reportedly engaged and contemplated committing suicide as a result of cyberbullying. Previous studies focused mostly on K-12 pupils and omitted university students entirely.

Anum Faraz [8] has surveyed many internet safety security mechanisms, including the many ways in which safety for children is being improved. The purpose of this study is to draw attention to the unanswered questions and propose workable answers. Despite the growing proportion of kids using the

Internet for research, learning, socializing, entertainment, and enjoyment, there has been little coordinated international action to safeguard them. The lack of a worldwide institution that assures children's safety, a global plan to safeguard children on the internet, global unambiguous criteria, rules, and recommendations, and cooperation among many parties likely contributes to this problem.

Conectado was evaluated by Antonio Calvo-Morata [9] as a resource for educators to utilize in the class to raise students' understanding of bullying and online bullying. Pupils, the game's intended audience, played an early version and gave it their stamp of approval. Furthermore, testing the gameplay with prospective instructors was needed to conclude its verification and reach its application of principles of becoming utilized as an instructional tool in the classroom.. This is because post-game lecture hall conversations are an important component of the instructional gamification. Individuals majoring in educational leadership, who represent the future generation of educators, have also participated in these studies. Researchers can partly explain for the high globalization and technology development by contrasting active instructors to pupils of education studies.

Fatma Elsafoury [10] reviewed the literature on cyberbullying detection software that works on autopilot. The research in this field is driven by a desire to mitigate the tragic outcomes—including mental health issues and even suicide— that may result from cyberbullying. As a result of a similarly comprehensive research in the content, the authors categorized the evaluated material around the phases of the computational intelligence pipeline used by another examined work. Difficulties and limits of existing material on cyberbullying identification were noted in the examined research. Several of them were connected to the cyberbullying databases utilized in the different publications. Specifically, there are issues with articulating what constitutes cyberbullying, with annotating resources, with multi-co-linearity, with information bias, as well as the scarcity of international datasets.

Mohammed Ali Al-Garadi [11] looked into the research on the use of machine learning techniques to identify hostile conduct on SM platforms. Collection of data, feature development, cyberbullying identification modeling creation, and assessment of developed cyberbullying detection techniques were the four particular elements addressed by the researchers. The several kinds of racist and discriminatory traits that have been utilized to identify cyberbullying on social media websites have also been summarized. Furthermore, the best supervised machine learning classifiers were found for categorizing cyberbullying posts on social media websites.

To improve the performance of different classifiers in the identification of cyberbullying incidents, Belal Abdullah Hezam Murshed [12] created a powerful tweet categorization model. The Dolphin Echolocation Algorithm improvement and Elman style Recurrent Neural Networks were combined to create DEA-RNN, which allows for precise parameter variation. In addition, it was subjected to a test on something like a Twitter collection that was culled using phrases associated with cyberbullying, alongside other approaches such as Bidirectional Long Short Term Memory, Recurrent Neural Networks, Support Vector Machine, Random Forest, and Multinomial Naive Bayes. The experimental research demonstrated that the DEA-RNN outperformed the state-ofthe-art approaches in every situation across a wide range of metrics, including precision, accuracy, F-measure, sensitivity, and uniqueness. This represents the influence of the Dolphin Echolocation Algorithm on the efficiency of Recurrent Neural Networks.

Based on the research of Farhan Bashir Shaikh [13], cyberbullying is on the rise in Malaysia at a concerning pace. The existing body of literature has so far proved unsuccessful in mitigating this issue. The present research will contribute to our understanding of this phenomenon and its mitigation in the accompanying directions: Initially, they will do original research by analyzing cyberbullying conduct through the lens of Dark Triad personal characteristics. Secondly, they will use a novel mix of the Theories of Planned Action and the theory of social cognition to foresee cyberbullying actions. Thirdly, college graduates have seldom been the subject of research. The majority of the research, students were the subjects. Indeed the investigations that narrowed down on college kids only scratched the surface of cyberbullying. As a result, this research will contribute to the growing body of knowledge by identifying the variables associated with cyberbullying amongst Malaysia's university students.

