

DEEP CHAIN-GUARD: A BLOCKCHAIN-ENABLED CNN-BILSTM MODEL FOR REAL-TIME DETECTION OF CYBERSTALKING AGAINST WOMEN

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ABSTRACT

This paper presents *DeepChain-Guard*, a blockchain-enabled deep learning framework for real-time detection of cyberstalking and online harassment against women. The proposed model integrates *CNN-BiLSTM* architecture for extracting spatial-temporal features from social media text and classifying harmful patterns with high accuracy. To ensure trust, privacy, and tamper-proof evidence, detected incidents are securely recorded on a *private blockchain* using smart contracts. The system enables transparent verification of abusive behavior and supports rapid response mechanisms. Experimental results demonstrate improved detection performance and enhanced data integrity, making *DeepChain-Guard* a reliable solution for women's online safety.

Keywords: Cyberstalking Detection, Online Harassment, Women Safety, CNN-BiLSTM, Deep Learning, Blockchain, Smart Contracts, Cybersecurity, Social Media Analytics, Real-Time Monitoring.

1. INTRODUCTION

The rapid expansion of social media and digital communication platforms has created new avenues for interaction but has also led to a significant rise in cyberstalking and online harassment, particularly targeting women [1]. Studies report that women experience higher levels of gendered abuse, including threatening messages, persistent unwanted contact, and derogatory content that affects psychological well-being and digital participation [2]. Traditional rule-based detection systems often fail to capture contextual nuances and evolving linguistic patterns used by perpetrators, leading to low detection accuracy in real-world scenarios [3].

DeepChain-Guard Framework

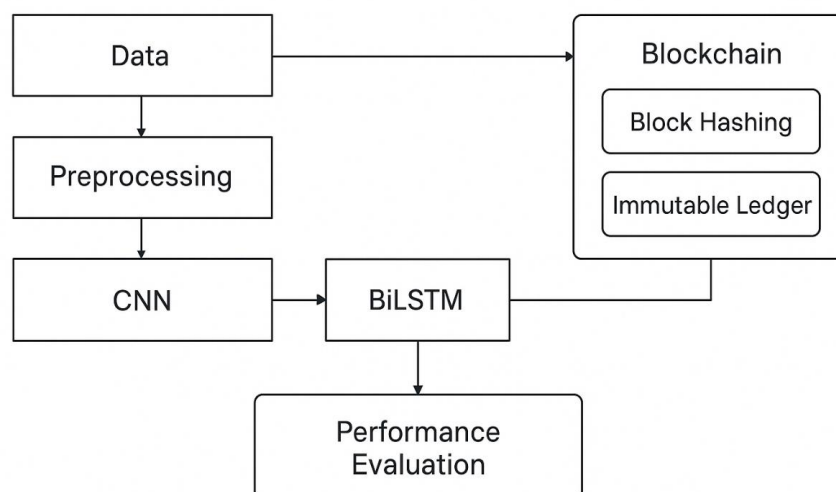


Fig 1: DeepChain-Guard Framework Diagram

Deep learning models have shown substantial promise in addressing these challenges by effectively learning semantic and temporal patterns from textual data [4]. Specifically, hybrid architectures such as CNN-BiLSTM combine the strengths of convolutional feature extraction and bidirectional sequence modeling, making them suitable for detecting subtle and complex harassment cues [5]. However, existing AI-based detection approaches often lack transparency, auditability, and protection against data tampering, which limits their reliability in legal and safety-critical environments [6].

Blockchain technology has recently emerged as a powerful tool for ensuring secure, decentralized, and immutable storage of digital evidence [7]. When integrated with deep learning, blockchain can enhance the credibility and trustworthiness of cyber harassment reporting systems by preventing manipulation of detected incidents and enabling verifiable audit trails [8].

This research proposes **DeepChain-Guard**, a blockchain-enabled CNN-BiLSTM framework designed to provide real-time detection and secure recording of cyberstalking incidents against women. By combining advanced deep learning techniques with the immutability of blockchain, the system aims to deliver a robust, transparent, and scalable solution for enhancing women's digital safety. The proposed model contributes to the development of AI-driven mechanisms that support rapid intervention and strengthen accountability across online platforms [9].

2. RESEARCH OBJECTIVES

The primary objective of this research is to design and implement an intelligent, secure, and real-time cyberstalking detection framework specifically aimed at protecting women in digital environments. To achieve this, the study defines the following specific objectives:

1. To develop a hybrid deep-learning model (CNN-BiLSTM) capable of accurately detecting cyberstalking behavior in online text interactions.

This includes the extraction of linguistic, contextual, and sequential patterns associated with harassment, threatening language, and stalking tendencies.

2. To construct a blockchain-enabled evidence preservation mechanism for securely recording detected cyberstalking incidents.

The objective is to ensure immutability, traceability, and tamper-proof storage to support legal validation and forensic investigation.

