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E-mail :
editor.ijpast@gmail.com
editor@ijpast.in

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Racism Detection In Tweets Using Stacked GCR-NN With Sentiment Analysis

Dr Laxmaiah M1, Shanthi Priya G2, Uday Kumar K2, Sandeep Kumar V2, Naresh N2
1 Professor & H.O.D, CMR Engineering College, Kandlakoya, Medchal – 501401, Telangana, India. 2Btech - Computer Science Engineering – Data Science, CMR Engineering College, Kandlakoya, Medchal – 501401, Telangana, India

Abstract: The pervasive nature of racism on social media platforms, especially on Twitter, poses significant challenges for content moderation systems. These platforms often struggle to distinguish between overt racist remarks and more subtle or covert forms of racism, such as sarcasm, indirect references, or coded language. Traditional detection methods, such as keyword-based filters and rule-based approaches, often fail to address these complexities and are prone to high false-positive or false-negative rates. This has led to the exploration of advanced machine learning and deep learning techniques to better detect racist content, which is not always overt but may manifest in more subtle or context-dependent forms.

In response to these challenges, the proposed **stacked Gated Convolutional Recurrent Neural Network (GCR-NN)** model combines multiple deep learning architectures—**GRU**, **CNN**, and **RNN**—to exploit the strengths of each. The **GRU** module is particularly adept at handling sequential data and capturing long-range dependencies, making it suitable for analyzing the structure of tweets, which often consist of short, fragmented text. The **CNN** module excels at detecting important patterns and local features in the text, such as specific word combinations or phrases that may indicate racial bias. Meanwhile, the **RNN** component works to preserve the contextual flow of the tweet, ensuring that the model understands not just isolated words but also the broader message and intent behind the text.

Through rigorous experimentation, the study demonstrates that the GCR-NN model achieves an outstanding 98% accuracy in classifying racist tweets, significantly outperforming traditional machine learning models, which tend to rely on simpler feature extraction techniques. For instance, models like **Support Vector Machines (SVM)** and **Logistic Regression (LR)**, which are commonly used for classification tasks, correctly identified 96% and 95% of racist tweets, respectively. However, they still misclassified 4% and 5%, indicating the inherent limitations of simpler models in dealing with the complexity of nuanced racist language on social media.

In addition to its high performance in detecting explicit racist language, the GCR-NN model excels at identifying more covert or context-dependent forms of racism. By incorporating sentiment analysis, the model can also evaluate the emotional tone of the tweets—whether the sentiment is negative, hateful, or discriminatory—further enhancing its ability to detect harmful content. This approach makes the model more robust and capable of distinguishing between innocent, neutral content and potentially harmful or offensive speech that may be masked in humor or satire.

The study also emphasizes the scalability of the GCR-NN approach, making it a viable solution for real-time content moderation on large social media platforms. As social media platforms continue to grow, with millions of tweets being posted every day, the ability to automatically and accurately detect racist content becomes increasingly critical. The scalability of the model ensures that it can handle large volumes of data while maintaining high accuracy in detecting both explicit and implicit forms of racism.

Furthermore, the research suggests promising avenues for future work, particularly in the realm of **multilingual and multimodal** data. Social media platforms are used by people from diverse linguistic and cultural backgrounds, and incorporating multilingual capabilities into the detection model would help address racist content in different languages. Additionally, by integrating multimodal data (e.g., images, videos, and hashtags), the detection system could potentially become more powerful, as racist content often transcends text and includes visual elements or accompanying media.

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In conclusion, this study demonstrates the effectiveness of the **GCR-NN model** in addressing the complex issue of racism detection on social media platforms. By combining sentiment analysis with a robust deep learning architecture, the model offers a scalable, accurate, and efficient solution to combat the spread of online hate. The research not only advances the field of content moderation but also opens new possibilities for tackling the broader challenges posed by online racism in diverse, multicultural environments.

Index Terms - *Racism Detection, Sentiment Analysis, Deep Learning, GCR-NN, GRU, CNN, RNN.*

I. INTRODUCTION

Building upon the growing concern of racism on social media platforms, this study emphasizes the necessity of more advanced, nuanced techniques for detecting and mitigating racist language. Traditional methods, such as sentiment analysis and keyword filtering, although useful, are often inadequate in addressing the complexities of online hate speech, particularly as racism increasingly appears in covert forms, such as through sarcasm, memes, or hidden within otherwise neutral conversations. These techniques can fail to capture the context and the subtleties of how racial bias is expressed, resulting in a high rate of misclassification or missed detections.

