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CYBERBULLYING DETECTION ON SOCIAL NETWORKS COMPARING MACHINE LEARNING AND TRANSFER LEARNING

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Abstract: Communication has been transformed by information and communication technologies, yet cyberbullying still presents significant difficulties that need for automated solutions for efficient detection on social media platforms. The PROJECT integrates both conventional Machine Learning and Transfer Learning methodologies, emphasizing feature extraction and selection strategies to improve the model's comprehension of cyberbullying situations. For reliable cyberbullying detection, the project makes use of a variety of models, including as LinearSVC, Logistic Regression, DistilBert, DistilRoBerta, and Electra. These models also use Machine Learning, Transfer Learning, and Deep Learning techniques.

Index terms *- Cyberbullying detection, DistilBert, machine learning, pre-trained language models (PLMs), transfer learning, toxicity features, AMiCa dataset, LIWC, empath.*

1. INTRODUCTION

With their subtle evolution throughout time, information and communication technologies (ICT) have become an essential element of everyone's life and have accelerated online contact between individuals. With the increasing usage of internet platforms, communication has become as simple as clicking a button, which has aided in the development of social networking. The prevalence of ICTs has a negative side when individuals abuse them with ease, such in the case of cyberbullying. The use of internet platforms to spread direct or conventional bullying is known as cyberbullying [1, 2, 3, 4, 5, 6,]. In order to safeguard online communities, social media becomes the virtual medium for bullying, hiding the identity of the aggressor and making cyberbullying detection a difficult and demanding task. [51]

Due to its ease of commission and anonymity, cyberbullying incidents rise as Internet usage increases [7–8]. This poses a serious threat to public health and has a range of adverse effects, including mental, psychological and social problems. While despair, anxiety, loneliness, and anhedonia are common mental health issues among cyberbullying victims, some have also been documented to engage in self-harming

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activity and entertain suicide thoughts [9]. Communities initially used manual methods to track cyberbullying cases. Japanese schools that started Internet patrols inspired parent associations to start laudable efforts to manually filter websites with inappropriate content. However, without computational approaches, it is impossible to process the vast amount of data on the Internet in a short time [10], [11], [12].

To streamline the process and ensure a safe atmosphere on social media sites, it is crucial to automate the identification of cyberbullying. The main objective of this research is to address the problem as a text classification task using state-of-the-art techniques using artificial intelligence and natural language processing to automate the detection of cyberbullying cases through inappropriate posts. Computer-aided text analysis can be effectively used to study social and cultural phenomena [13]. Text classification is widely used in natural language processing to determine the category of a given corpus through a series of steps such as feature extraction, text preprocessing, and building a classification model [14].

To keep social media platforms regulated, social media corporations have created procedures and rules. Nevertheless, the social media platform was falling short in its efforts to combat cyberbullying [15], [16]. In order to passively reduce cyberbullying, users must typically report material, block, or unfriend other users using the user-dependent tools that are accessible [17]. While supervised machine learning algorithms are effective in identifying instances of cyberbullying and in removing offensive language from posts, user reports of their accuracy are higher in this regard [17].

Moreover, privacy protection means that user data and metadata related to the online platform are not always accessible [18], [19]. In that instance, the foundational input for the cyberbullying detection algorithm is textual information that users of the online platform publish [20].

The presence of "bad" words (insult and curse words) or profane keywords was identified in the early research on automatic cyberbullying identification as one feature that increased the likelihood that a post would be cyberbullied. However, as the words or sentences can be readily mispronounced or obscured, searching for a list of words to identify such events is not particularly successful and requires a regular list update [21]. The use of textual characteristics, such as the use of "bad" words (profane, insulting, or swearing terms), to identify cyberbullying in a post has limitations because it's not always possible to identify cyberbullying based just on the explicit presence of these phrases [22]. To enhance the effectiveness of the cyberbullying detection model, more characteristics must be extracted by enlarging the standard bag-of-words text representation [18].

