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Deep Learning Framework for Prior Identification of Threats in Social Media Interactions

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Abstract: Social Media Interactions are digital platforms that enable users to create profiles, connect with others, and interact through various forms of communication. These platforms facilitate social interaction, content sharing, and collaboration across geographical boundaries. Threats in Social media interactions refer to risks and malicious activities that exploit vulnerabilities in online platforms, posing harm to users, data, and digital ecosystems. These threats can impact personal security, privacy, and overall platform trustworthiness. The Deep Learning-Based Framework for Prior Identification of Threats (DLPIT) is designed to proactively detect and mitigate harmful content in social media interactions, such as hate speech, cyberbullying, and violent language, before they escalate. By leveraging a Recurrent Neural Network (RNN), which is particularly effective for sequential data processing, the system analyzes Twitter language and classifies information as either harmful or non-threatening. The framework is trained on a preprocessed labeled Twitter dataset that incorporates both textual and behavioral data, ensuring comprehensive threat detection. The RNN's ability to capture contextual relationships and temporal dependencies enables DLPIT to monitor social media platforms in real time with high efficiency. Furthermore, the framework enhances detection accuracy by integrating social network interactions and user engagement patterns, which help in identifying the potential influence and reach of harmful content. To quantify the severity of a detected threat, the system calculates a Threat Level Score (TLS) based on multiple factors, including the intensity and frequency of harmful words, user history, past engagement patterns, and the influence of the content within the social network. A higher TLS signifies a greater risk, enabling moderators to prioritize intervention and take necessary actions accordingly. The performance of DLPIT is rigorously evaluated and compared with existing methods using F1-score, recall, accuracy, and precision.

Keywords: Recurrent Neural Network (FFNN), Threat Level Score, Explainable AI, Cyber Bulling

1. INTRODUCTION

Twitter, as one of the most popular social media platforms, is essential for online conversations, news dissemination, and social interactions. However, its open nature and rapid information flow make it a breeding ground for negative activities such as cyberbullying, hate speech, misinformation, and online harassment. Malicious users take advantage of Twitter's real-time engagement features, utilizing coordinated attacks, abusive language, and misinformation campaigns to harass individuals or disseminate destructive narratives. Given the large number of tweets created per second, manual content moderation is impracticable, necessitating automated methods for early threat detection and mitigation. Detecting threats at an early stage is critical for preventing their escalation and providing a safer online environment for users.

Deep learning (DL) algorithms offer an advanced and efficient method for recognizing threats on Twitter. Unlike traditional rule-based systems that rely on keyword filtering, deep learning models examine text, find patterns, and classify information as harmful or non-threatening. These models can capture conversational context, recognize implicit threats, and react to changing language patterns such as coded language and sarcasm. Deep learning-based systems can use natural language processing (NLP) techniques to automatically evaluate vast amounts of Twitter data and detect harmful behavior with high accuracy.

Recurrent Neural Networks (RNNs) are extremely effective at interpreting consecutive data, making them ideal for tracking Twitter conversations and engagement trends. Unlike traditional models, which consider tweets as isolated occurrences, RNNs preserve contextual memory, allowing them to detect dangerous content across several tweets. This skill is critical for detecting rising threats, such as coordinated harassment campaigns or persistent hate speech. Variants like as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) improve the ability to process

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long-term dependencies, resulting in more accurate threat detection. RNNs detect possible threats before they gain traction, allowing for proactive response through continuous analysis of tweet sequences.Other deep learning models, such as Convolutional Neural Networks (CNNs) and Transformer-based architectures like BERT, can help in threat identification on Twitter. CNNs are good at detecting patterns in short text chunks, which makes them excellent for evaluating individual tweets, hashtags, or comments. Meanwhile, BERT and other Transformer models use attention techniques to comprehend complicated language patterns, which improves the identification of subtle threats. Twitter's moderation algorithms can improve detection accuracy, reduce false positives, and monitor hazardous content in real time by incorporating numerous deep learning approaches.

The inclusion of deep learning into Twitter's threat detection architecture allows for proactive content moderation, preventing damaging tweets from spreading widely. These models can be used in real-time systems to automatically detect suspect content, issue warnings, or escalate cases to human moderators. While adversarial threats and computational costs remain problems, constant developments in DL architectures and training approaches make these systems more robust and efficient. Twitter can make its platform safer by using deep learning algorithms to detect risks ahead of time, enabling constructive debates while limiting the spread of bad content.

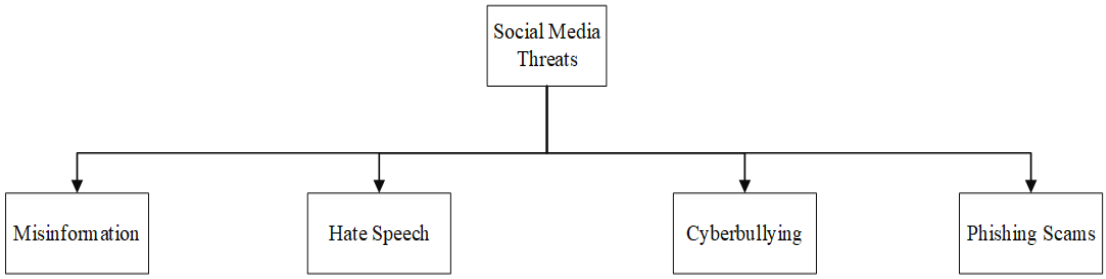

Fig1: Different Types of Threats

In figure 1 the diagram shows many forms of social media risks. The diagram classifies social media risks into the following categories:

Misinformation: It is the dissemination of inaccurate or misleading information that can confuse, affect public perception, or sway opinions. This includes false news, inaccurate health information, and political propaganda.

Hate speech: it is any sort of offensive or abusive words directed at individuals or groups based on qualities such as race, gender, religion, or nationality. Hate speech frequently results in harassment, discrimination, or incites violence.