PROPOSED METHODOLOGY

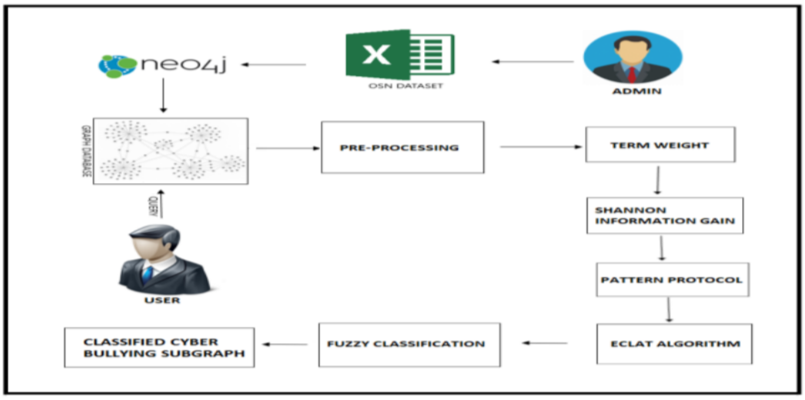

Figure 1: Proposed Methodology

The proposed approach for the purpose of achieving cyberbullying detection on online social networks through the use of ECLAT algorithm and Fuzzy classification has been depicted in the figure 1 above and the steps taken to achieve this system are elaborated below.

Step 1: Data Collection and Preprocessing – The system initiates with the admin registration and login wherein the admin performs the registration by signing up and providing the relevant details. This allows the admin to gain access into the system. Once the admin logs into the system, the admin and provide the Bag of Words. The Bag of Words is a collection of words that are useful in determining the bad of words. For which the input dataset is provided. The input dataset is used to extract the cyberbullying keywords. These Bag of Words will be used further in the approach.

The proposed methodology necessitates the utilization of a dataset comprising of responses submitted by people in the format of tweets published on the Twitter social media platform. To achieve the intended objective, a dataset comprising tweets has been retrieved from the following URL: https://www.kaggle.com/datasets/saurabhshahane/cyberbullyi ng-dataset.

The dataset comprises conversational data from tweets published on the Twitter social media platform, documenting interactions that occurred on the platform. The aforementioned event holds significant importance for the construction of our software, as it provides relevant information along with tweet content that is well-suited for our purposes. The tweets are comprised of various attributes, including but not limited to index, id, text, annotation, and label.

Prior to feeding the tweets into the system, it is necessary to preprocess them in order to mitigate the occurrence of errors or redundancies that could potentially have a detrimental effect on effectiveness. The following phase of the strategy involves the elaboration of the preprocessing approach.

Step 2: Preprocessing – The preprocessing methodology represents the primary logical step in an intended a stance aimed at streamlining tweet processing prior to being added to the system as a whole. The dataset that was obtained in the preceding step is utilized as an input in the current phase of the methodology. As the dataset is presented in workbook format, the JXL library will be utilized to establish an interface between this file and the Java code. Subsequently, the dataset is transformed into a two dimensional list, facilitating streamlined processing by the system.

The efficacy of preprocessing is demonstrated in the attainment of conditioned input tweets. The efficacy of this phase in this process is of utmost importance as it significantly impacts the outcome of the its operation. The inclusion of extraneous information may have adverse effects on the system, potentially leading to inaccuracies and errors. Data that is redundant may result in longer processing times, thereby impeding efficiency. The procedure of preprocessing has been outlined as follows.

Special Symbol Removal – The first phase of the process involves the provision of an input string that included a tweet, from which special symbols are subsequently eliminated. The utilization of specific symbols serves the purpose of introducing grammatically incorrect breaks and additional subtleties to the written language. The elimination of this particular element in our approach would not result in any adverse impact on the tweet, rendering it redundant. The symbols present in a tweet, including the question mark and comma, are eliminated.