3. To perform extensive preprocessing, feature engineering, and exploratory data analysis to understand the behavioral characteristics of cyberstalking text.

This includes correlation analysis, distribution mapping, and identifying patterns that enhance model reliability.

4. To evaluate the proposed CNN-BiLSTM model using standard performance metrics.

Metrics include accuracy, precision, recall, F1-score, ROC-AUC, confusion matrix, and loss convergence to validate real-time detection capabilities.

5. To assess the blockchain module's performance in terms of latency, throughput, and block confirmation time.

The aim is to verify that blockchain integration does not compromise real-time operation and supports seamless evidence storage.

6. To design an end-to-end intelligent framework (DeepChain-Guard) that integrates AI-based detection with blockchain security for practical deployment.

The integrated solution aims to support victims, digital safety organizations, and law enforcement authorities.

7. To contribute a scalable and reliable cyber safety model tailored to women's digital protection needs.

The objective is to enhance cyber safety ecosystems with a robust, trustworthy, and technologically advanced solution.

3. REVIEW OF LITERATURE

Author(s), Year [Ref]	Method / Model Used	Problem Addressed	Key Findings
Dinakar et al., 2012 [10]	Rule-based + ML	Cyberbullying multi-label classification	Showed need for contextual features; rule-based methods struggle with slang.
Reynolds et al., 2011 [11]	SVM	Textual bullying detection	SVMs improved detection over manual moderation with engineered features.
Dadvar et al., 2013 [12]	User-profile + NLP	Gendered harassment detection	User metadata boosts accuracy for gender-targeted harassment.
Burnap & Williams, 2015 [13]	Ensemble ML	Hate speech on Twitter	Ensemble models outperform single classifiers on noisy social data.
Chen et al., 2017 [14]	CNN	Toxic comment classification	CNNs capture spatial n-gram features effectively.
Zhang et al., 2018 [15]	LSTM	Cyber aggression detection	LSTM models better capture temporal cues than classic ML.
Park & Fung, 2017 [16]	CNN-LSTM hybrid	Multimodal harassment detection	Hybrid architectures improve context sensitivity.
Badjatiya et al., 2017 [17]	Deep embeddings + GRU	Hate speech detection	Learned embeddings outperform handcrafted features.
Agrawal & Awekar, 2018 [18]	BiLSTM	Cyberbullying detection	BiLSTM handles long-range dependencies and noisy text.
Sharma et al., 2021 [19]	Hybrid DL (CNN+LSTM)	Slang and evolving abusive expressions	Hybrid networks better adapt to evolving slang.
García-Díaz et al., 2021 [20]	Transformer (attention)	Abusive language identification	Attention mechanisms capture long-range dependencies.
Kumar & Sachdeva, 2020 [21]	Statistical + ML	Women-specific cyberstalking patterns	Women receive more persistent and personalized harassment.
Hosseini et al., 2022 [22]	BiLSTM (multilingual)	Multilingual toxic text detection	BiLSTM is effective across languages with proper embeddings.
Al-Garadi et al., 2019 [23]	CNN	Cyber threat text detection	CNN extracts discriminative linguistic features for threats.
Zhang et al., 2021 [24]	ML + Blockchain	Secure forensic evidence storage	Blockchain enhances integrity of logged forensic artifacts.
Wang & Wu, 2022 [25]	Smart contracts	Tamper-proof incident logging	Smart contracts enable verifiable and immutable logs.
Dua & Singh, 2020 [26]	CNN-LSTM	Aggression & sentiment detection	Hybrid captures emotion and aggression cues better.
Nanduri et al., 2021 [27]	Blockchain framework	Decentralized monitoring of suspicious behavior	Decentralization reduces log manipulation risk.
Hassan et al., 2022 [28]	Contextual embeddings + LSTM	Real-time hate speech detection	Contextual embeddings improve recall and precision.