Cyberbullying: it is defined as online harassment, intimidation, or threats directed at someone, most commonly through repeated messages, public shaming, or impersonation. Cyberbullying can lead to significant emotional and psychological hardship.

Phishing scams: These are fraudulent actions that attempt to obtain sensitive user information by fooling people into submitting personal information such as login credentials or financial data. This is typically accomplished through false messaging, or harmful links.

Merits of DLPIT:

The proposed system offers following advantages over existing threat detection methodologies on social media platforms like Twitter.

I. **Effective Sequential Data Analysis:** DLPIT uses temporal patterns to detect emerging threats such as hate speech and cyberbullying. It improves accuracy with NLP approaches.
II. **Multi-Source Threat Identification:** Uses user behaviour, graph analysis, and tracking to detect explicit and organized threats. This includes bot-generated falsehoods.
III. **Real-Time Threat Monitoring:** Scans contacts on a constant basis to detect dangers before they escalate. It reduces the dependency on post-event reporting.
IV. **Scalable and Efficient Deployment:** Designed for large-scale platforms with low computational costs. Enables effective real-world application.

Here, the further sections are organized like, in section 2, the literature survey explores existing techniques in threat detection, including traditional machine learning models and deep learning architectures, identifying their shortcomings

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in handling evolving threats and adversarial modifications. In section 3, The Proposed Method provides an in-depth explanation of DLPIT's architecture, covering its use of Recurrent Neural Networks (RNNs) model to analyse textual and behavioural patterns. It also describes how the framework adapts to new threats using continuous learning and real-time data processing. In section 4, The Experimental Setup and Results details the dataset, evaluation metrics, and a comparative analysis of DLPIT's performance against conventional models. In section 5, the work is concluded with future research directions.

2. LITERATURE REVIEW

With Twitter's growing popularity as a platform for communication and information exchange, detecting and combating fraudulent user conduct has become a critical concern. Researchers have investigated deep learning algorithms to solve challenges such as fake account detection, bot identification, disinformation spread, cyberbullying, and coordinated harmful activity. Comprehensive surveys and deep learning-based methods have been proposed to detect malevolent users and bogus accounts [1]. Graph Neural Networks (GNNs) have also been used to assess user interactions, with higher accuracy in coordinated activity identification [5]. Transformer-based models have demonstrated improved performance in real-time harmful behaviour detection and coordinated attack identification [9]. Hybrid learning models, which combine convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have also improved threat detection accuracy [12]. Furthermore, research have used deep learning to analyse the evolution of hate speech and radicalization tendencies [18], while the importance of explainable AI (XAI) for social media moderation has been underlined [13]. Privacy-preserving techniques, such as federated learning, have also been proposed to protect data while maintaining detection efficiency [16].

Bot detection solutions include behavioural analysis and graph-based algorithms to identify automated accounts that distribute misinformation [8]. Hierarchical and reinforcement learning models have shown increased scalability and adaptability in danger identification in social networks [4]. To increase classification accuracy in malicious user identification, researchers have also investigated sentiment-aware and influence-aware detection algorithms [11]. Dynamic and temporal models have been used to monitor the evolution of hazards over time, enabling adaptive moderation solutions [19]. Furthermore, hybrid techniques that include several deep learning architectures have showed potential for enhancing precision and recall in harmful content identification [7].

Several studies have also been conducted to detect false news campaigns and disinformation networks utilizing hypergraph-based and graph attention networks [21]. Personalized moderation systems that leverage AI and graph learning have been developed to tailor moderation techniques based on user behaviour [22]. The combination of anomaly detection approaches, including spectral clustering and deep learning, has resulted in a more robust approach to detecting small-scale coordinated attacks [14]. Transformer networks have also been used for real-time identification of fake news campaigns, hence improving misinformation mitigation measures [30]. Multi-agent systems and federated learning models have also been investigated as privacy-preserving social media threat detection methods [17].

Table 1: Literature Survey

S. No	Paper Title	Methodology	Key Findings
1	"Deep Learning for Fake Account Detection on Twitter" [2]	Uses CNNs and RNNs to detect patterns in user behavior for identifying fake accounts.	Improves detection accuracy by learning complex user interaction patterns.
2	"Graph Neural Networks for Malicious User Detection" [5]	Leverages GNNs to model user interactions and identify suspicious behavior.	Outperforms traditional methods in detecting coordinated malicious activities.
3	"Anomaly Detection Using Spectral Clustering and Deep Learning" [14]	Uses spectral clustering combined with deep learning for anomaly detection.	Effectively identifies small-scale coordinated attacks.
4	"Self-Supervised Learning for Fake Account Detection in Twitter" [20]	Employs self-supervised learning to detect fake accounts without labeled data.	Reduces dependence on manually labeled datasets while maintaining high accuracy.

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5	"Transformer-Based Detection of Coordinated Malicious Activities" [15]	Uses transformer models to analyze textual and behavioral patterns in malicious activities.	Enhances real-time detection of coordinated malicious actions.
6	"Federated Learning for Privacy-Preserving Threat Detection" [16]	Implements federated learning to train models without sharing user data.	Improves privacy while ensuring effective threat detection.
7	"Hypergraph-Based Disinformation Detection on Social Networks" [21]	Uses hypergraph structures to capture multi-user relationships in misinformation campaigns.	Provides better accuracy in identifying misinformation networks.
8	"Harassment and Cyberbullying Detection Using LSTM Networks" [26]	Uses LSTM-based deep learning models to detect harassment patterns.	Improves cyberbullying detection efficiency on Twitter.
9	"Hierarchical Learning Models for Multi-Stage Cyber Threat Detection" [28]	Uses hierarchical learning models to detect and analyze threats at multiple levels.	Enhances scalability and adaptability of threat detection.
10	"Real-Time Detection of Fake News Campaigns Using Transformer Networks" [30]	Uses transformer-based models for detecting large-scale fake news campaigns.	Improves early detection of coordinated misinformation efforts.