Stemming – The following phase of the preprocessing methodology involves utilizing the tweet that has been stripped of any special symbols as an input. This stage pertains to the reduction of input weight, resulting in a significant decrease in system time required for processing. A significant number of English words share a common etymological origin and are distinguished from each other primarily by their suffixes. The aforementioned terms are subsequently subjected to stemming, a process that preserves the semantic content of the word by reducing it to its base form. As an illustration, the term "sleeping" shall be simplified to "sleep," thereby preserving the semantic meaning of the phrase while rendering the tweet more concise.

Stop Word Removal – This stage of the preprocessing procedure is responsible for removing stop words, and it receives the stemmed tweet as its input. Words that are utilized in the context of English to establish an association among two distinct statements or to merge two distinct 5 elements of the same statement are referred to as stop words. Our technique does not necessitate this, and removing the stopwords is not detrimental to the reader's ability to understand the statements in any way. Consequently, words like and, is, and others like them are removed from the tweet in order to accomplish the preprocessed tweet, that is transmitted to the following step so that it can be treated more thoroughly.

The process of preprocessing can be described using the algorithm 1 given below.

ALGORITHM 1: PREPROCESSING

Step 0: Start
Step 1: Get contents of Tweet
Step 2: Split in Words
Step 3: Remove Special Symbols
Step 4: Identify Stopwords
Step 5: Remove Stopwords
Step 6: Identify Stemming Substring
Step 7: Replace Substring to desire String
Step 8: Concatenate Strings
Step 9: Preprocessed String

Step 10: Stop

Step 3: Term Weight – In order to accomplish this part of the method, the preprocessed string that was produced in the previous phase has been brought forward and used as an input. This input phrase is being utilized in order to accomplish the goal of retrieving words or phrases from the tweets that have been preprocessed. These terms are employed in order to achieve the desired term weight for the words that are going to be recovered. The input string's pattern of use of individual terms is extracted and evaluated by the term weight function. This is accomplished by locating the character in the string that represents a space, and subsequently dividing the string at the points where it occurs in order to separate the syllables.

After the words have been extracted, they are transferred to a list, and the process is carried on in the same manner for each of the tweets contained in the preprocessed list. After compiling a list containing all of the words, the hash set function is then used with the intention of identifying the words in the list that are distinct from one another. After that, these one-of-a-kind words are put to use for the objective of tallying the number of times they appear in the string that has been preprocessed. In order to achieve an accurate and helpful implementation of the entropy assessment in the subsequent phase of the process, the Term Weight is an important feature that is obtained from the data. This is done for the intent of accomplishing the goal.

Step 4: Shannon Information Gain – During this stage of the process, the term weight that was determined in the preceding phase through the admin is utilized for the goal of calculating the entropy for the preprocessed data fed by the user. In this stage of the process, an analysis and measurement of the distribution factor of the terms that appear in the tweets that are used as an input are carried out. The Shannon Information Gain method is used to make a calculation of the entropy, and the equation 1 that is supplied below is used to do so.

$$IG(E) = -(P/T)\log(P/T) - (N/T)\log(N/T) \text{ --------(1)}$$

Where,

P = Frequency of the present count
N = Non presence count
T = Elements Size.
IG (E) = Information Gain for the given Entity

Step 5: ECLAT Algorithm – This is the primary component of the suggested methodology, in which a powerset is utilized by the system in order to recognize the words that are most readily apparent for the intent of rule mining. In this stage of the process, the extraction of data is being carried out using comparative recursion for an assortment of terms. In the current phase of the suggested strategy, the words that were obtained in the previous phase of information gain are employed as an input.

The input word list is utilized to create word pairs with the other corresponding words in the bag of words list. The first word from the word list is taken and paired with all the other words in the list. This is performed iteratively over for all the words in the first list. Once the word pairs are collected, they are used to generate the subgraph and over to the next step for fuzzy classification. And the algorithm for Eclat is shown below.

