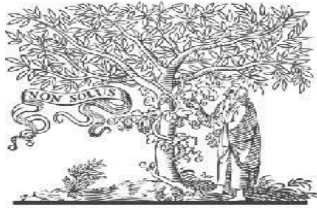




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Racism Detection by Analyzing Differential Opinions Through Sentiment Analysis of Tweets Using Stacked Ensemble GCR-NN Model

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ABSTRACT: Because of social media's dominance in the sociopolitical scene, numerous current and new types of racism emerged on the platform. Racism has appeared on social media in several forms, both hidden and open, hidden via the use of memes and open through racist statements made under false identities to provoke hate, violence, and societal instability. Racism, although frequently connected with ethnicity, is now prospering on the basis of colour, origin, language, culture, and, most crucially, religion. Social media thoughts and statements inciting racial tensions have been seen as a severe danger to social, political, and cultural stability, as well as the peace of several nations. As a result, social media, which is the major source of racist beliefs propagation, should be watched, and racist statements should be recognised and banned as soon as possible.

The purpose of this project is to identify racist tweets using sentiment analysis of tweets. Because of deep learning's improved performance, a stacked ensemble deep learning model is created by merging gated recurrent units (GRU), convolutional neural networks (CNN), and recurrent neural networks RNN, which is known as Gated Convolutional Recurrent- Neural Networks (GCR-NN). In the GCR-NN model, GRU is at the top for extracting acceptable and conspicuous characteristics from raw text, while CNN extracts key aspects for RNN to produce correct predictions. Obviously, numerous tests are carried out to study and assess the performance of the proposed GCR-NN within the context of machine learning and deep learning models, demonstrating that GCR-NN has better performance with enhanced 0.98 accuracy. The

suggested GCR-NN model can identify racist statements in 97% of tweets.

Keywords – Racism, social media, online abuse, Twitter, deep learning.

1. INTRODUCTION

Social media has become a dominant factor in sociopolitical possibilities, controlling our ideas and behaviours in many ways. With the widespread use of social media platforms and the freedom of expression, various vices have grown in recent years, racism being one of the most prominent. Twitter, for example, is a new environment in which racism and associated stress seem to thrive. Currently, 22% of US people use Twitter, and the platform has 1.3 billion accounts and 336 million active users worldwide, 90% of whom have a public profile, resulting in 500 million tweets every day. Tweets are publicly viewable until they are kept private, and Twitter users may reply and participate by publishing them on their profile (retweet), tagging someone's user name, clicking the like button, or commenting to the author of the tweet. The raw data of sentimental analysis is built on the expression of sentiments, emotions, attitudes, and views on Twitter. The increased popularity of social media platforms has resulted in their widespread usage for a variety of old and new types of racism. Racism

is represented on such platforms in many covert ways, such as memes, and overtly, such as publishing racist Tweets under false names. Racism, although frequently connected with ethnicity, is now prospering on the basis of colour, origin, language, culture, and, most crucially, religion. Social media thoughts and statements inciting racial tensions have been seen as a severe danger to social, political, and cultural stability, as well as the peace of several nations. Social media, being the primary source of racist beliefs, should be monitored, and racist statements should be caught and banned as soon as possible.

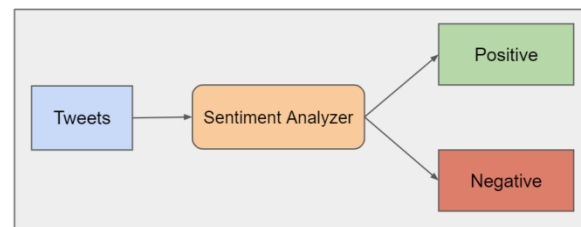


Fig.1: Example figure

Racist remarks and tweets on social media have been linked to a variety of mental and physical illnesses, resulting in negative health consequences [7–12]. Racism on social media may be classified into three types: institutionalised, individually mediated, and internalised [13]. Racism may be experienced personally via racial discrimination or unequal racial treatment, as well as knowledge of

prejudice against relatives and friends. As a result, society's racist conduct has a negative impact on people and causes many types of psycho-social stress, which frequently increases the risk of chronic illnesses [14]-[16]. Furthermore, racist organisations and individuals promote cyber-racism by using increased skill levels and complexities through numerous channels and techniques [5]. Special attention have been made to the area of sentiment analysis in order to evaluate text from social media platforms for a wide range of tasks such as hate speech identification, sentiment-based market prediction, and racism detection, among others.