2. LITERATURE SURVEY

Cyberbullying in Turkish High Schools. Scandinavian Journal of Psychology. Cyberbullying is a new form of bullying that has migrated to electronic environments (social media, online gaming environments, blogs, etc.) and is mostly deliberate hostility by teenagers. This study [1] measured cyberbullying among high school students in eastern Turkey and identified demographic and socio-economic characteristics that lead to bullying and cyberbullying. The survey involved 470 participants aged 15-19. Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) showed that the Turkish Cyberbullying Scale (CBS) has a single factor structure. Independent samples t-tests, one-way ANOVA, and Tukey HSD were used to compare demographic and socioeconomic characteristics. To summarize the main findings, gender, type of school, number of siblings, mobile phone ownership, duration of ownership, Internet access at home, family supervision, purpose of Internet use, duration of exposure to Internet, and type of messaging app significantly affect students' CBS scores [34,35].

This study investigates how high school students in Hanoi, Vietnam deal with cyberbullying and the relationship between daily Internet use and risk of cyberbullying. At least 215 teenagers between the ages of 13 and 18 completed an online survey using response-driven sampling [2]. Cyberbullying was assessed using the modified Patchin Scale and the Hinduja Scale. 45.1% of respondents were victims of cyberbullying. The most common form of cyberbullying was insults and ridicule. Daily Internet use had a dose-response relationship with risk of cyberbullying: 54% of those who used the Internet for more than 3 hours a day were victims of cyberbullying, compared with 39% of those who used the Internet for 1-3 hours and 30% of those who used the Internet for less than 3 hours. This difficulty was solved most often by talking to friends (60.8%). Cyberbullying victimization was prevalent in Hanoi, and students' responses were ineffective, according to research. Online time and cyberbullying risk were dose-response [34,35]. Hanoi needs more society/school awareness to avoid cyberbullying.

Bullying is intentional physical and psychological assault by other youngsters [54, 55, 56, 57]. Cyberbullying is a new sort of bullying that occurs on internet networks where stalkers can target vulnerable victims. In extreme circumstances, harassment has caused irreversible harm or suicide. The scientific community is creating techniques to identify cyberbullying quickly, however these systems are still in development and must be improved. [3] CyberDect, an online tool, detects harassment on social media. Our idea analyzes postings for victim-abusing language using Open Source Intelligence and Natural Language Processing. Our idea was evaluated by monitoring two Spanish high school accounts.[53]

Lev Vygotsky and Jean Piaget are the most prominent developmental psychologists. Though distinct, their developmental psychology contributions are extraordinary and distinctive. Despite these similarities, Piaget's and Vygotsky's ideas diverge in a critical, sometimes overlooked aspect that affects how they approach cognitive development [5]. Which theory is right? This study will explain what underlies both psychologists' beliefs, how they are similar and distinct, and why educational textbooks have included them so much. Since Piaget and Vygotsky's learning theories vary yet still affect cognitive development, they are often contrasted.

Cyberbullying (WCB) is a new form of workplace hostility that uses technology to bully employees. This study investigates the relationship between WCB and victims' interpersonal deviance (ID) [6] through simultaneous mediation by employees' ineffective silence and emotional exhaustion (EE). Using conservation of resources theory (COR) and affective events theory, the study analyzed data from 351

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employees in the banking, telecommunications, education, health, insurance, and consulting sectors in Lahore, Pakistan. Ineffective silence negatively moderated the relationship between cyberbullying and deviance, decreasing deviance for employees who used silence as a coping strategy. Cyberbullying and deviance were favorably mediated through EE. This suggests that emotionally exhausted employees retaliated by engaging in deviant behaviors and bullying their colleagues. According to COR and affective events theory, WCB affects ID. According to ID reports, WCB can cause significant economic impacts and business interruptions. Therefore, because WCB harms both employees and the company, companies need to build a culture that prevents WCB and implement prevention and response strategies.[55]

3. METHODOLOGY

i) Proposed Work:

