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Detection of Cyberbullying in Social Media Streams: Metaheuristic-Tuned Temporal Fusion Network for High- Accuracy Text Interpretation

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Abstract: Online communication growth has led to an increase in cyberbullying incidents while existing systems find it difficult to interpret evolving and abusive communication, creating the need for a better and context, and time-sensitive detection system. The current research is to introduce metaheuristic - tuned Temporal Fusion Network supported by specialized module designed as Dynamic Vortex Search - driven temporal attention with Long Short-Term Memory (DVS-TA-LSTM) to provide the high accuracy text interpretation for Cyberbullying detection. The dataset to identify cyberbullying was obtained from different types of social media (SM) platforms such as YouTube, Wikipedia Talk pages, Twitter, and Kaggle. Pre-processing consists of token normalization, removal of contextual noise, and textual data lexical correction. Feature extraction uses a Bidirectional Encoder Representations from Transformers (BERT) embedding model to represent part of the essential semantic meaning, contextual relationships, and information of sentiment in the text. The proposed framework integrates these components into a unified flow where cleaned data is embedded, processed through the fusion network, and further refined by the DVS-TA-LSTM module. Within this module, the DVS optimizer dynamically adapts LSTM hyper-parameters and efficiently detects cyberbullying by capturing sequential dependencies, and temporal attention reveals significant time-dependent patterns. The overall architecture is tailored to elevate cyberbullying detection accuracy across streaming environments. When compared to standard DL classifiers, the classifiers had the highest accuracy of 97.28%, the highest precision of 93.45%, the highest recall of 95.78%, the highest F1-measure of 94.55%, and the highest specificity of 97.54%, according to the Python simulation tool for experimental assessment. The framework concludes with the capability to support real-time, scalable, and context-aware cyberbullying mitigation.

Keywords: Cyberbullying Detection, Social Media Streams, Text Interpretation, Metaheuristic Tuning, Linguistic Feature Analysis.

1. Introduction

Cyberbullying occurs anytime someone uses a website to threaten or intimidate another person. Any behavior carried out by persons via digital media is commonly referred to as cyberbullying [1]. However, there were significant concerns associated with this astounding increase in online connections, chief among them being cyberbullying. As social media platforms have grown, cyberbullying has grown more common, which impacts both victims and offenders [2, 3]. Cyberbullying is mostly visible through text-based interactions and is especially prevalent on SM platforms, leaving victims feeling helpless and without the means to deal with the problem. Intelligent technologies and automated detection is carried out to detect cyberbullying on SM websites [4].

Cyberbullying detection on SM has attracted attention, even though the current algorithms have considerable limitations [5]. Many approaches are based on short, unbalanced or of low quality datasets with insufficient representation of demographics, language styles, as well as situations [6], which end up not generalizing at all cross-platform. Simple text classification methods are tested by the way SM discourse: slang, sarcasm, coded idioms, mixed languages, emoticons [7]. Additionally, most models do not capture temporal dynamics in conversations and treat posts in isolation.

Deep learning models frequently lack adaptability they soon become outdated as language evolves and requires constant retraining. Computer resource limitations also hinder real-time detection on massive SM streams [8]. Furthermore, a potential way to manage the high dimensionality and complexity of textual features (embeddings, sentiment scores, contextual embeddings) while preventing overfitting and enhancing generalization is to tune such a temporal model using metaheuristic optimization [9, 10].

The proposed objective combining temporal modeling with metaheuristic tuning is motivated by the need to overcome data, context, and scalability challenges, and to develop an accurate, adaptive, and generalizable cyberbullying detection system suitable for real-world SM streams.

1.1 Research contribution

It contributes to the development of a high-accuracy cyberbullying detection model by using a DVS-TA-LSTM to improve feature and advanced temporal text analysis.

- The suggested design combines these elements into a single flow in which the DVS-TA-LSTM module improves the cleaned data after it has been embedded and processed by the temporal attention network.
- This module's DVS optimizer dynamically modifies TA-LSTM hyperparameters to improve long- range temporal interpretation, minimize vanishing effects, and increase gradient flow.
- To boost predictive accuracy and facilitate efficient interpretation of sequential textual data to spot cyberbullying patterns, it uses a meta-heuristic optimization to fine-tune the temporal attention network. The entire architecture is intended to increase the precision of cyberbullying detection in streaming contexts.

The significant background of the research is provided in section I. The research discusses some of related work in Section II; Section III explains how to analyze the Kaggle dataset, and DVS-TA- LSTM discusses recommended methods. Evaluation metrics used to gauge the effectiveness and stability of the suggested approach are described in Section IV, along with a comparison of the results with those of several other previously published approaches in this field. Finally, in Section V, we provide a summary of this work.

2. Related Words

Recent research on cyberbullying detection spans a wide range of machine learning and deep learning architectures, datasets, and evaluation settings. Several studies rely on traditional classifiers with hand-crafted linguistic features, while more recent works employ CNNs, RNN variants such as BiLSTM and BiGRU, transformers, and hybrid or ensemble models to capture contextual and sequential patterns in social media text. These approaches differ in terms of modality (text-only vs. multimodal), platform coverage, and robustness across datasets, motivating a structured comparison of their characteristics and limitations as summarized in Table 1.

2.1 Research Gap

As noted in prior research, ML and DL to detect cyberbullying have gained a lot of ground over the past few years. There were numerous new techniques, such as CNN, BiLSTM, BiGRU, Transformers, and ensemble methods that have all been applied [11, 15]. However, there were still many areas that had yet to be explored. The majority of current approaches focus primarily on text, which leaves out multimodal (visual), temporal, and cross-platform capabilities. There were also problems associated with having either small or unbalanced datasets, and the higher cost of running these models at scale in real time has also affected the performance of many models [29, 30]. The proposed DVS-TA-LSTM approach focuses on text-based cyberbullying detection while being designed so that multimodal information (images, user metadata) can be integrated in future extensions.