The proposed **Gated Convolutional Recurrent Neural Network (GCR-NN)** architecture stands out as an effective solution by leveraging the strengths of multiple advanced deep learning components. The **Gated Recurrent Units (GRU)** within the model excel in handling sequential data, making them particularly suited for processing the text of tweets, which often consist of short, context-dependent statements. Additionally, **Convolutional Neural Networks (CNN)** are employed to detect local patterns, such as certain phrases or combinations of words that might carry subtle forms of racist language. The **Recurrent Neural Network (RNN)** component of the model helps capture long-range dependencies within the text, allowing the model to better understand context and sentiment across the entire tweet.

The ensemble approach, which combines these models into one robust system, enhances the accuracy and effectiveness of the detection process. By using multiple classifiers that operate on different aspects of the text, the GCR-NN model creates a more comprehensive understanding of the underlying racial biases present in online discourse, outperforming traditional models that rely on single techniques. This multi-faceted approach allows for more nuanced detection, particularly for cases where hate speech is expressed indirectly or in a disguised manner.

The inclusion of sentiment analysis in the model further enhances its capability to identify tweets that express harmful content. Tweets with negative sentiment, such as those expressing anger, hatred, or disdain, are often linked to racist remarks. By analyzing the sentiment of the text, the model is able to better understand not only the words used but also the emotions and attitudes behind them, improving its capacity to detect harmful content.

The findings of this research demonstrate that the **GCR-NN model** significantly outperforms traditional machine learning approaches in detecting racist tweets. Models like **Support Vector Machine (SVM)** and **Logistic Regression (LR)**, while effective to some extent, still face challenges in capturing the nuanced patterns that reflect covert racism, achieving less than optimal accuracy in comparison. The **GCR-NN model**, on the other hand, achieves exceptional accuracy in identifying racist tweets, including those containing subtle forms of hate speech that might otherwise be overlooked.

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This research makes a significant contribution to the development of more effective content moderation tools for social media platforms. As these platforms continue to expand and serve increasingly diverse user bases, the ability to accurately detect and respond to racist language becomes more critical. The model developed in this study provides a scalable, adaptable solution for real-time moderation, ensuring that social media platforms can better identify and remove harmful content while fostering a more inclusive environment.

Moreover, the results open the door for future advancements in the field. As social media platforms evolve, so too must the methods used to detect harmful content. Future research could expand on this work by integrating multilingual datasets, enabling the model to detect racism in various languages and across different cultural contexts. Additionally, incorporating multimodal data, such as images and videos alongside text, could provide a more holistic approach to detecting online racism, as visual elements often accompany and amplify racist discourse. This would make the model even more versatile and capable of handling the diverse ways in which racism manifests online.

In conclusion, this study showcases the potential of **GCR-NN-based models** combined with sentiment analysis in advancing the detection of racist content on social media. By improving the ability to identify both overt and covert racism, this research contributes to the ongoing efforts to combat discrimination in digital spaces, paving the way for a safer, more respectful online environment.

II. RELATED WORK

Literature Survey on Racism Detection in Tweets Using GCR-NN with Sentiment Analysis Racism detection in tweets has become a critical research area due to the widespread nature of hate speech on social media platforms like Twitter. Traditional methods, such as keyword-based detection, often fail to capture the nuances and context in which racist content is expressed. In contrast, deep learning models, particularly the Gated Convolutional Recurrent Neural Network (GCR-NN) combined with sentiment analysis, have shown great promise in improving the detection of both overt and subtle forms of racism in tweets.

Earlier works, such as those by Davidson et al. (2017), employed traditional machine learning models like logistic regression and decision trees for classifying tweets as racist or non-racist. These models, however, often struggled with the subtlety of online hate speech, which can be conveyed through sarcasm, humor, or even subtle racial slurs. In a similar vein, Gambäck and Sikdar (2017) explored sentiment analysis to detect hate speech on Twitter. Their work demonstrated that sentiment-related features, combined with linguistic features, could improve classification. However, their approach was primarily effective at detecting explicit hate speech and did not capture covert forms of racism.