The suggested system detects social network cyberbullying using sophisticated machine learning and transfer learning methods. The approach improves contextual comprehension through subtle feature extraction and selection. Using LinearSVC, Logistic Regression, DistilBert, DistilRoBerta, and Electra, the system handles cyberbullying in several situations and content forms. Advanced deep learning models including LSTM [24] and a hybrid LSTM+GRU architecture were included to the project along with the Voting Classifier. This ensemble approach (voting classifier) used soft voting to combine AdaBoost and RandomForest predictions to improve cyberbullying detection. User testing was made easier using a user-friendly Flask framework linked with SQLite for safe signup and signin.

ii) System Architecture:

Cyberbullying detection begins with dataset preparation [49]. This requires noise reduction, normalization, and cleaning. The preprocessed data is separated into training and testing sets. Traditional machine learning algorithms (LinearSVC, Logistic Regression, and a Voting Classifier combining AdaBoost and Random Forest as an extension) are used in the model building phase, along with transfer learning models (DistilBert, DistilRoBerta, and Electra) and deep learning architectures. On a specialized test set, trained models are assessed for cyberbullying classification accuracy, precision, recall, and F1 score. This multidimensional system architecture provides a strong and flexible cyberbullying detection solution for many situations and content forms.

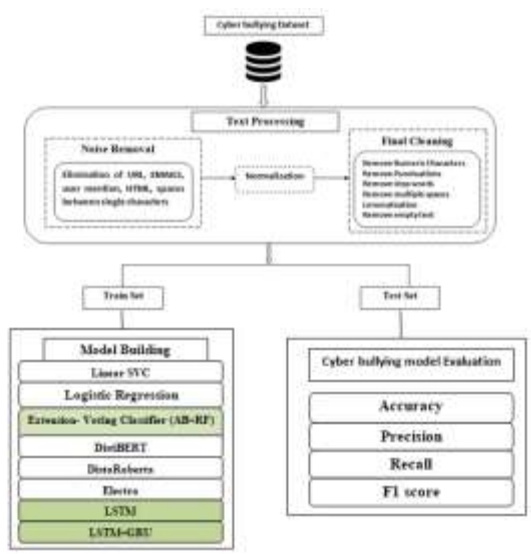

Fig 1 Proposed architecture

iii) Dataset collection:

The cyberbullying dataset [49] is imported and examined to determine its structure, properties, and

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distribution. This initial investigation reveals cyberbullying features.

	Emotion	Content	Original Content
0	disappointed	oh fuck did i wrote fi grinningfacewithsweat ...	b'RT @Davbingodav: @mcrackins Oh fuck ... did ...
1	disappointed	i feel nor am i shamed by it	i feel nor am i shamed by it
2	disappointed	i had been feeling a little bit defeated by th...	i had been feeling a little bit defeated by th...
3	happy	imagine if that reaction guy that called jj kf...	b"@KSIOlajidebt imagine if that reaction guy t...
4	disappointed	i wouldnt feel burdened so that i would live m...	i wouldnt feel burdened so that i would live m...

Fig 2 Dataset

iv) Data Processing:

Data processing turns raw data into business-useful information. Data scientists gather, organize, clean, verify, analyze, and arrange data into graphs or papers. Data can be processed manually, mechanically, or electronically. Information should be more valuable and decision-making easier. Businesses may enhance operations and make critical choices faster. Computer software development and other automated data processing technologies contribute to this. Big data can be turned into relevant insights for quality management and decision-making.

v) Feature selection:

Feature selection chooses the most steady, non-repetitive, and pertinent elements for model turn of events. As data sets extend in amount and assortment, purposefully bringing down their size is significant. The fundamental reason for feature selection is to increment prescient model execution and limit processing cost.

One of the vital pieces of feature engineering is picking the main attributes for machine learning algorithms. To diminish input factors, feature selection methodologies take out copy or superfluous elements and limit the assortment to those generally critical to the ML model. Rather than permitting the ML model pick the main qualities, feature selection ahead of time enjoys a few benefits.

vi) Algorithms:

Linear Support Vector Classifier (LinearSVC) is used for binary classification applications including cyberbullying detection. It finds the best hyperplane to split data points, maximizing class margin, making it suited for social media bullying detection[58].