In table1, Existing systems face several limitations despite advancements in deep learning. One major challenge is the reliance on large labelled datasets, requiring extensive manual annotation, which is time-consuming, biased, and struggles to keep up with evolving malicious language patterns. Additionally, deep learning models like LSTMs and CNNs, trained on historical data, often fail to detect newly emerging threats and adversarial modifications, while their inability to generalize across languages and cultural contexts further reduces efficiency. Additionally, privacy concerns arise when analysing user interactions, leading to ethical debates on data usage. Addressing these challenges requires continuous model adaptation, improved interpretability, to ensure effective, reliable, and fair threat detection on platforms like Twitter.

3.DEEP LEARNING FRAMEWORK FOR PRIOR IDENTIFICATION OF THREATS IN SOCIAL MEDIA INTERACTIONS

In this study, we propose Prior Identification of Threatening tweets model for DLPIT. The model is trained on tweet content, user engagement dynamics, and network interactions to identify threats such as misinformation campaigns, bot activity, hate speech, spamming, and phishing attacks. Our method integrates Natural Language Processing (NLP) for textual analysis, sequential behavioral modeling for anomaly detection, and network-based features to enhance classification accuracy. In Figure 2 architecture diagram of DLPIT is described. The process begins with data collecting, which involves gathering relevant data from social media platforms such as tweets, user engagement patterns, and metadata. This dataset includes both threatening and non-threatening interactions, allowing for full model training Once acquired, the data is pre-processed to increase accuracy and consistency. This phase comprises cleaning up the content by deleting special characters, URLs, and extraneous stop words. To standardize textual material, tokenization and lemmatization are used, with missing values imputed or eliminated. This ensures that the data is properly formatted before being supplied into the model.

Following pre-processing, feature extraction is carried out to improve model learning. Natural Language Processing (NLP) analysis is one of the retrieved characteristics, with an emphasis on sentiment recognition, keyword frequency, and n-grams to capture textual patterns. Graph analysis is used to investigate user interactions and linkages, as well as to uncover coordinated malicious conduct. Additionally, behavioural tracking is used to track user activity trends such as post frequency, fluctuations in content sentiment, and engagement levels. The collected features are then used to train a DLPIT, which is created specifically for sequential data. The model learns temporal correlations between textual content and human behaviour, allowing it to categorize content as harmful or nonthreatening. By exploiting RNN's sequential learning capacity, the system improves contextual comprehension and threat detection accuracy.

Once trained, the model is used to forecast social media threats in real time. Incoming tweets and exchanges are continuously monitored, and possible threats are identified based on previously acquired patterns. The system's real-time nature enables proactive moderation, which detects and addresses problematic content before it escalates. The procedure

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ends with an end-stage decision-making mechanism in which identified content is either reported, evaluated by human moderators, or filtered automatically. This system provides an effective and scalable solution for early threat detection on social media platforms by combining deep learning techniques with NLP, graph-based analysis, and behavioural tracking, helping to create a safer online environment.

3.1 Prior Identification of Threatening Tweets

Prior Identification of Threatening Tweets analyses threats on Twitter by monitoring tweet sequences and recognizing malicious information before it spreads. When a new tweet is received, it is pre-processed to remove extraneous characters and turn words into numerical vectors using word embeddings such as Word2Vec or GloVe. The tweet is then given to the RNNs, which process words one by one while keeping recollection of prior words via hidden states. This enables the model to recognize the context of a tweet rather than just its individual words. Advanced versions, such as LSTM (Long Short-Term Memory) or GRU (Gated Recurrent Unit), are frequently employed to manage long-term dependencies and improve threat detection accuracy.