2. LITERATURE REVIEW

Using social media to understand and guide the treatment of racist ideology:

Social media platforms, such as Facebook, Twitter, and Instagram, give a forum for racist ideas, highlighting the brokenness of American society. Social media may give insight into the world of racists who adhere to their tribal identities, logically rejecting those who they consider to be different. Studying social media may give insight into processes that might aid in the healing of segregationist beliefs in American society—a step toward mending the racist. The goal of this article is to analyse social media postings in order to better understand racism, its

causes, and to build first measures toward combating racist ideology. A content analysis of 600 American Facebook postings was used to uncover trends in cognition, problem-solving, personality structures, belief systems, and coping techniques. The content analysis includes a descriptive explanation of the data as well as an interpretative interpretation. A. M. Rackham (2018). Understanding and guiding the treatment of racist ideology via social media.

Using social media for health research: Methodological and ethical considerations for recruitment and intervention delivery:

As social media platforms grow in popularity and variety, so does their value for health research. Using social media to recruit participants for clinical research and/or offer health behaviour interventions may allow you to reach a larger audience. However, evidence supporting the effectiveness of these techniques is scarce, and fundamental concerns like optimum benchmarks, intervention development and methodology, participant participation, informed permission, privacy, and data management remain unanswered. Researchers interested in utilising social media for health research have little methodological advice. We outline the content of the 2017 Society for Behavioral Medicine Pre-Conference Course titled 'Using Social Media for Study,' during



which the authors shared their experiences with methodological and ethical challenges related to social media-enabled research recruitment and intervention delivery. We highlight frequent problems and provide advice for social media recruiting and intervention. We also explore the ethical and appropriate use of social media in research for each of these reasons.

Online networks of racial hate: A systematic review of 10 years of research on cyberracism:

A growing amount of research across disciplines has examined how the Internet might assist the expression and spread of racist thoughts and ideologies. There have, however, been no comprehensive reviews of this study to yet. To synthesise existing knowledge on the problem and offer future research options, we conduct a systematic evaluation of a decade of research on cyber-racism committed by organisations and individuals (i.e., according to the source of cyber-racism). Overall, the studied cyber-racism research reveals that racist organisations and individuals utilise various communication channels, are motivated by different aims, use different techniques, and the outcomes of their communication are dissimilar. Despite these variations, both organisations and individuals have a high degree of competence and complexity when it comes to expressing cyber-

racism. The majority of the research examined used qualitative analysis of online textual data. Our review suggests that researchers should use a broader range of methods, pay more attention to targets' perspectives, and broaden their scope by investigating issues such as the Internet's roles in mobilising isolated racist individuals and enabling ideological clustering of supporters of racist ideologies.

Reducing racial inequities in health: Using what we already know to take action:

This document gives an overview of the scientific data pointing to essential actions to eliminate racial health disparities. To begin, it contends that communities of opportunity should be created in order to mitigate some of the negative effects of systematic racism. These are communities that provide resources for early childhood development, adopt policies to minimise childhood poverty, provide employment and income assistance options to adults, and promote healthy housing and community circumstances. Second, the healthcare system requires new emphasis on ensuring universal access to high-quality care, strengthening preventive health care approaches, addressing patients' social needs as part of healthcare delivery, and diversifying the healthcare workforce to better reflect the patient population's demographic composition. Finally,

additional research is required to determine the best tactics for mobilising political will and support to address health-related socioeconomic disparities. This will include initiatives to raise awareness of the prevalence of health inequities, build empathy and support for addressing inequities, strengthen individuals' and communities' capacity to actively participate in intervention efforts, and implement large-scale efforts to reduce racial prejudice, ideologies, and stereotypes in the larger culture that underpin policy preferences that initiate and sustain inequities.

3. METHODOLOGY

Because of social media's dominance in the sociopolitical scene, numerous current and new types of racism emerged on the platform. Racism has appeared on social media in several forms, both hidden and open, hidden via the use of memes and open through racist statements made under false identities to provoke hate, violence, and societal instability. Racism, although frequently connected with ethnicity, is now prospering on the basis of colour, origin, language, culture, and, most crucially, religion. Social media thoughts and statements inciting racial tensions have been seen as a severe danger to social, political, and cultural stability, as well as the peace of several nations. As a result, social media, which is the major source of racist

beliefs propagation, should be watched, and racist statements should be recognised and banned as soon as possible.

Disadvantages:

1. Existing techniques cannot be identified and halted automatically to prevent future spread.
2. Poor performance.

The purpose of this project is to identify racist tweets using sentiment analysis of tweets. Because of deep learning's improved performance, a stacked ensemble deep learning model is created by merging gated recurrent units (GRU), convolutional neural networks (CNN), and recurrent neural networks RNN, which is known as Gated Convolutional Recurrent- Neural Networks (GCR-NN). In the GCR-NN model, GRU is at the top for extracting acceptable and conspicuous characteristics from raw text, while CNN extracts key aspects for RNN to produce correct predictions.