LinearSVC

```
from sklearn.svm import LinearSVC
svc = LinearSVC()
svc.fit(X_train, y_train)
y_pred = svc.predict(X_test)
```

Fig 3 LinearSVC

Logistic Regression is used in the project because it improves binary classification problems like cyberbullying detection. It predicts the likelihood of an instance belonging to a class, enabling system discrimination [20, 47].

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
LR = LogisticRegression(random_state=0)
LR.fit(X_train, y_train)
y_pred = LR.predict(X_test)
```

Fig 4 Logistic regression

Soft voting combines AdaBoost and RandomForest predictions to average class probabilities in the **Voting Classifier**. Different algorithms improve the system's

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robustness and cyberbullying detection across social network circumstances in this ensemble method. Multiple algorithms working together to classify online cyberbullying more accurately and comprehensively supports the project's objective of tackling its many complexities.

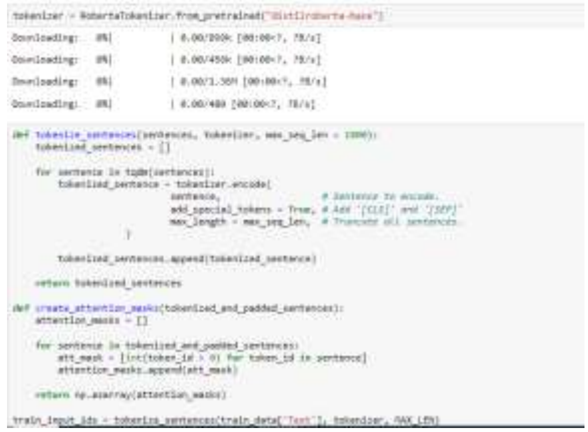
```
Voting CLassifier

from sklearn.ensemble import RandomForestClassifier, VotingClassifier, AdaBoostClassifier
clf1 = AdaBoostClassifier(n_estimators=100, random_state=0)
clf2 = RandomForestClassifier(n_estimators=10, random_state=1)

eclf = VotingClassifier(estimators=[('ad', clf1), ('rf', clf2)], voting='soft')
eclf.fit(X_train, y_train)

y_pred = eclf.predict(X_test)
```

Fig 5 Voting classifier

BERT-distilled **DistilBERT** preserves contextual language knowledge with fewer parameters. For cyberbullying detection, where model sophistication and resource efficiency must be balanced for processing huge amounts of social media data, it removes unneeded components to improve computational efficiency [53, 54, 55].

Fig 6 DistilBERT

DistilRoBERTa refines RoBERTa [53, 54, 55], a robust transformer-based language model. It uses knowledge distillation to condense RoBERTa's language comprehension. This project uses DistilRoBERTa because its efficient representation learning balances cyberbullying detection performance and computing resources.[57]



```
tokenizer = RobertaTokenizer.from_pretrained("distilroberta-base")
Downloading:   0%|          | 0.00/899k [00:00<?, ?B/s]
Downloading:   0%|          | 0.00/456k [00:00<?, ?B/s]
Downloading:   0%|          | 0.00/1.36M [00:00<?, ?B/s]
Downloading:   0%|          | 0.00/480 [00:00<?, ?B/s]

def tokenize_sentences(sentences, tokenizer, max_seq_len = 1000):
    tokenized_sentences = []

    for sentence in tqdm(sentences):
        tokenized_sentence = tokenizer.encode(
                            sentence,                  # Sentence to encode.
                            add_special_tokens = True, # Add '[CLS]' and '[SEP]'
                            max_length = max_seq_len,  # Truncate all sentences.
                    )

        tokenized_sentences.append(tokenized_sentence)

    return tokenized_sentences

def create_attention_masks(tokenized_and_padded_sentences):
    attention_masks = []

    for sentence in tokenized_and_padded_sentences:
        att_mask = [int(token_id > 0) for token_id in sentence]
        attention_masks.append(att_mask)

    return np.asarray(attention_masks)

train_input_ids = tokenize_sentences(train_data['Text'], tokenizer, MAX_LEN)
```

Fig 7 DistilRoBERTa

Pre-trained language model **Electra** substitutes a portion of input text with wrong words and teaches it to distinguish authentic from changed material. It strengthens the proposed approach by increasing the model's awareness of small linguistic differences, essential for reliable cyberbullying detection in varied social network environments.