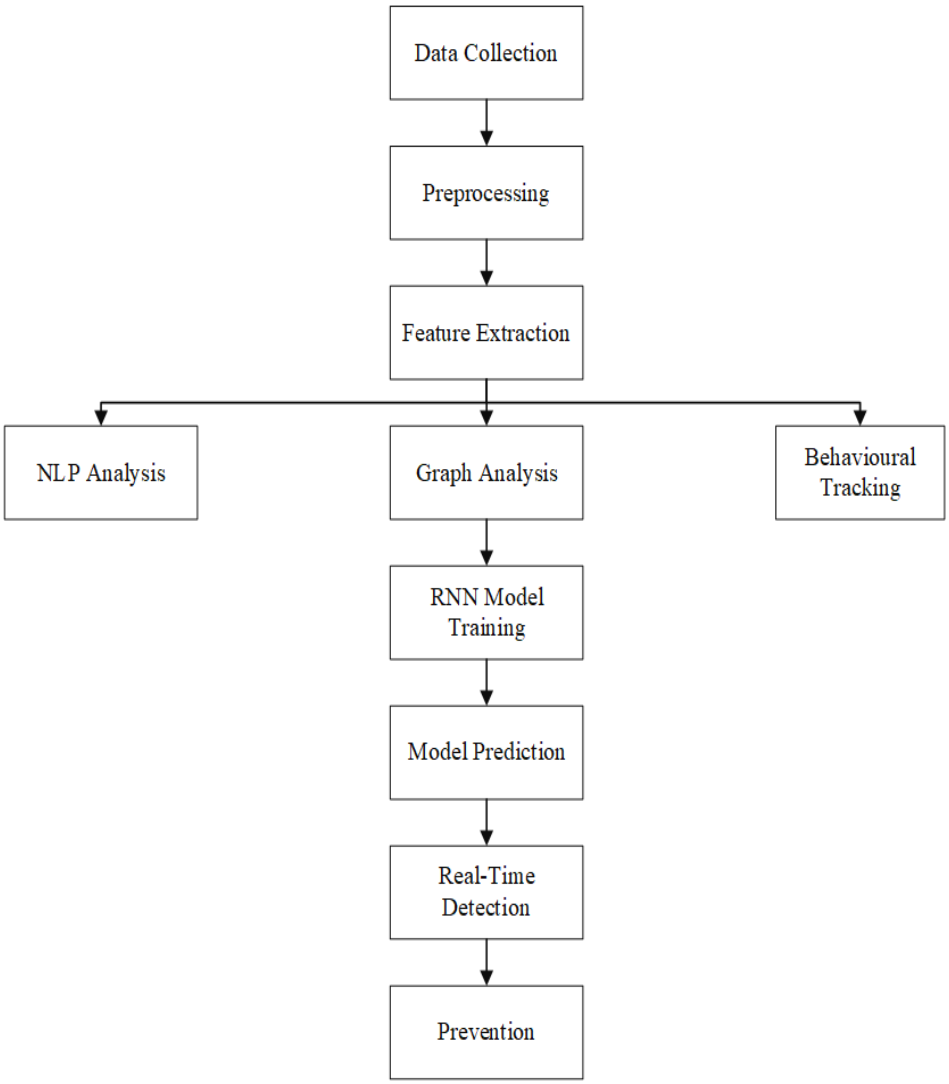

Fig:2 Architecture Diagram

As the RNN examines the tweet, it constantly updates its hidden state, identifying patterns that signify hazardous language. After analysing the entire tweet, the final hidden state is routed through a fully connected layer, where a SoftMax function delivers a probability score for threat identification. If the score is low, the tweet is considered non-threatening and permitted to remain. If the score is high, it is highlighted for manual or automated moderation. The model is constantly learning from fresh data, adapting to changing threats and improving accuracy to ensure early detection of hazardous content before it increases.

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3.2 Threat Identification Framework

In figure 3, Step-by-Step Explanation of the Threat Identification Framework is described.

Tweet Input (Raw Text): The method starts with the acquisition of raw textual data from Twitter. This input is made up of user-generated tweets, which may include informal language, acronyms, slang, and potential noise like emojis, URLs, or special characters. Tweets are short and context-dependent, necessitating sophisticated pre-processing to enable correct analysis.

Pre-processing (cleaning and tokenization) : At this point, the raw tweets are cleaned and tokenized to standardize the data. Cleaning entails eliminating extraneous features such as punctuation, special characters, URLs, and stop words. Tokenization divides the text into meaningful words or sub words, making it easier to evaluate. This phase is critical for reducing data inconsistencies and ensuring that only relevant textual information is provided to the model.

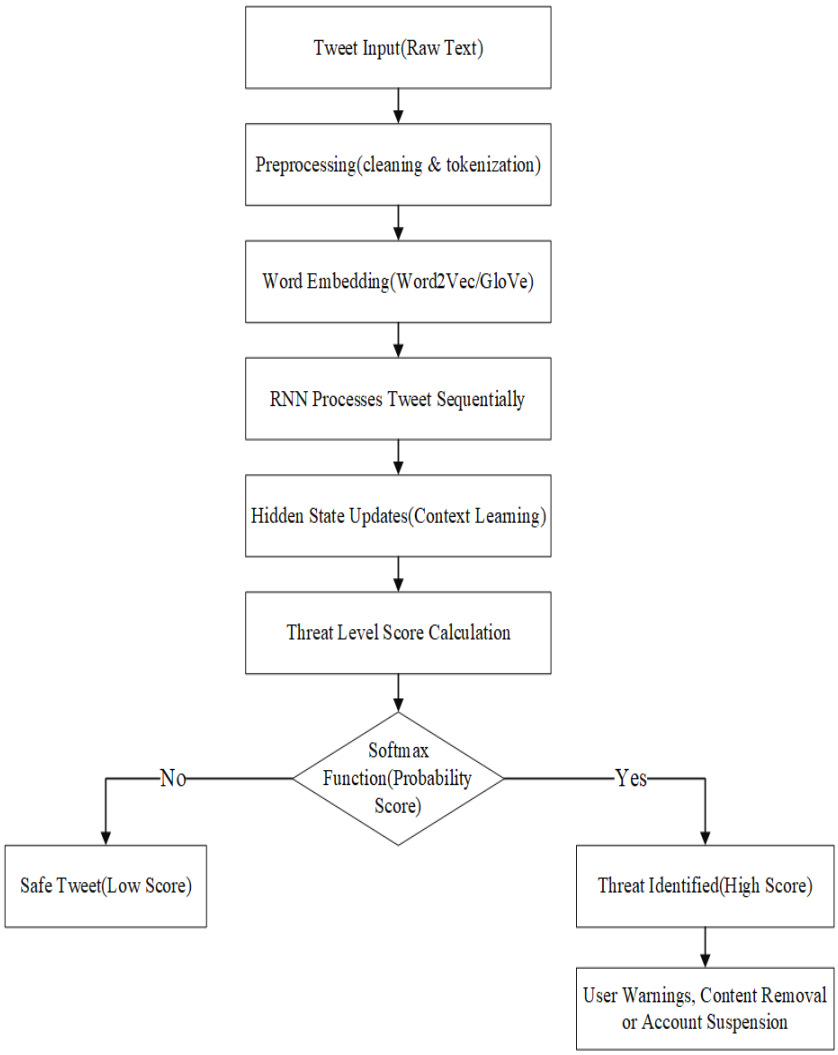

Fig:3Working of Prior Identification of Threatening tweets

Word embedding (Word2Vec, GloVe) :To convert textual data to numerical format, the system employs word embedding techniques such as Word2Vec or GloVe. These embeddings convert words into high-dimensional vector representations that preserve semantic links and contextual meaning. Unlike typical one-hot encoding, word embeddings enable the model to discover word similarities, allowing the RNN to better understand subtle language subtleties and detect threats.

RNN processes tweets sequentially:A Recurrent Neural Network (RNN) is used to analyze tweets word by word while keeping track of previous utterances. RNNs, unlike traditional feedforward networks, are built for sequential data processing, which allows them to capture dependencies across time steps. This is critical for comprehending the whole context of a tweet, especially for recognizing threats that may involve many words or phrases.

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Hidden State Updates (Context Learning): As the RNN processes each word in the tweet, it updates its hidden states, which store learned contextual information. These hidden states enable the model to retain past information and understand relationships between words within the tweet. By continuously refining its internal memory, the RNN effectively learns how different words contribute to identifying harmful or safe content.