Advantages:

1. The suggested GCR-NN within the context of machine learning and deep learning models demonstrating higher performance with greater accuracy.

2. The suggested GCR-NN model can identify racist statements in 97% of tweets.

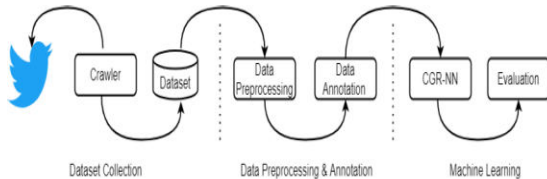


Fig.2: System architecture

MODULES:

To carry out the aforementioned project, we created the modules listed below.

- **Data exploration:** we will put data into the system using this module.
- **Processing:** we will read data for processing using this module.
- **Using this module,** data will be separated into train and test models.
- **Model generation:** GCN with BERT, LSTM, GRU, RNN, CNN, Ensemble Method LSTM + GCN with BERT, Logistic Regression, Random Forest, KNN, Decision Tree, Support Vector Machine, Voting Classifier.

- **User signup and login:** Using this module will result in registration and login.
- **User input:** Using this module will result in prediction input.
- **Prediction:** the final predicted value will be presented.

4. IMPLEMENTATION

ALGORITHMS:

GCN: A Graph Convolutional Network, or GCN, is a semi-supervised learning strategy for graph-structured data. It is based on an efficient variation of convolutional neural networks that act on graphs directly.

BERT: BERT is a machine learning framework for natural language processing that is open source (NLP). BERT is intended to assist computers in understanding the meaning of ambiguous words in text by establishing context from surrounding content.

LSTM: A deep learning architecture based on an artificial recurrent neural network, long short-term memory (LSTM) (RNN). For situations requiring sequences and time series, LSTMs offer a promising solution.

GRU: Gated recurrent units (GRUs) are a recurrent neural network gating technique established in 2014 by Kyunghyun Cho et al. The GRU functions similarly to a long short-term memory (LSTM) with a forget gate, but with fewer parameters since it lacks an output gate.

RNN: Recurrent neural networks (RNNs) are the cutting-edge algorithm for sequential data, and they are employed in Apple's Siri and Google's voice search. It is the first algorithm to recall its input thanks to its internal memory, making it ideal for machine learning issues involving sequential data.

CNN: A CNN is a kind of network architecture for deep learning algorithms that is primarily utilised for image recognition and pixel data processing jobs. There are different forms of neural networks in deep learning, but CNNs are the network design of choice for identifying and recognising things.

Ensemble Method: Ensemble methods are strategies that try to improve model accuracy by mixing numerous models rather of utilising a single model. The integrated models considerably improve the accuracy of the findings. As a result, ensemble approaches in machine learning have grown in favour.

Logistic Regression: This statistical model (also known as a logit model) is often used in classification and predictive analytics. Based on a collection of independent variables, logistic regression calculates the likelihood of an event happening, such as voting or not voting.

Random Forest: A Random Forest Method is a supervised machine learning algorithm that is widely used in Machine Learning for Classification and Regression issues. We know that a forest is made up of many trees, and the more trees there are, the more vigorous the forest is.

KNN: The k-nearest neighbours method, often known as KNN or k-NN, is a non-parametric, supervised learning classifier that employs proximity to create classifications or predictions about an individual data point's grouping.

Decision tree: A decision tree is a non-parametric supervised learning technique that may be used for classification and regression applications. It has a tree structure that is hierarchical and consists of a root node, branches, internal nodes, and leaf nodes.

SVM: Support Vector Machine (SVM) is a supervised machine learning technique that may be used for both classification and regression. Though we call them regression issues, they are best suited for categorization. The SVM

algorithm's goal is to identify a hyperplane in an N-dimensional space that clearly classifies the input points.

Voting classifier: A voting classifier is a machine learning estimator that trains numerous base models or estimators and predicts based on the results of each base estimator. Aggregating criteria may be coupled voting decisions for each estimator output.