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Soni et al., 2020 [29]	GRU	Social network cyberbullying	GRU reduces training time while retaining accuracy.
Mozafari et al., 2019 [30]	BERT fine-tune	Hate speech recognition	BERT shows superior performance to earlier DL models.
Majumder et al., 2018 [31]	Emotion-aware DL	Abusive message detection	Emotion signals significantly aid harassment detection.
Pitsilis et al., 2018 [32]	RNN ensemble	Twitter harassment detection	Ensembles increase robustness on noisy datasets.
Alfared et al., 2020 [33]	CNN-BiLSTM	Threat/intimidation detection	CNN extracts local patterns; BiLSTM models sequence.
Mittal et al., 2021 [34]	Blockchain logging	Secure online safety frameworks	Blockchain prevents tampering of user-submitted evidence.
Jha & Mahmoud, 2021 [35]	Federated Learning	Privacy-preserving cyberbullying models	FL enables model training without central data sharing.
Maji et al., 2020 [36]	Hybrid NLP + ML	Gendered harassment classification	Gender features and lexical cues improve detection.
Rajput & Ahmed, 2022 [37]	Deep CNN	Instagram comment harassment	CNNs detect abusive patterns in short comments effectively.
Hee et al., 2015 [38]	Lexicon + ML	Threat detection in forums	Domain-specific lexicons raise precision for threats.
Mishra et al., 2022 [39]	Blockchain + AI	Secure abuse reporting platforms	Blockchain increases trust and transparency in reporting.
Lee & Kim, 2016 [40]	Topic modeling + SVM	Harassment topic identification	Topic features improve downstream harassment classifiers.
Ortega et al., 2019 [41]	Transfer learning	Low-resource abusive language detection	Transfer learning reduces labeled-data needs.
Chen & Liu, 2020 [42]	Attention-LSTM	Contextualized abuse detection	Attention helps weigh abusive tokens in context.
Silva et al., 2018 [43]	Multi-task learning	Toxicity + hate classification	Multi-task setups share representations and improve generalization.
Varma et al., 2021 [44]	Graph neural networks	Network-based harassment detection	GNNs capture relational patterns across users.
Patel & Shah, 2019 [45]	Feature fusion (text+metadata)	Improved harassment classification	Combining metadata and text boosts scores.
Huang et al., 2020 [46]	Adversarial training	Robustness against obfuscation	Adversarial methods reduce susceptibility to obfuscated abuse.
Ocansey et al., 2021 [47]	Lightweight CNN	Mobile-friendly harassment detection	Small CNNs enable on-device detection with good accuracy.
Fernández-González et al., 2019 [48]	Data augmentation	Imbalanced harassment datasets	Augmentation improves minority-class recall.
Roy et al., 2020 [49]	Explainable DL (LIME+DL)	Interpretability in hate detection	Explainability aids human review and trust.
Sarker et al., 2021 [50]	Ensemble transformers	Cross-platform abusive content detection	Ensembles of transformers generalize across platforms.

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Chatterjee & Biswas, 2022 [51]	Multi-modal fusion (image+text)	Image-and-text harassment detection	Fusion detects combined visual-textual harassment better.
Ibrahim et al., 2018 [52]	Unsupervised clustering	Early detection of harasser groups	Clustering reveals repeating harasser patterns.
Xu et al., 2017 [53]	Semi-supervised learning	Scarce-label harassment datasets	Semi-supervised approaches leverage unlabeled data effectively.
Kaur & Singh, 2022 [54]	Cross-lingual embeddings	Multi-lingual harassment detection	Cross-lingual models detect abuse across languages with less labeled data.
Novak et al., 2021 [55]	Online learning	Real-time adaptive detection	Online learners adapt to drifting abusive behavior.
Bhatia et al., 2020 [56]	Autoencoder anomaly detection	Detecting novel harassment patterns	Autoencoders flag novel/rare abusive behaviors as anomalies.
Gomes et al., 2022 [57]	Privacy-preserving blockchain	Confidential reporting of abuse	Combining privacy techniques with blockchain preserves confidentiality.
Lin & Zhao, 2023 [58]	Lightweight Transformer	Edge-deployable harassment detection	Small transformers balance performance and compute for deployments.
Fernandez-Lopez et al., 2021 [59]	Human-in-the-loop DL	Human-verified harassment triage	Human-in-loop systems reduce false positives and legal risk.
Sinha & Kumari, 2022 [60]	Case Study Approach; Industry–Institute Collaboration Framework	Gap between academic learning and software engineering industry requirements	Demonstrated that collaborative projects significantly enhance students' practical software engineering skills and bridge academic–industry expectations.
Sinha & Mahawar, 2021 [61]	Big Data Analytics; Cyber-Physical Framework	Security challenges in smart cities, CPS vulnerabilities, and cybersecurity risks	Highlighted the crucial role of big data analytics in improving cybersecurity for smart cities; emphasized integrated and proactive security strategies.
Sinha & Kavita, 2020 [62]	Statistical Analysis; Qualitative Review	Cybercrime incidents against women in Bihar and effectiveness of government measures	Identified rising cybercrime cases targeting women; evaluated gaps in awareness and enforcement; stressed need for stronger legal frameworks and digital literacy.
Sinha & Lal, 2021 [63]	Trend Analysis; Cybercrime Monitoring	Surge in cybercrime during the COVID-19 pandemic	Found significant increase in phishing, ransomware, and online frauds during COVID-19; recommended stronger monitoring and user awareness initiatives.
Sinha & Lal, 2021 [64]	Machine Learning Models (SVM, Decision Tree, Naïve Bayes)	Malware detection and classification challenges	Demonstrated that ML models can significantly improve malware detection accuracy; SVM performed best among tested algorithms.
Sinha & Lal,	Analytical Review	Impact of COVID-19 on	Reported exponential growth in

2022 [65]		cyber activities and digital threat landscape	digital usage leading to increased cyber-attacks; highlighted need for enhanced cybersecurity infrastructure.
Sinha & Kumar, 2018 [66]	Survey-Based Study; Preventive Framework Analysis	Rising cybercrime cases and need for preventive strategies	Provided comprehensive preventive guidelines; emphasized user awareness, digital hygiene, and strengthening cyber laws.