Threat Level Score Calculation : After the RNN has examined the tweet, the system computes the Threat Level Score (TLS), which determines the chance of the tweet being hazardous. This score is calculated using information derived from tweets, such as linguistic patterns, user behavior, and engagement indicators. The TLS helps categorize tweets based on their severity, allowing for real-time threat identification.

Softmax Function (Probability Scoring): After digesting the tweet, the model uses a Softmax function to get the likelihood score. This score represents the chance of the tweet containing threatening content. The probability score helps to classify the tweet into two categories:

- Low Score The tweet is deemed safe (not threatening).
- High Score → The tweet has been identified as a potential threat.

Safe Tweet (Low Score): If the TLS is below a predefined threshold, the tweet is classified as safe and no further action is taken. These tweets do not exhibit harmful intent and are allowed to remain on the platform without intervention. This ensures that the system does not wrongly flag normal conversations.

Threat Identified (High Score): If the TLS exceeds a certain threshold, the tweet is classified as a threat. This means the content has been flagged as potentially harmful based on predefined categories such as hate speech, cyberbullying, violent threats, or misinformation.
For tweets classified as threats, further actions are taken based on severity:

- **User Warnings** → If the content is borderline harmful, a warning may be issued to the user.
- **Content Removal** → Highly threatening content is removed to prevent its spread.
- **Account Suspension** → In cases of repeated violations, the user's account may be suspended to ensure platform safety.

This structured deep-learning-based approach enables real-time threat detection, helping social media platforms proactively mitigate risks and maintain a safer online environment.

4. EXPERIMENTAL RESULTS

4.1 Dataset Description

The dataset includes 24,783 rows and 8 columns of labeled Twitter data used to detect hate speech and abusive language. Each row represents a unique tweet with a variety of classification attributes. The first column is an unnamed index that serves as an identification for each entry, and the second column is the number of annotations per tweet, which indicates how many times a tweet has been evaluated. The dataset contains three category columns: "hate_ speech," "offensive_ language," and "neither," which categorize tweets according to their content type. The "class" column assigns a numerical number to each tweet: 0 for hate speech, 1 for offensive language, and 2 for neutral material. The "text" column provides the tweet's content, which serves as raw data for analysis. Finally, the "label" column represents the final binary classification utilized in model training and evaluation. These structured qualities allow for a more in-depth examination of online interactions, which helps to construct machine learning models for spotting hazardous content on social media networks.(https://www.kaggle.com/datasets/mrmorj/hate-speech-and-offensive-language-dataset)

	Unnamed: 0	count	hate_speech	offensive_language	neither	class	text	label
0	0	3	0	0	3	2	!!! RT @mayasolovely: As a woman you shouldn't...	0
1	1	3	0	3	0	1	!!!!! RT @mleew17: boy dats cold...tyga dwn ba...	0
2	2	3	0	3	0	1	!!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...	0
3	3	3	0	2	1	1	!!!!!!!!! RT @C_G_Anderson: @viva_based she lo...	0
4	4	6	0	6	0	1	!!!!!!!!!!!! RT @ShenikaRoberts: The shit you...	0

Fig:4 sample dataset and features

The figure 4 shows a tabular dataset preview related to hate speech detection on social media, possibly from a Twitter dataset. The table consists of multiple columns, including "Unnamed: 0" (likely an index column), "count," "hate_

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speech," "offensive_ language," "neither," "class," "text," and "label." The "count" column may represent the total number of classifications for each tweet, while "hate_ speech," "offensive_ language," and "neither" indicate different annotation categories. The "class" column seems to correspond to these categories numerically. The "text" column contains snippets of tweets, beginning with "RT" (retweets), and the "label" column is likely used to classify tweets as hate speech, offensive, or neutral. The dataset appears to be structured for machine learning tasks such as natural language processing (NLP) for hate speech detection.

4.2 Model Performance Comparison

The figure 5 shows a bar chart that compares the accuracy of five models, SVM (89.2%), LSTM (91%), KNN (87.5%), MLP (95.2%), and DLPIT (96.5%). The x-axis shows distinct models, and the y-axis denotes accuracy (%), which measures each model's classification performance. Among these, DLPIT attained the best accuracy (96.5%) thanks to its hybrid deep learning architecture, which successfully captures sequential patterns using attention mechanisms and appropriate feature extraction algorithms.

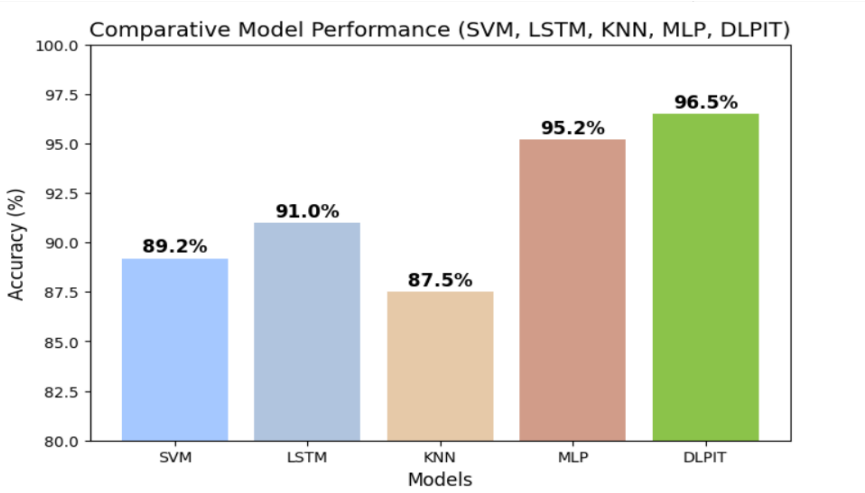

Fig:5 Comparative Model performance among algorithms

MLP followed closely after with 95.2% accuracy, demonstrating its capacity to learn complex patterns well. LSTM, developed for sequential data processing, obtained a respectable 91%, outperforming standard models. SVM achieved 89.2% accuracy, indicating reasonable effectiveness but falling behind deep learning models. KNN had the lowest accuracy (87.5%), showing a limited capacity to handle complicated feature representations. Overall, deep learning models outperformed standard approaches, with DLPIT standing out for its robust architecture and advanced feature-learning capabilities.