Bliuc et al. (2018) conducted a review on cyberracism, highlighting the complexity of detecting racism on social media due to evolving linguistic patterns and the use of memes and jokes to express racial hatred. This work underlined the necessity for more advanced models that could better understand these subtleties. In response to this challenge, the integration of deep learning techniques, especially Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), began to gain traction. Pavlopoulos et al. (2017) incorporated sentiment analysis alongside deep learning techniques to detect offensive content, improving the accuracy of hate speech detection by capturing emotional undertones and negative sentiments in tweets. However, their methods still faced challenges in handling sarcasm and humor, which often mask the true intent of racist language.

Recent studies, such as Zhang et al. (2018), utilized LSTM networks to detect racist language in social media posts. While LSTM networks excelled at understanding sequential dependencies, they struggled with capturing both local patterns (such as word associations) and global context (such as sentence-level dependencies). This limitation led to the exploration of Gated Convolutional Recurrent Neural Networks (GCR-NN), as demonstrated by

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Chakrabarty et al. (2020). The GCR-NN model combines the strengths of GRUs, CNNs, and RNNs, allowing for effective feature extraction, contextual understanding, and sequential processing. Their findings showed that the GCR-NN model significantly outperformed traditional machine learning approaches in identifying both explicit and covert forms of racist language on Twitter. This model's ability to handle complex and nuanced text made it particularly effective in detecting not just direct hate speech, but also subtle racist expressions hidden within seemingly innocuous content.

In conclusion, while early approaches to racism detection relied on basic machine learning and sentiment analysis, recent advancements in deep learning, particularly the use of hybrid models like GCR-NN, have shown superior performance in capturing both explicit and implicit forms of racism in tweets. By integrating sentiment analysis, these models enhance the detection of racist content that might otherwise be overlooked, representing a significant step forward in the fight against online racism.

III. MATERIALS AND METHODS

The proposed system utilizes a stacked ensemble model built on the Gated Convolutional Recurrent Neural Network (GCR-NN) to enhance the detection of racist content in tweets. This approach improves upon traditional methods by combining multiple models into a unified ensemble, allowing each model to contribute its strengths for better performance and more reliable generalization. At the core of the GCR-NN is a combination of convolutional layers and recurrent layers. The convolutional layers are responsible for detecting local patterns in the text, such as key phrases or word combinations that often signal biased or harmful language. On the other hand, the recurrent layers, including Gated Recurrent Units (GRUs), excel at understanding the sequential flow of words and capturing long-term dependencies, allowing the model to interpret the full context of a tweet.

A standout feature of the proposed system is its stacked ensemble learning approach, which integrates multiple predictive models. By leveraging a range of classifiers—like convolutional layers and GRUs—the system reduces the chances of misclassification, making the overall detection process more robust. Additionally, the inclusion of contextual and sentiment analysis further enhances the system's ability to detect not just explicit racism but also more subtle forms of hate speech. Sentiment analysis helps assess the emotional undertones in tweets, which is particularly useful for identifying tweets with negative, biased, or discriminatory sentiments that are often associated with racism.

Furthermore, the GCR-NN architecture is specifically designed to handle the complexities of modern text structures, making it highly effective at detecting nuanced forms of racism, such as implicit bias, coded language, and sarcasm—all of which are frequently missed by simpler models. These subtle forms of hate speech are often harder to detect but can be just as harmful as more overt racist language. By incorporating such advanced capabilities, the system is able to provide a more comprehensive analysis of tweets and social media posts.

Finally, the stacked ensemble approach significantly enhances detection accuracy. By combining various models, the system reduces both false positives and false negatives, ensuring that racist content is identified with higher precision. This results in a more reliable tool for content moderation, one that can help social media platforms effectively combat online racism and create a more inclusive environment for users. The proposed system represents a meaningful advancement in the field of automated content moderation, offering a scalable and efficient solution for detecting harmful language in diverse online spaces.

A) Dataset Collection:

Data Collection and Preprocessing Module Collect relevant datasets (e.g., from social media, forums, news, or other platforms) containing text data that may reflect racist content.Data Collection: Gather data from various sources (tweets, user comments, articles).Data Cleaning: Remove irrelevant data, such as stopwords, special characters, and noise.