ALGORITHM 2: ECLAT ALGORITHM

Input: Alphabet A with ordering ≤ multiset $T \subseteq P(A)$ of sets of Items, Minimum support value minsup $\in \mathbb{N}$.
Output: Set F of frequent Itemsets and their support counts.
$F := \{(\emptyset, |T|)\}$.
$C\emptyset := \{(x, T(\{x\}))| \; x \in A\}$.
$C'\emptyset := \text{freq}(C\emptyset) := \{(x,Tx)|(x,Tx) \in C\emptyset, |Tx| \geq \text{minsup}\}$
$F := \{\emptyset\}$.
Add frequent supersets (Ø, C'Ø).

Step 6: Fuzzy Classification – In this stage of the procedure, the frequent supersets that were accomplished in the steps that came before will be incorporated as an input. In this stage of the methodology, the frequently occurring supersets and the numbers associated with them are utilized, and then categorized in accordance with the fuzzy crisp measurements. Finding the lowest and highest value in the frequent supersets is the first step in arriving at the fuzzy crisp values. The next step is to use the difference between these two values to produce five groups, which include low, very low, medium, high, and very high. Finally, the fuzzy crisp 6 ratings are obtained. The categorizations that fall under the very high category are the ones that are currently utilized, and the result, which comes in the format of a frequent pattern sub graph for cyberbullying, is presented to the user.

RESULT AND DISCUSSIONS

The approach that has been shown for the objective of accomplishing the identification of cyberbullying on social media platforms has been accomplished by utilizing the Java Programming language, and the NetBeans Integrated Development Environment (IDE) has been used for the coding and Neo4j Graph Database for showing the cyber bullying pattern over the graph. The strategy was implemented on an experimental workstation with a standard build that included 8 gigabytes of random access memory (RAM), 1 terabyte of hard disk drive (HDD), and was propelled by an Intel Core i5 CPU.

Perform operation on Excel file in that all the tweet with their ID's present in table form. On file data we perform pre process operation. It filters all data, remove non bullying messages, and display only bullying messages or text.

Word	Frequency	Information_Gain_Value
mkr	23	0.9082
http	7	0.0
sexist	7	0.2665
kat	6	0.3277
girls	6	0.3277
notsexist	5	0.3976
youre	5	0.3976
islam	4	0.4774
mkr2015	4	0.4774
andre	4	0.4774
bad	3	0.5694
men	3	0.5694
good	3	0.5694
muslim	3	0.5694
people	3	0.5694
ash	3	0.0
women	3	0.5694
girl	3	0.5694
fuck	3	0.5694
feel	3	0.5694
&amp	3	0.5694
theyre	2	0.6772
answer	2	0.6772
&gt&gt	2	0.0

Table 1: Information Gain Data

There are 3 columns in Table 1 i.e. word, Frequency and Information_Gain_value. In word column, all the bully words which is used in messages or tweet. In Frequency column, that particular word used how many times for texting someone. In Information_Gain_Value column, information gain value is display.

Word 1	Word 2	Classified Value
mkr	http	Very-High
mkr	sexist	Very-High
mkr	kat	Very-High
mkr	girls	Very-High
mkr	notsexist	Very-High
mkr	youre	Very-High
mkr	islam	Very-High
mkr	mkr2015	Very-High
mkr	andre	Very-High
mkr	bad	Very-High
mkr	men	Very-High
mkr	good	Very-High
mkr	muslim	Very-High
mkr	people	Very-High
mkr	ash	Very-High
mkr	women	Very-High
http	sexist	Very-High
http	kat	Very-High
http	girls	Very-High
http	notsexist	Very-High
http	youre	Very-High
http	islam	Very-High
http	mkr2015	Very-High
http	andre	Very-High

Table 2: Cyber Classified Word

In Table 2, two words are grouped, that words are taken from in the Table 1. In Classified Value column, displays range of the bully word with respect to that group of words. There are 5 Classified value range i.e. Very-High, High, Medium, Low and Very-Low.