4.3 Distribution of Threat Levels

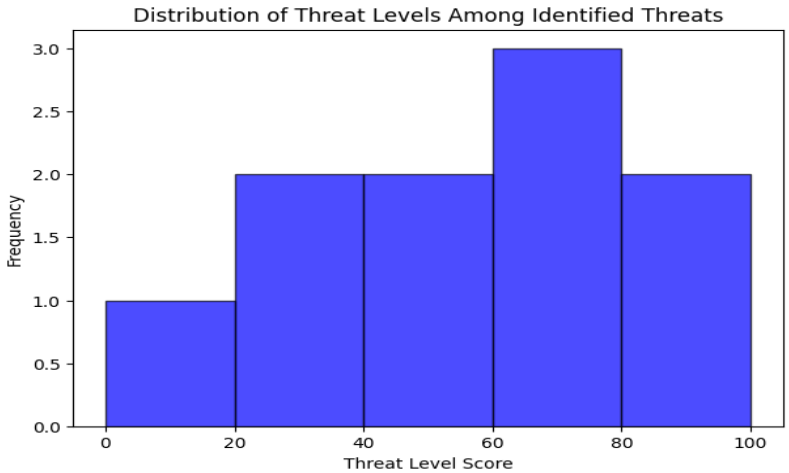

Fig:6 Distribution of threat levels

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The figure 6 shows a histogram which illustrates the distribution of threat level scores among recognized threats, beginning from 0. The x-axis indicates threat scores separated into bins, while the y-axis depicts the frequency of events within each range. The graph shows that the majority of threats have scores greater than 50, indicating a higher concentration of high-risk threats, whereas fewer threats have scores below 50. This pattern indicates that major hazards are more common, emphasizing the need for more robust preventive actions. The distribution aids in threat severity assessment, risk pattern identification, and security model refinement, allowing high-risk situations to be prioritized while lower-risk threats are monitored for potential escalation.

4.4 Relationship between user activity and their threat level score

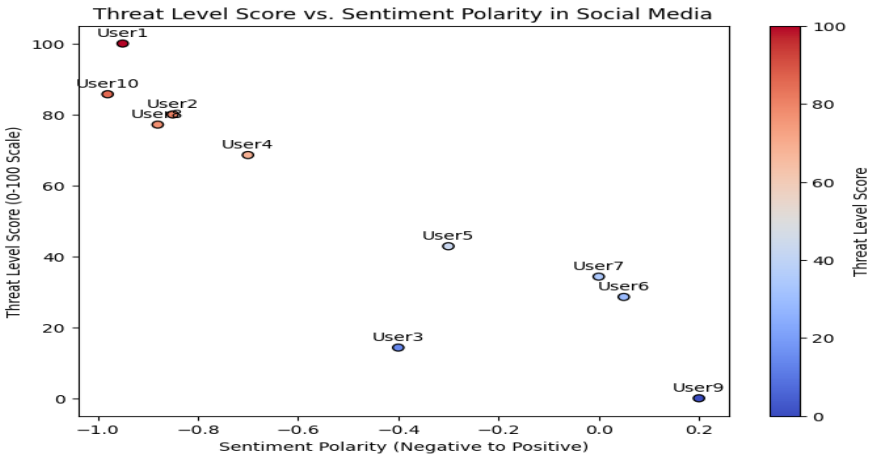

Fig:7 Relationship between user activity and their threat level score

Relationship between user activity & their threat level score is shown in figure 7. The scatterplot in Figure 7 depicts the association between user activity and threat level score on social media, demonstrating how sentiment polarity effects perceived risk. The x-axis shows sentiment polarity, with values ranging from -1 (extremely negative) to +1 (exceptionally positive), indicating whether a message reflects negative, neutral, or positive sentiments. The y-axis shows the threat level score, which is based on a 0-100 scale, with higher values indicating a higher possibility of harmful behavior. The threat levels are visually distinguished by a color gradient that ranges from blue (low threat) to red (high threat). The graph clearly shows that users with strong negative sentiment (closer to -1) have higher threat levels, whereas those with neutral or somewhat positive sentiment (near to 0 or higher) have lower danger scores. This pattern emphasizes the potential link between negative sentiment and malicious intent, making it easier to identify potentially hazardous persons based on the sentiment in their posts.