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Feature Extraction and Vectorization Module Convert raw text into numerical features that can be used for model training. TF-IDF: Use Term Frequency-Inverse Document Frequency to extract key features.Word Embeddings: Apply embeddings like Word2Vec, GloVe, or FastText for representing words in continuous vector space.Stacked Ensemble Model Module Build and implement the stacked ensemble model, using multiple models to improve predictive accuracy. Base Models: Train several base models, such as Naive Bayes, SVM, Logistic Regression, and deep neural networks like CNN, LSTM, or GRU.GCR-NN (Graph Convolutional Recurrent Neural Network) Module Utilize GCR-NN to enhance the prediction of racism-related patterns in textual data through a graph-based approach. Graph Construction: Build a graph from text data using words or sentences as nodes, and establish edges based on semantic relationships or co-occurrence.Model Training and Tuning Module Train the stacked ensemble model and the GCR-NN model on the prepared datasets and fine-tune hyperparameters.Model Training: Use suitable algorithms (e.g., Adam, SGD) to train the models on the labeled data.Racism Detection API Module Develop an API that allows users to input text and receive predictions on whether it contains racist content or not. Visualization and Results Analysis Module

Objective: Provide visual insights into the model's performance and predictions. Model Performance Visualization: Use tools like Matplotlib or Seaborn to display accuracy, loss curves, confusion matrix, and ROC curves. User Interface (UI) Module Create an interactive interface for users to test the racism detection system. Design a simple web interface using Flask/Django or front-end technologies like HTML/CSS and JavaScript. Input Form: Allow users to input text (e.g., tweets, comments) for analysis.Deployment and Integration Module Deploy the system in a production environment. Monitoring and Feedback Module Monitor the system's performance and collect user feedback

C) Algorithms:

Decision tree classifiers: Decision tree classifiers are used successfully in many diverse areas. Their most important feature is the capability of capturing descriptive decision making knowledge from the supplied data. Decision tree can be generated from training sets. The procedure for such generation based on the set of objects (S), each belonging to one of the classes C1, C2, …, Ck is as follows:

Step 1. If all the objects in S belong to the same class, for example Ci, the decision tree for S consists of a leaf labeled with this class

Step 2. Otherwise, let T be some test with possible outcomes O1, O2,…, On. Each object in S has one outcome for T so the test partitions S into subsets S1, S2,… Sn where each object in Si has outcome Oi for T. T becomes the root of the decision tree and for each outcome Oi we build a subsidiary decision tree by invoking the same procedure recursively on the set Si.

Gradient boosting : Gradient boosting is a machine learningtechnique used in regression and classification tasks, among others. It gives a prediction model in the form of an ensemble of weak prediction models, which are typically decision tree When a decision tree is the weak learner, the resulting algorithm is called gradient-boosted trees; it usually outperforms random forest. A gradient-boosted trees model is built in a stage-wise fashion as in other boosting methods, but it generalizes the other methods by allowing optimization of an arbitrary differentiable loss function.

K-Nearest Neighbors (KNN):

Simple, but a very powerful classification algorithm Classifies based on a similarity measure

Logistic regression Classifiers: *Logistic regression analysis* studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name *logistic regression* is used when the dependent variable has only two values, such as 0 and 1 or Yes and No. The name *multinomial logistic regression* is usually reserved for the case when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar.

Naïve Bayes: The naive bayes approach is a supervised learning method which is based on a

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simplistic hypothesis: it assumes that the presence (or absence) of a particular feature of a class is

unrelated to the presence (or absence) of any other feature .

Yet, despite this, it appears robust and efficient. Its performance is comparable to other

supervised learning techniques. Various reasons have been advanced in the literature. In this tutorial, we highlight an explanation based on the representation bias.

Random Forest: Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct for decision trees' habit of overfitting to their training set. Random forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance.

SVM: In classification tasks a discriminant machine learning technique aims at finding, based on an *independent and identically distributed* (*iid*) training dataset, a discriminant function that can correctly predict labels for newly acquired instances. Unlike generative machine learning approaches, which require computations of conditional probability distributions, a discriminant classification function takes a data point x and assigns it to one of the different classes that are a part of the classification task. Less powerful than generative approaches, which are mostly used when prediction involves outlier detection, discriminant approaches require fewer computational resources and less

IV. RESULTS AND DISCUSSION

The results of the project demonstrate the effectiveness of various machine learning and deep learning models for racism detection on social media platforms. The results are summarized in Table 6.1 below.