5. EXPERIMENTAL RESULTS

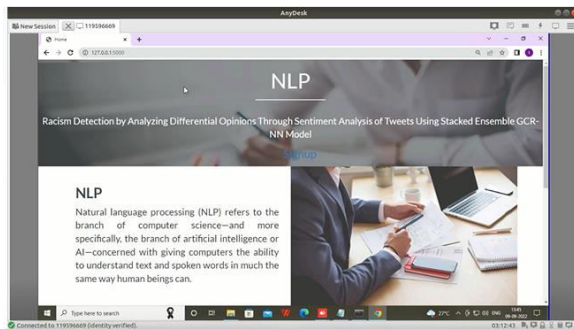


Fig.3: Home screen

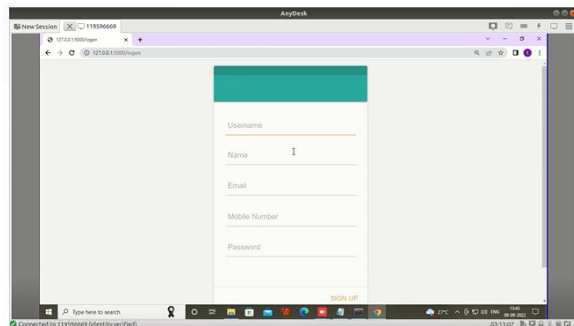


Fig.4: User registration

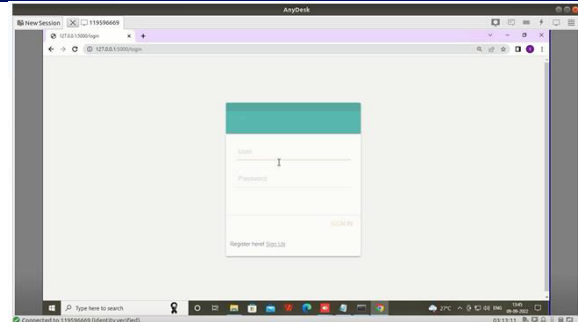


Fig.5: user login

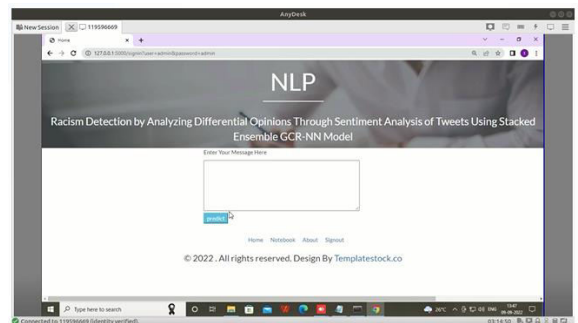


Fig.6: Main screen

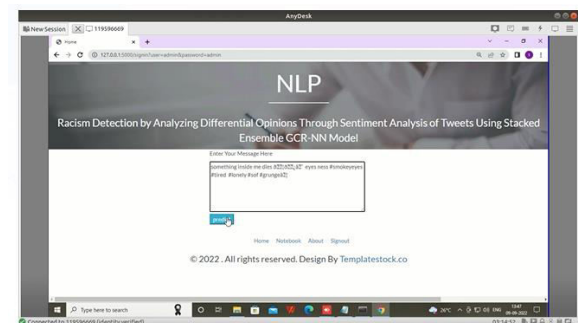


Fig.7: User input

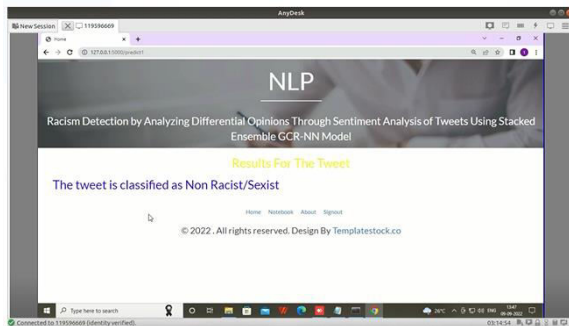


Fig.8: Prediction result

6. CONCLUSION

Racist remarks are becoming increasingly common on social media sites such as Twitter and should be caught and blocked automatically to prevent further dissemination. This work approaches racism detection using sentiment analysis and identifies racist tweets by recognising negative feelings. Deep learning is supplemented by the ensemble technique, in which GRU, CNN, and RNN are stacked to build the GCR-NN model, to achieve high-performance sentiment analysis. A huge dataset gathered from Twitter and annotated using TextBlob is used to test several machine learning, deep learning, and suggested GCR-NN models. Racist statements were found in 31.49% of the 169,999 tweets surveyed. The results reveal that deep learning models outperform machine learning models, with the suggested GCR-NN achieving an average accuracy score of 0.98 for sentiment analysis for positive,

negative, and neutral classifications. Because the negative class is key in detecting racism, a second investigation shows that SVM and LR properly identify 96% and 95% of racist tweets, respectively, whereas 4% and 5% of racist tweets are misclassified. The suggested GCR-NN, on the other hand, properly detects 97% of racist tweets with just a 3% error rate.

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