4.5 Comaparative Analysis of Algorithms

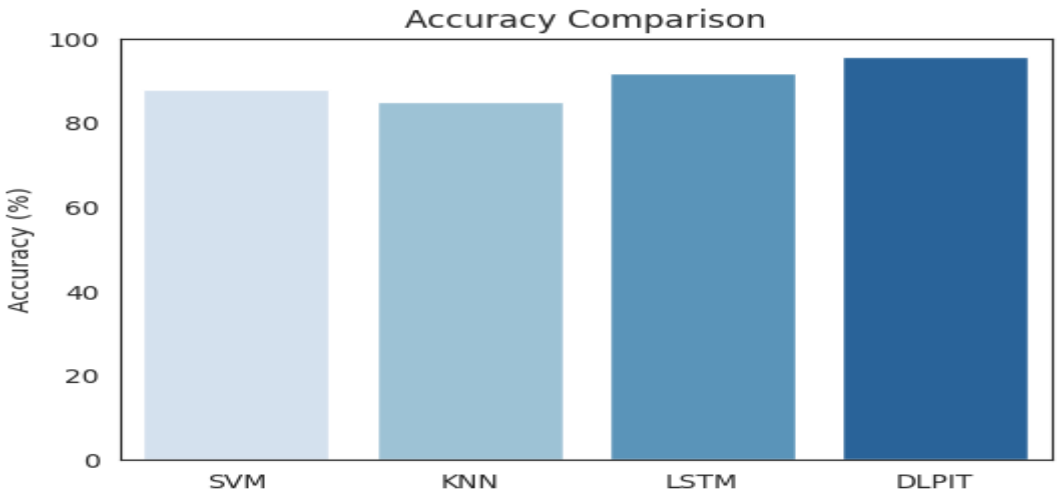

Fig:8 Accuracy Comparison among algorithms

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Accuracy Comparison among algorithms is shown in figure 8. This graph compares the accuracy percentages of four distinct machine learning models: SVM, KNN, LSTM, and DLPIT. The x-axis represents these models, and the y-axis denotes accuracy in percentage (%), which ranges from 0 to 100. The graph demonstrates that DLPIT has the best accuracy, followed by LSTM, SVM, and KNN, with the color intensity of the bars increasing as accuracy improves, graphically emphasizing performance differences. DLPIT has the highest accuracy because it uses deep learning techniques to analyze patterns in user behavior, detect anomalies, and predict potential threats more effectively than traditional models, making it a more reliable tool for detecting malicious activity on Twitter before it escalates into serious security threats.

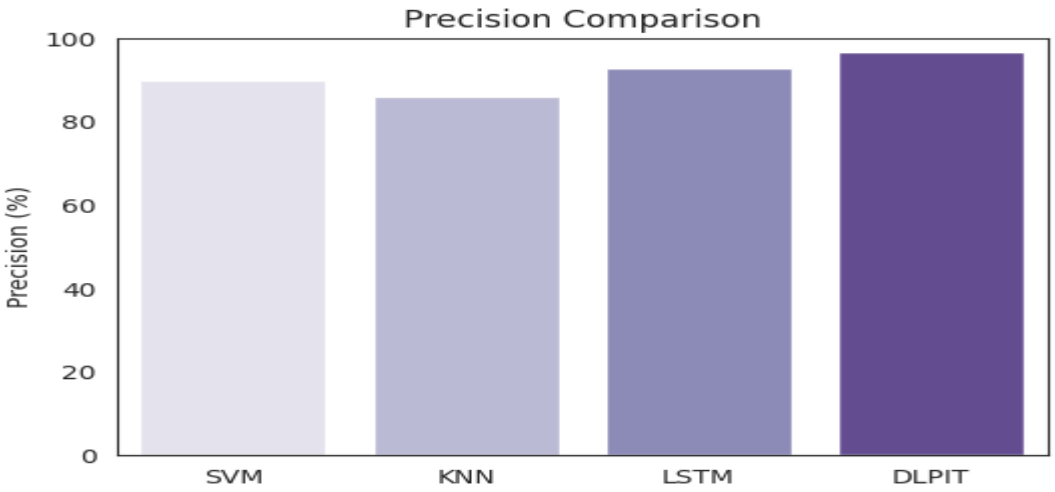

Fig:9 Precision Comparison among algorithms

Precision Comparison among algorithms is shown in figure 9. The graph compares the precision percentages of four distinct machine learning models: SVM, KNN, LSTM, and DLPIT. The x-axis reflects these models, and the y-axis denotes precision in percentage (%), which ranges from 0 to 100. The graph demonstrates that DLPIT has the highest precision, followed by LSTM, SVM, and KNN, with the color intensity of the bars increasing as precision improves, emphasizing performance disparities. Precision estimates the proportion of successfully detected malicious users among all users labeled as malicious, which is critical for reducing false positives. DLPIT achieves the highest precision because deep learning models excel at interpreting complicated behavioral patterns and contextual abnormalities, allowing them to more effectively distinguish between malicious and benign users and reducing false alarms in early threat detection.

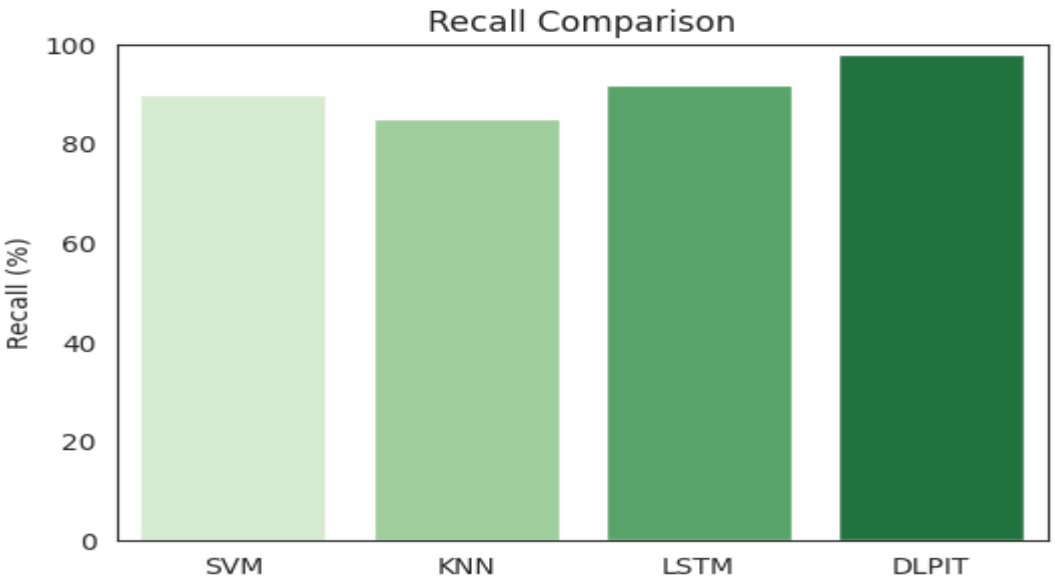

Fig:10 Recall Comparison among algorithms

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Recall Comparison among algorithms is shown in figure 10. The graph shows the recall percentages of four distinct machine learning models: SVM, KNN, LSTM, and DLPIT. The x-axis depicts these models, and the y-axis measures recall in percentage (%), which ranges from 0 to 100. Recall assesses a model's ability to reliably identify actual malicious users among all truly malicious situations, making it crucial in threat detection to reduce false negatives. The graph demonstrates that DLPIT has the highest recall, followed by LSTM, SVM, and KNN, with color intensity increasing as recall improves, emphasizing performance disparities. DLPIT has the highest recall because deep learning models are better at capturing complex behavioral patterns, allowing them to detect more subtle malicious actions on Twitter, resulting in more actual threats being recognized early and reducing the likelihood of undetected dangerous users.