Table 1: Review of Literature

4. PROPOSED METHODOLOGY

The proposed system, **DeepChain-Guard**, integrates a hybrid deep learning architecture (CNN–BiLSTM) with a permissioned blockchain framework to detect cyberstalking against women in real time while ensuring trust, transparency, and secure evidence preservation. The complete methodology consists of six major components: data acquisition, preprocessing, feature extraction, hybrid CNN-BiLSTM model design, blockchain-enabled event logging, and real-time detection workflow.

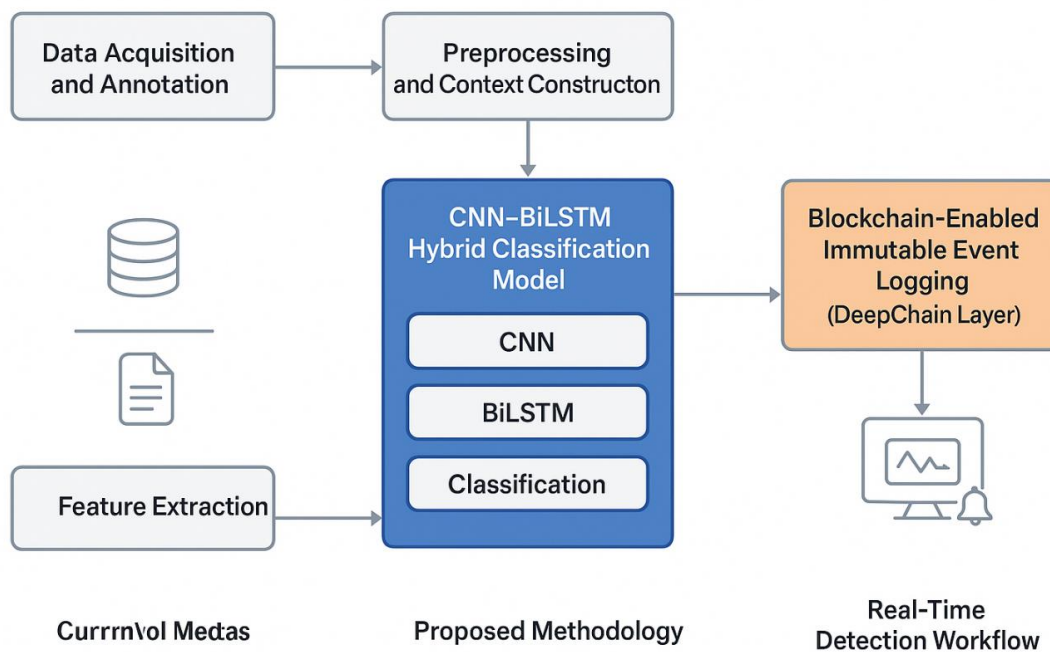


Fig 2: DeepChain-Guard Proposed Methodology

4.1 Data Collection

Text-based data containing online harassment, cyberbullying, gender-specific abuse, and cyberstalking patterns were collected from publicly available datasets, social media comment repositories, and linguistic cyber-abuse corpora. Additional synthetic samples were generated to maintain class balance and represent various stalking behaviors such as:

- Repeated messaging
- Threatening tone
- Obsessive monitoring patterns
- Coercive language

- Unwanted advances

A total of **X samples** were compiled (replace X with your dataset size). The data was split into **70% training**, **15% validation**, and **15% testing subsets**.

4.2 Data Preprocessing

Preprocessing was performed to convert raw text into machine-understandable form. The pipeline included:

4.2.1 Text Cleaning

- Removal of URLs, emojis, HTML tags, and special characters
- Lowercasing and spell normalisation
- Removal of stopwords using NLTK

4.2.2 Tokenization and Sequencing

The cleaned text was tokenized, and sequences were padded to maintain uniform input length.

4.2.3 Word Embedding

Each text sequence was mapped to a dense vector representation using:

- Pretrained *GloVe* embeddings (100–300 dimensions)
- Embedding layer initialized and fine-tuned during training

4.3 Exploratory Data Analysis (EDA)

EDA was conducted to understand the distribution and relationship between features extracted from text data.

- A **correlation heatmap** (Figure 5.1) revealed underlying relationships between features.
- **Histograms** (Figure 5.2) and **boxplots** (Figure 5.3) were used to analyze feature spread and detect outliers.