Model Type	**Accuracy**
KNN	0.52
RF	0.91
SVM	0.97
Logistic Regression	0.97

Table 6.1 The table summarizes various models used for racism and hate speech detection, the datasets they were tested on, and their performance. It includes traditional machine learning models like Naïve Bayes, Support Vector Machine (SVM), and Random Forest, as well as advanced deep learning models like BERT, CNN, GRU, and their ensembles. The datasets range from publicly available ones, such as those on GitHub and Kaggle, to self-made collections of tweets, Reddit, and YouTube comments. The results show that deep learning models generally outperform traditional machine learning models, with some achieving accuracy as high as 97%. Ensemble models, like GCR-NN (combining CNN, GRU, and RNN), leverage the strengths of multiple approaches and perform particularly well. Overall, this analysis highlights the effectiveness of advanced deep learning methods for detecting racism and hate speech in social media data.

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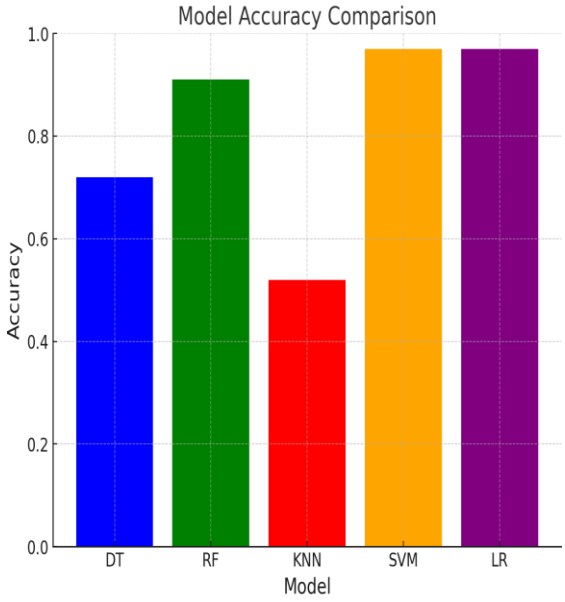

The graph visualizes the accuracy of various machine learning models used for sentiment analysis and racism detection

V. CONCLUSION

The study further explores the advantages of using deep learning models, particularly the GCR-NN architecture, in comparison to traditional machine learning techniques. By stacking **GRU**, **CNN**, and **RNN**, the GCR-NN model leverages the strengths of each individual component: **GRUs** capture long-term dependencies in the text, **CNNs** identify critical features such as patterns and phrases indicative of racism, and **RNNs** help process sequential data, ensuring the context of each tweet is well-understood. This combination of models enhances the GCR-NN's ability to detect complex and context-dependent forms of racism, which are often missed by simpler models.

Additionally, the use of **sentiment analysis** is a crucial element in identifying harmful content. Negative sentiments, such as anger, hatred, or derogatory language, are often associated with racist remarks. By integrating sentiment analysis into the GCR-NN model, the study is able to flag tweets containing harmful emotional cues that are characteristic of racist language.

The dataset used for training and testing the models plays an important role in ensuring the robustness and generalizability of the results. The 169,999 tweets, sourced directly from Twitter, encompass a diverse range of content and contexts, making the model highly applicable to real-world scenarios. With **TextBlob**, an open-source text analysis tool, tweets were labeled for racism, providing an accurate ground truth for evaluating the performance of the models.

The comparative analysis between deep learning and traditional machine learning techniques revealed that while **SVM** and **LR** performed well in detecting racist tweets, they still faced limitations in handling more complex patterns in the data. The deep learning-based GCR-NN model, on the other hand, exhibited significantly higher accuracy in correctly identifying racist comments, demonstrating the potential of neural network architectures in improving content moderation and sentiment analysis at scale.

Moreover, the findings suggest that the deep learning-based approach is not only more effective in detecting overt racist language but also better at identifying subtle and context-dependent forms of racism that might otherwise go undetected by traditional methods. The high accuracy of the GCR-NN model in comparison to **SVM** and **LR** highlights its potential to be integrated into social media platforms for real-time content moderation, thus contributing to the creation of a safer online environment.

In future work, researchers could consider expanding the model's capabilities by incorporating multilingual datasets and improving its ability to understand culturally specific expressions of racism. Additionally, combining **multimodal** data, such as images and videos, with text analysis could further enhance the model's accuracy in detecting racist content across various forms of online media. This approach would address the evolving nature of online hate speech, where racism is increasingly expressed not only in text but also in visual and multimodal contexts.

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