```
tokenizer = ElectraTokenizer.from_pretrained("google/electra-small-discriminator")
Downloading:   0%|          | 0.00/232k [00:00<?, ?B/s]
Downloading:   0%|          | 0.00/29.0 [00:00<?, ?B/s]
Downloading:   0%|          | 0.00/466k [00:00<?, ?B/s]
Downloading:   0%|          | 0.00/665 [00:00<?, ?B/s]

def tokenize_sentences(sentences, tokenizer, max_seq_len = 1000):
    tokenized_sentences = []

    for sentence in tqdm(sentences):
        tokenized_sentence = tokenizer.encode(
                            sentence,                  # Sentence to encode.
                            add_special_tokens = True, # Add '[CLS]' and '[SEP]'
                            max_length = max_seq_len,  # Truncate all sentences.
                    )

        tokenized_sentences.append(tokenized_sentence)

    return tokenized_sentences

def create_attention_masks(tokenized_and_padded_sentences):
    attention_masks = []

    for sentence in tokenized_and_padded_sentences:
        att_mask = [int(token_id > 0) for token_id in sentence]
        attention_masks.append(att_mask)

    return np.asarray(attention_masks)

train_input_ids = tokenize_sentences(train_data['text'], tokenizer, max_len)
```

Fig 8 Electra

The **LSTM** recurrent neural network (RNN) variation used in this experiment analyzes social media

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interactions. Memory cells and gating mechanisms help LSTMs learn complex patterns over long sequences. This architecture allows LSTMs to record and recall long-term connections, making them ideal for cyberbullying detection, where complex contextual interactions are essential for proper categorization.

Fig 9 LSTM

Specialized recurrent neural networks include **LSTM and GRU.** The model improves memory retention and processing efficiency by integrating LSTM with GRU, which is necessary for understanding sequential data like social media interactions. This hybrid design improves the system's capacity to discover and comprehend long-term linkages, making cyberbullying detection in social networks more successful [47, 48].