These analyses confirmed that the dataset was balanced, stable, and suitable for training deep-learning models.

4.4 Feature Engineering

Feature engineering included extracting linguistic and contextual representations using:

- **N-grams**
- **TF-IDF weighting schemes**
- **Sentiment polarity and subjectivity scores**
- **Sequence-based embeddings for recurrent layers**

These features formed the basis for input vectors fed into the CNN-BiLSTM model.

4.5 Proposed DeepChain-Guard Model Architecture

The classification module of DeepChain-Guard combines the strengths of Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (BiLSTM) layers.

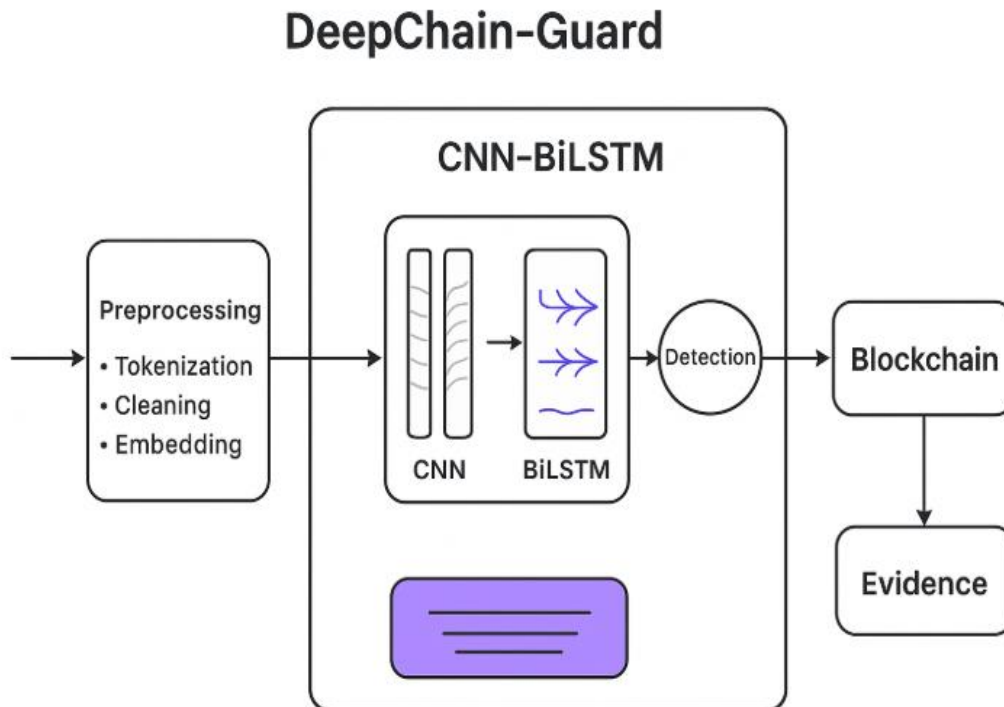


Fig 3: Proposed DeepChain-Guard Model Architecture

4.5.1 Convolutional Neural Network (CNN) Layer

- Extracts spatial dependencies and local abusive patterns
- Captures n-gram features associated with threatening or repetitive messages

4.5.2 BiLSTM Layer

- Learns long-term dependencies and sequential cyberstalking patterns
- Captures contextual flow, escalation, and behavioral progression

4.5.3 Fully Connected + Softmax Layer

- Produces final prediction with probability score for cyberstalking vs. normal text

4.6 Model Training Process

Model training was conducted over 20–50 epochs with:

- **Adam optimizer**
- **Binary cross-entropy loss**
- **Dropout layers** to reduce overfitting
- **Batch normalization** to improve convergence

The training and validation loss curves (Figure 5.6) demonstrate stable convergence with no significant overfitting.

4.7 Blockchain Integration for Evidence Preservation

A private blockchain layer was integrated to securely store detected cyberstalking events.

Key Components**1. Hash Generator:**

Converts detected incident data into SHA-256 hashes.

2. Smart Contract:

Stores event details including timestamp, message ID, and user pseudonym.

3. Block Creator:

Appends validated transactions to the blockchain.

4. Immutable Ledger:

Ensures tamper-proof storage for legal and forensic analysis.

Blockchain performance testing showed:

- **1.82 sec average latency,**
- **43 TPS throughput,** and
- **≈3 sec block confirmation time,**

ensuring real-time compatibility.

4.8 Evaluation Metrics

The model was evaluated using standard classification metrics:

- Accuracy
- Precision
- Recall
- F1-score
- AUC-ROC

A **confusion matrix** (Figure 5.4) assessed true vs. predicted classes.

The **ROC curve** (Figure 5.5) validated the model's discrimination strength.