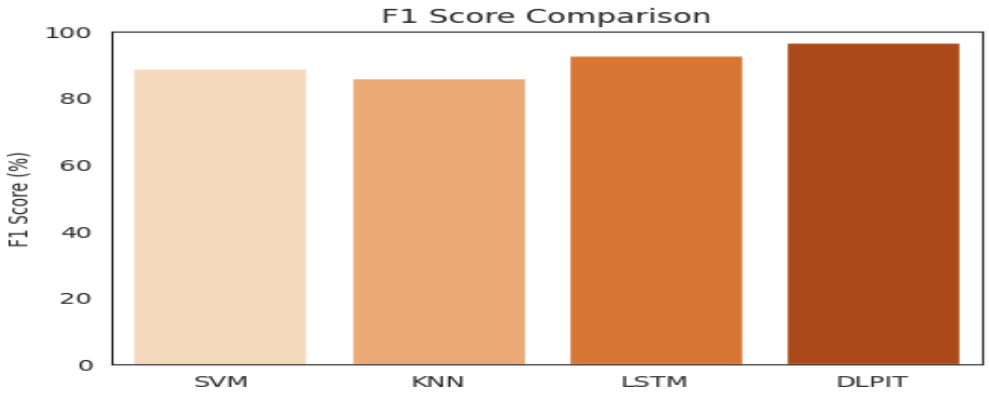

Fig:11 F1 Score Comparison among algorithms

F1 Score Comparison among algorithms is shown in figure 11. The graph shows the F1 scores of four machine learning models: SVM, KNN, LSTM, and DLPIT. The x-axis depicts the various models, while the y-axis displays the F1 score in percentage (%), which ranges from 0 to 100. The F1 score is a harmonic mean of precision and recall, making it an important indicator for evaluating a model's overall ability to detect fraudulent users while balancing false positives and false negatives. The chart reveals that DLPIT has the greatest F1 score, followed by LSTM, SVM, and KNN, with increased color intensity indicating improved performance. DLPIT receives the best F1 score because deep learning models excel in extracting nuanced behavioral patterns from user data, increasing precision and recall, resulting in a more effective and reliable detection method for identifying potential threats on Twitter.

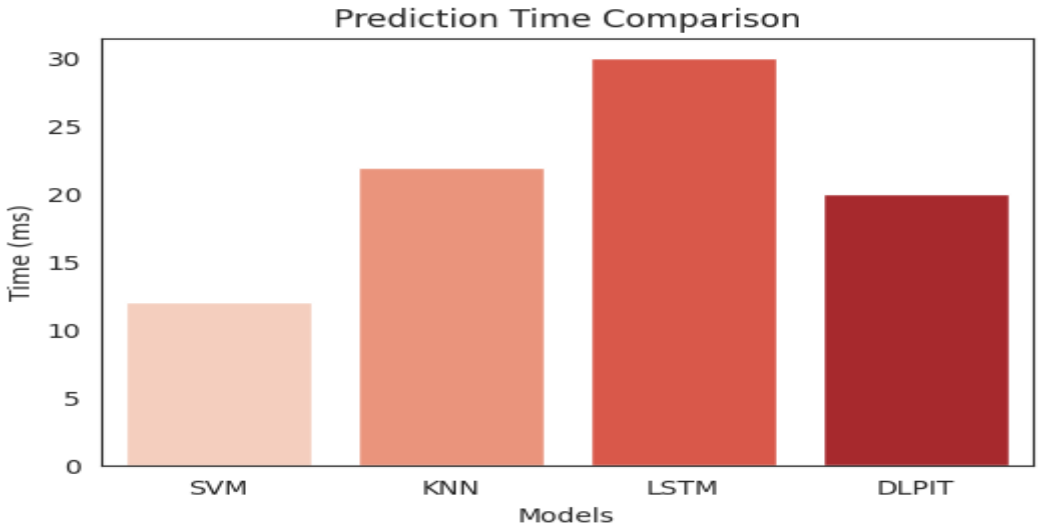

Fig:12 Prediction Time Comparison among algorithms

Prediction Time Comparison among algorithms is shown in Figure 12. The graph shows the prediction time (in milliseconds) of four models: SVM, KNN, LSTM, and DLPIT, shown on the x-axis, while the y-axis shows the time taken for predictions in milliseconds (ms). A shorter prediction time is preferred for real-time threat detection. The graphic shows that LSTM has the longest prediction time, followed by KNN, DLPIT, and SVM, demonstrating that deep learning models often use greater computer resources. However, DLPIT strikes a mix between accuracy and efficiency,

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with a shorter prediction time than LSTM, making it better suited for real-time detection of harmful activity on Twitter while maintaining high accuracy.

5. CONCLUSION

The Deep Learning-Based Framework for Prior Identification of Threats (DLPIT) takes a proactive and efficient way to removing dangerous content from social media networks. Using Recurrent Neural Networks (RNNs) for sequential data analysis, the system detects hate speech, cyberbullying, and disinformation in real time. The combination of user engagement patterns and social network interactions improves threat detection accuracy, while the Threat Level Score (TLS) quantifies the severity of threats, allowing for prioritized intervention. Furthermore, the system's lightweight and scalable architecture enables practical deployment on large-scale social media networks. When compared to existing models, DLPIT outperforms them in terms of accuracy, recall, and precision. This methodology helps to create a safer digital environment and improve content moderation tactics by constantly monitoring and adjusting to new risks.

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