Fig 10 LSTM + GRU

4. EXPERIMENTAL RESULTS

Precision: Precision estimates the level of positive cases or tests precisely sorted. Precision is determined utilizing the recipe:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

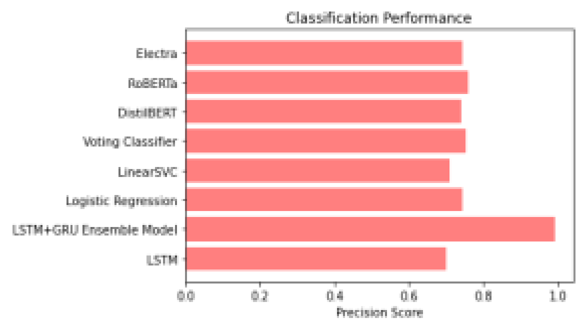

Fig 11 Precision comparison graph

Recall: Machine learning recall assesses a model's ability to perceive all significant examples of a class. It shows a model's culmination in catching occasions of a class by contrasting accurately anticipated positive perceptions with complete positives.

$$Recall = \frac{TP}{TP + FN}$$

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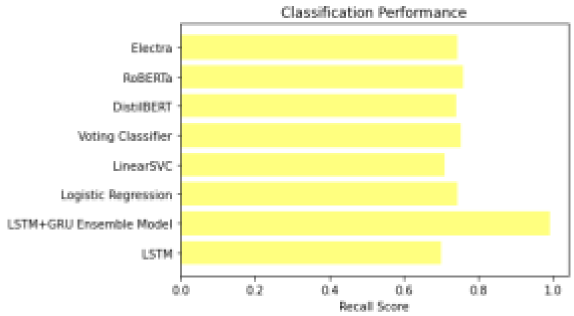

Fig 12 Recall comparison graph

Accuracy: A test's accuracy is its ability to recognize debilitated from sound cases. To quantify test accuracy, figure the small part of true positive and true negative in completely broke down cases. Numerically, this is:

$$\text{Accuracy} = \text{TP} + \text{TN}\ \text{TP} + \text{TN} + \text{FP} + \text{FN}.$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$$

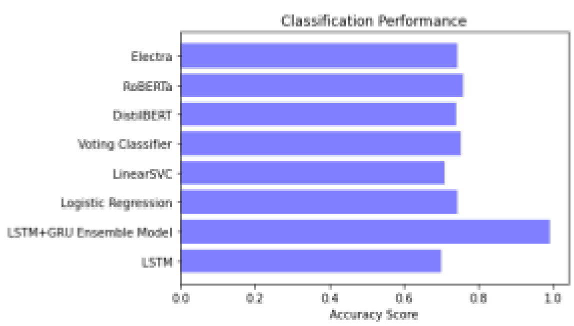

Fig 13 Accuracy graph

F1 Score: Machine learning model accuracy is estimated by F1 score. Consolidating model precision and recall scores. The accuracy measurement estimates how frequently a model anticipated accurately all through the dataset.

$$\text{F1 Score} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} * 100$$

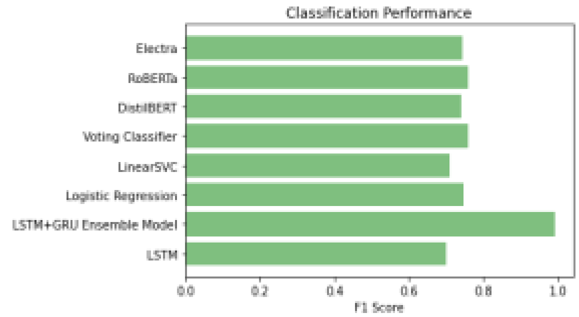

Fig 14 F1Score

	ML Model	Accuracy	Precision	Recall	f1_score
0	LSTM	0.699	0.698	0.698	0.698
1	LSTM+GRU Ensemble Model	0.991	0.991	0.991	0.991
2	Logistic Regression	0.744	0.743	0.744	0.746
3	LinearSVC	0.708	0.707	0.708	0.708
4	Voting Classifier	0.752	0.753	0.752	0.757
5	DistilBERT	0.738	0.738	0.738	0.738
6	RoBERTa	0.757	0.758	0.758	0.758
7	Electra	0.744	0.743	0.743	0.743

Fig 15 Performance Evaluation

Fig 16 Home page