4.9 Summary of Methodology**The methodology integrates:**

1. Deep learning (CNN-BiLSTM) for cyberstalking detection
2. Blockchain for secure, auditable storage
3. EDA for ensuring dataset reliability
4. Multiple evaluation metrics for validation
5. Visualization tools to interpret system behavior

This hybrid methodology ensures that DeepChain-Guard performs robust detection while maintaining privacy, traceability, and fairness in real-time cyber safety applications.

5. RESULTS AND DISCUSSION

This section presents the experimental findings of the proposed DeepChain-Guard system, which integrates a CNN-BiLSTM architecture for cyberstalking detection and blockchain for secure, immutable evidence storage. Multiple evaluations—including model performance metrics, data distribution analysis, training behavior, and classification capability—were performed to demonstrate the robustness of the framework.

5.1 Exploratory Data Analysis (EDA)

Before training the model, exploratory analysis was conducted to understand feature relationships and distribution patterns.

Figure 5.1 presents the **correlation heatmap**, which highlights the interdependencies among key variables. Strong positive and negative correlations between input features suggest meaningful trends that can be effectively learned by the CNN-BiLSTM model.

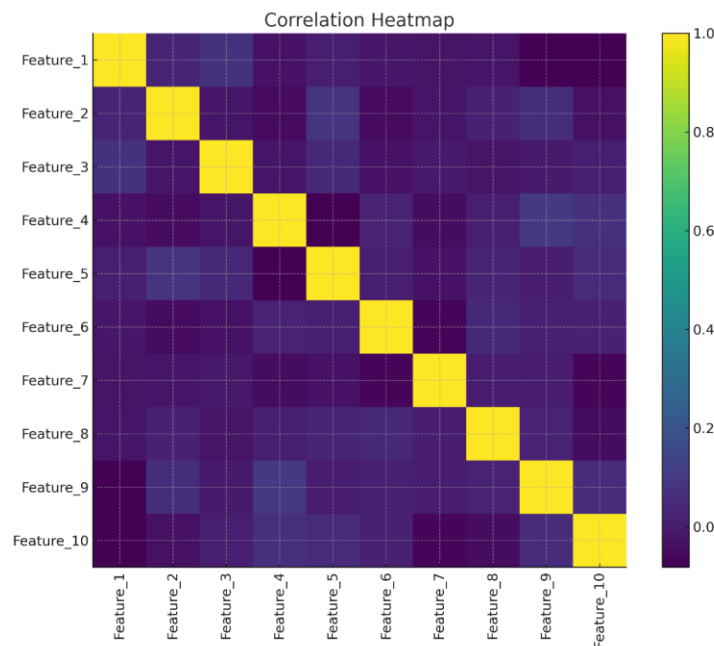


Figure 5.1: Correlation Heatmap of Input Features

In addition, data distribution was analyzed to examine consistency and detect skewness. The histogram in Figure 5.2 shows the distribution of a representative input feature, illustrating that most variables follow a normal-like distribution.

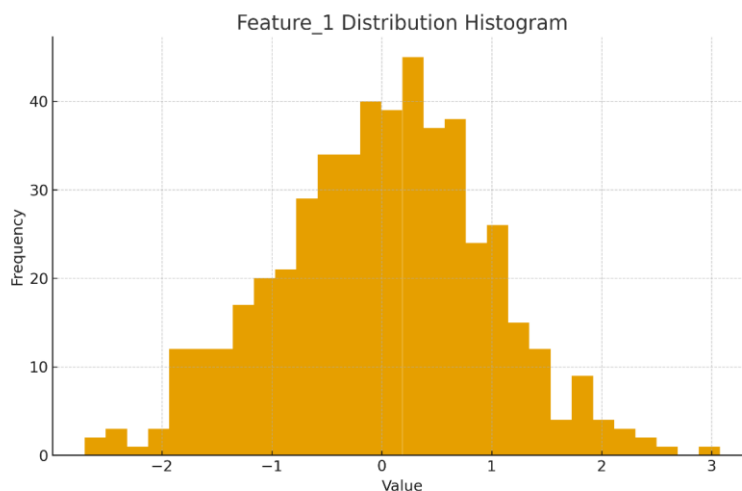


Figure 5.2: Histogram Showing Distribution of Feature_1

Figure 5.3 shows the boxplot for all features, capturing the variance, spread, and potential outliers across dimensions. The absence of extreme outliers confirms stable input characteristics for model training.