Using Neo4j graph database, Created a graph according to table 2 data or values which is shown in Figure 2. All the circles or nodes are represent as words and lines and edges are displays the range of classified value between that particular nodes or group of two words.

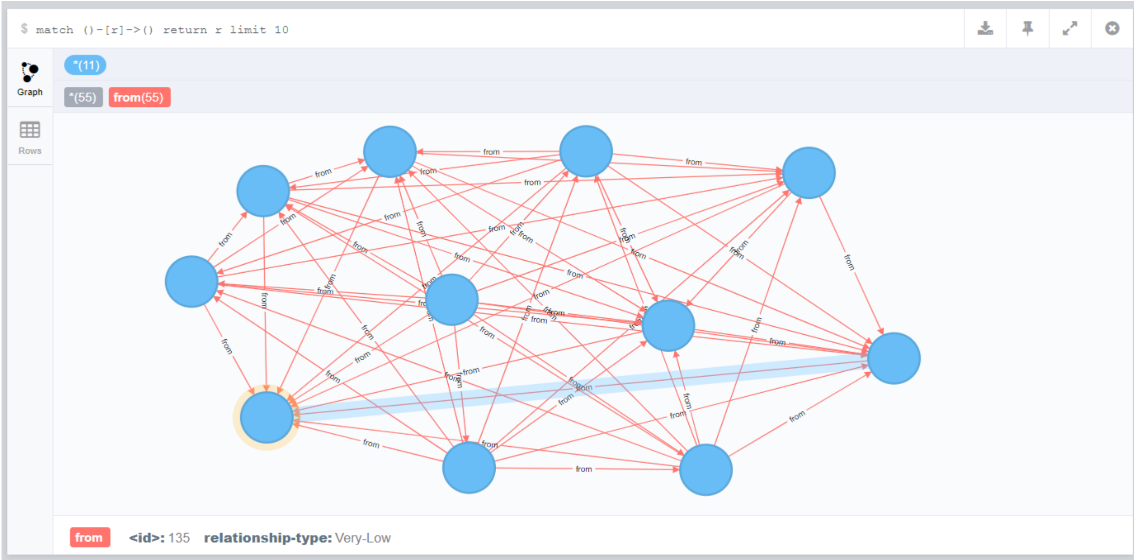

Figure 2: Neo4j Graph

The visualization that can be found in figure 2 above demonstrates very clearly that the recommended approach for sub graph matching achieves a mean precision of 97.30% and a mean recall of 94.70% when applied to the Twitter data that is provided. This is significant and makes reference to the concept that was meant for being executed effectively.

The precision scores that were analysed for the purpose of accomplishing the Frequent Pattern Sub Graph validated in significant detail the effectiveness of the approach suggested. The results that were obtained are extremely satisfying, and they have been of critical importance in gaining a comprehension of the internal functioning of the methodology. We have ensured that the ECLAT algorithm is executed with the highest possible precision and recall numbers.

CONCLUSION AND FUTURE SCOPE

The proposed approach for the purpose of achieving cyberbullying detection on online social networks through the use of ECLAT algorithm and Fuzzy classification has been outlined in this research article. The approach initiates with the admin logging into the standalone application with the valid credentials and then uploading the Online Social Network dataset into the system. This dataset is effectively 7 converted into a graph database using Neo4j as it allows for a much better visual representation of the data. This content in the graph database can be effectively queried by the user which passes the query to the system. The dataset is then preprocessed to eliminate unnecessary values after which the term weight is calculated. The term weight is then utilized in the next step for entropy estimation through the use of Shannon Information Gain and then pattern protocol is initiated. The pattern protocol provides its output to the ECLAT algorithm that effectively identifies the instances of cyberbullying that are then preprocessed through the use of Fuzzy Classification that employs the fuzzy crisp values. The approach is quantified through detailed experimentations that have resulted in lucrative outcomes.

In the future this research can be extended further to deploy the mode in real time social networking platform using their API's to ensure more security.

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