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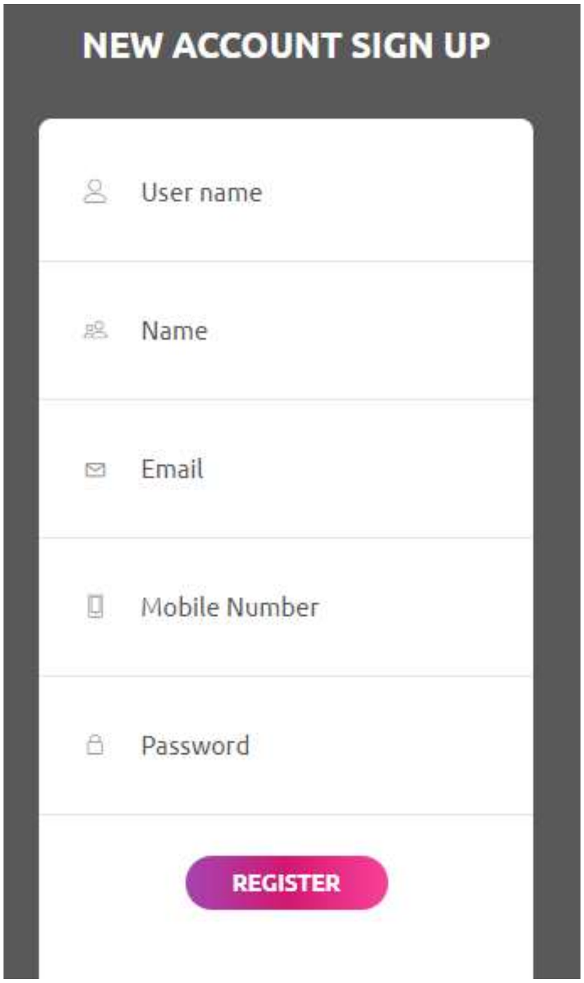

Fig 17 Signin page

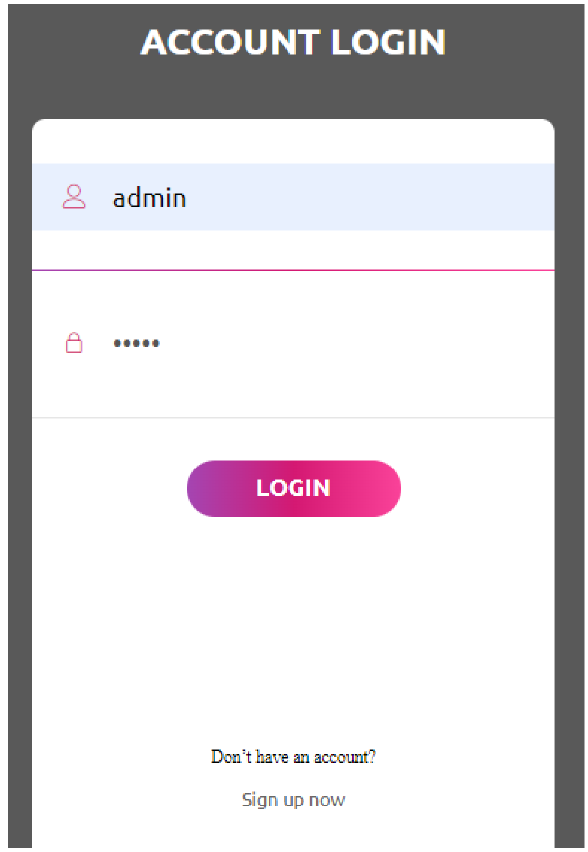

Fig 18 Login page

Fig 19 User input

Fig 20 Predict result for given input

5. CONCLUSION

Cyberbullying is addressed by using LinearSVC, Logistic Regression, DistilBert, DistilRoBerta, and Electra machine learning techniques. This enables a comprehensive cyberbullying detection method in online material. Text normalization, tokenization, and bag-of-words representation are implemented using sophisticated natural language processing techniques. This helps identify cyberbullying by interpreting internet post language. The research uses LSTM, LSTM+GRU, and a voting classifier that combines model predictions [47,48]. LSTM+GRU topped all models. Cyberbullying predictions are more accurate and reliable using this novel method. Flask front-end development delivers a user-friendly system experience. SQLite user authentication makes the cyberbullying detection system more secure. User testing, input validation, and seamless model predictions improve usability in the front-end. The study extends beyond categorization by using Latent Dirichlet Allocation (LDA) [33, 37] for topic modeling to reveal cyberbullying content topics. This deepens understanding and helps reduce cyberbullying in online groups.

6. FUTURE SCOPE

Expanding the system to analyze photos, movies, and audio is planned. This update seeks to better comprehend cyberbullying across modalities. The real-time cyberbullying detection mechanism will be improved [23, 47]. This will enable prompt action and support, making the internet safer. The project will integrate continuous learning and model adaption. This guarantees that the system continues to guard against developing cyberbullying. Multilingual capabilities will expand the project's applicability. This development seeks to identify cyberbullying in many languages, making the service more inclusive and worldwide.[60]

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