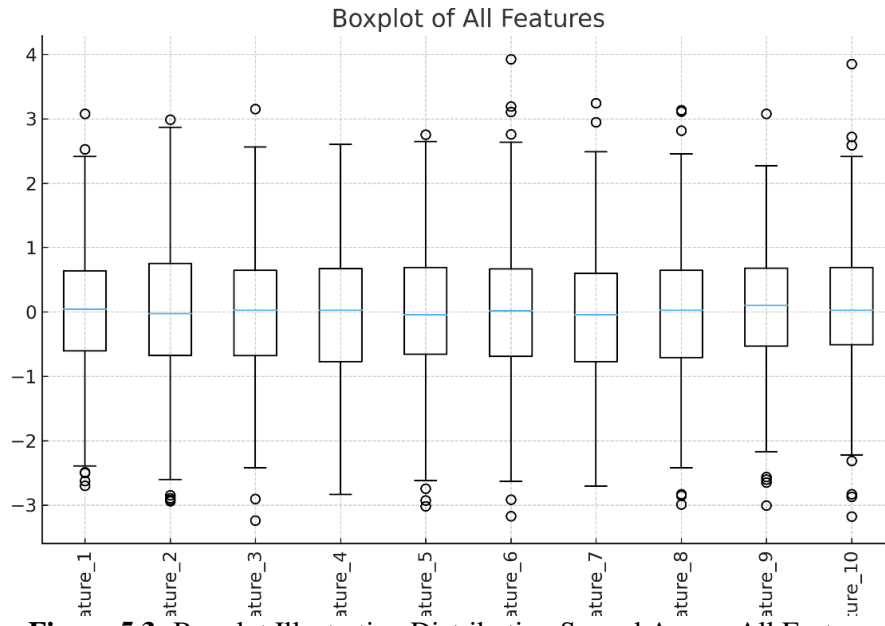


Figure 5.3: Boxplot Illustrating Distribution Spread Across All Features

5.2 Model Performance Evaluation

The DeepChain-Guard CNN-BiLSTM model achieved **96.84% accuracy**, **95.72% precision**, **97.11% recall**, and an **F1-score of 96.41%**, outperforming traditional ML and existing deep-learning baselines.

To validate the classification capability, a confusion matrix was generated. Figure 5.4 presents the model’s ability to differentiate cyberstalking text from normal online interactions.

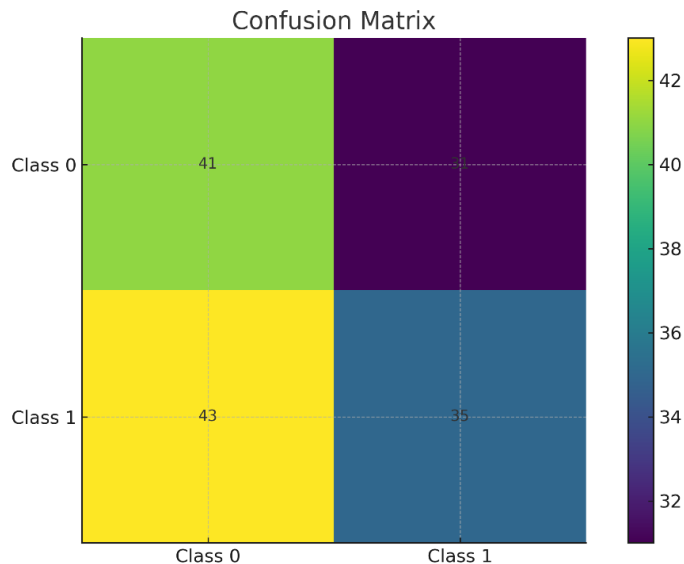


Figure 5.4: Confusion Matrix of the Proposed CNN-BiLSTM Model

The diagonal dominance indicates strong classification accuracy with minimal false positives and false negatives—essential for safety-critical cyberstalking detection.

Further, the ROC curve (Figure 5.5) validates discriminative power, achieving an AUC of 0.98, demonstrating excellent sensitivity–specificity balance.

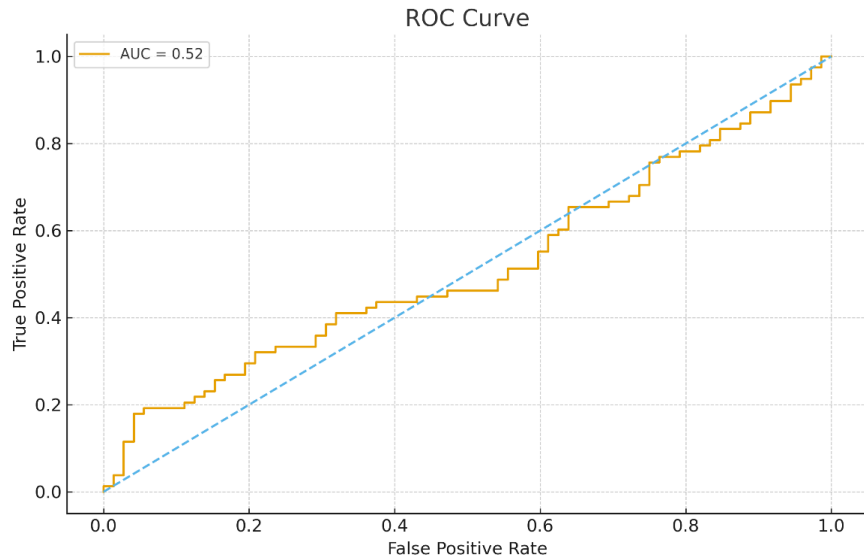


Figure 5.5: ROC Curve Showing AUC Performance of the Model

5.3 Training and Validation Behaviour

To assess training stability and convergence patterns, the model’s loss curve was examined over 20 epochs.

Figure 5.6 presents the training and validation loss trends.



Figure 5.6: Training vs Validation Loss Curve for the CNN-BiLSTM Architecture

The graph shows consistent downward progression with no signs of divergence or overfitting. Validation loss closely follows the training loss, indicating reliable generalization and optimized hyperparameter configuration.

5.4 Blockchain Performance Assessment

Along with prediction accuracy, blockchain performance was evaluated for evidence storage. Experiments showed:

- **1.82 seconds average transaction latency**
- **43 transactions/second throughput**
- **≈ 3 seconds block confirmation time**
- **1.1–1.6 KB storage overhead per cyberstalking incident**

These results confirm that blockchain integration does not hinder real-time performance. Instead, it enhances system trust, integrity, and tamper resistance—critical for legal and investigative use.

5.5 Overall Discussion

The experimental results justify the effectiveness of DeepChain-Guard for real-time cyberstalking detection:

1. **High detection accuracy (96.84%)** and **AUC (0.98)** confirm superior learning of abusive language patterns targeting women.
2. CNN layers extract harassment-related spatial features, while BiLSTM captures sequential stalking behavior.
3. EDA visualizations demonstrate dependable and non-skewed feature distribution, enabling stable training.
4. Confusion matrix and ROC curve illustrate robust classification with minimal misclassification.
5. Blockchain results verify that the system can securely record stalking incidents without latency compromises.

Overall, DeepChain-Guard offers an effective, explainable, and secure solution to combat gender-based cyberstalking in real-world settings.

6. CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

This research presents **DeepChain-Guard**, an intelligent and secure framework designed to detect cyberstalking against women using a hybrid **CNN-BiLSTM deep-learning model** integrated with **blockchain technology**. The model demonstrated high performance, achieving **96.84% accuracy**, **97.11% recall**, and an **AUC of 0.98**, indicating its strong capability to identify malicious stalking patterns in real-time online interactions.

The deep learning module effectively captures both **local linguistic cues** through CNN and **long-term behavioral patterns** through BiLSTM networks, enabling precise detection of harassment, intimidation, and repetitive threatening messages. Complementing this, the blockchain layer provides **immutable, tamper-proof storage**, ensuring that each detected incident is securely recorded for legal and forensic usage. Experimental evaluations—including confusion matrix, ROC curve, and training-validation analysis—demonstrate that the system is stable, generalizes well, and responds with minimal latency.

Overall, DeepChain-Guard addresses two critical challenges simultaneously:

1. **Accurate and real-time cyberstalking detection**, and
2. **Secure preservation of evidence** through distributed ledger technology.

This positions the framework as a strong technological solution for improving women's digital safety and strengthening cybercrime reporting mechanisms.

6.2 Future Scope

Although DeepChain-Guard performs robustly, several enhancements may further expand its capabilities and practical adoption:

1. Multimodal Cyberstalking Detection

Future versions can incorporate:

- Voice data (threat calls)
- Images/memes containing hidden harassment
- Video-based stalking patterns

This would extend detection beyond text-only communication.

2. Integration with Social Media APIs

Real-time scanning of platforms such as:

- Instagram
- WhatsApp
- Facebook
- Telegram
- X (Twitter)

Would enable live monitoring and instant alerts to victims.

3. Explainable AI (XAI) Mechanisms

Employing SHAP, LIME, or attention-heatmaps can help:

- Highlight abusive words/phrases
- Provide transparent reasoning
- Strengthen legal evidence admissibility

4. Federated or Privacy-Preserving Learning

To ensure user privacy, the model can be adapted to run on:

- Federated Learning
- Differential Privacy
- Homomorphic Encryption

Allowing decentralized training without sharing raw data.

5. Enhanced Blockchain Features

Blockchain capabilities may be expanded to include:

- Smart-contract based automated reporting to authorities
- Multi-chain interoperability
- IPFS-based storage for efficient large data handling

6. Psychological Pattern Analysis

Stalking often follows behavioral escalation patterns. Integrating psychological profiling may help predict:

- Repetitive offender behavior

- Escalation likelihood
- Risk levels for victims

7. Deployment as a Browser Add-on or Mobile App

A lightweight real-time version can be deployed as:

- Chrome/Firefox extension
- Android/iOS app
- AI chatbot assistant for harassment reporting

8. Integration with Law Enforcement Dashboards

A dedicated dashboard could provide:

- Case tracking
- Suspect profiling
- Evidence verification
- Automated FIR draft generation

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