3. Proposed Methodology

A system for detecting cyberbullying that uses dynamic vortex search classification and transformer-based feature extraction. The framework gathers SM data, preprocesses, uses a Transformer encoder to extract features, uses Dynamic Vortex Search to classify content, and uses metrics like loss curves, accuracy, confusion matrices, and precision-recall analysis to assess performance. The suggested method for identifying cyberbullying in SM is shown in Figure 1.

3.1 Data collection

Cyberbullying Dataset is a collection of information about the automatic detection of cyberbullying from different sources. https://www.kaggle.com/datasets/saurabhshahane/cyberbullying-dataset.

We use the public 'Cyberbullying Dataset' hosted on Kaggle, which aggregates posts collected from YouTube, Wikipedia Talk pages, Twitter, and other social media platforms. All experiments in this paper are conducted on this single Kaggle-hosted dataset.

3.2 Data Preprocessing

Lexical correction corrects errors and colloquial words that are frequently found on SM. It makes use of libraries such as SymSpell or TextBlob. Candidates are generated using a quick non-contextual pass (SymSpell), which is then validated using a context model. Tune conservative to avoid eliminating bullying cues in low-resource or noisy language.

Table 1. Recent Studies of Proposed research

Author(s), Year	Data	Main Technique	Key Features	Performance	Limitations
Alotaibi *et al.*, 2021 [11]	Social media text	Multichannel DL framework (BiGRU, transformers, CNN)	Textual posts only (no multimodal signals)	Accuracy 87.99, F1 upto 89 for offensive class	Multimodal elements (user metadata, images) omitted; generalizability limited
Neelakandan *et al.*, 2022 [12]	Social media text	SSA-DBN (Salp Swarm Algorithm–Deep Belief Network)	Textual features for cyberbullying classification	Accuracy ≈ 99.983	Small and imbalanced dataset; limited generalization
Murshed *et al.*, 2023 (FAEO-ECNN) [13]	Social media (English posts)	FAEO-ECNN (topic modelling + CNN)	Topic-model Features + convolutional features	Accuracy 92.91 and 91.89 on two datasets	Performance on multilingual data uncertain; restricted to English
Jaradat *et al.*, 2025 [14]	Social media text	BiLSTM, CNN-BiLSTM, BiLSTM-GRU, ANN	Sequential textual features	Best accuracy 91 with BiLSTM	Temporal activity and network structure ignored
Cheng *et al.*, 2021 (HANCD) [15]	Timestamped social media posts	Hierarchical Attention Networks for cyberbullying detection	Temporal patterns in conversation threads	Improved detection of temporal patterns (no specific metric quoted)	Requires timestamped posts; high computational expense
Kumar & Sachdeva, 2022 (Bi-GAC) [16]	MySpace, Formspring	Bi-GRU Attention + Capsule Network	Text sequences with attention and capsule layers	F-score gains ≈ 9 (MySpace) and 3 (Formspring)	Longer training time; hyperparameter sensitive
Nahar *et al.*, 2023 [17]	Social media text	Random Forest, SVM (ML classifiers)	Hand-crafted textual features	Accuracy 94.97 (RF) and 94.66 (SVM)	Only text; no multimodal content
Aldhyani *et al.*, 2022 [18]	Social media text	Hybrid Bi-LSTM + CNN	Sequential + local textual features	Accuracy 94; effective hostile language detection	Overfitting and imbalance issues; limited cross-platform validation
Prabha *et al.*, 2025 [19]	Social media (bot accounts)	DNN and CNN for multiclass bot cyberbullying detection	Textual features of bot-generated content	Accuracy 98.92, high F1 for bot bullying	Focus on bots; human-driven bullying less addressed
Pranith, 2025 [20]	Social media big data	Ensemble ML (Random Forest, SVM, etc.)	Textual and big-data analytics features	Higher efficacy with big-data analytics; metrics not fully detailed	Limited real-time capability due to processing latency
Vivekananth & Sharma, 2025 [21]	Social media text	NLP-based MTF-IDF + classifiers	Modified TF-IDF textual features	Accuracy 83.63, balanced accuracy 83.42	Conversation context ignored; text-only
Balaji *et al.*, 2021 [22]	Online e-learning platforms	ML-based detection on social networked e-learning	Textual interactions in e-learning	Reported improved accuracy on cooperative systems	Limited applicability to general social media

Abarna *et al.,* 2023 [23]	Social media platforms	XGBoost-based ensemble for cyber-harassment	Textual features with ensemble learning	F1-score 92.04; lower error rate	High computational overhead; real-time use constrained
Akula & Ramana, 2025 [24]	Twitter (primarily)	ML classifiers (Naive Bayes, RF, SVM)	Textual features from posts	Macro-average F1 up to 0.6 (≈60)	Cross-platform generalization uncertain
Sahana *et al.,* 2023 [25]	Formspring text	AdaBoost, RF, SVM, Logistic Regression	Text-only features	AdaBoost best: accuracy 86.52	No multimodal detection; only textual modality
Sherly & Jeetha, 2021 (ECSO-HFA NN) [26]	Twitter data	Enhanced Cuckoo Search + Hybrid Firefly-ANN	Optimized ANN with metaheuristic tuning	Accuracy 90; faster convergence	Performance sensitive to dataset and optimization parameters
Agbaje & Afolabi, 2024 [27]	Twitter/X text	CNN and RNN for aggression and cyberbullying	Text sequences	Accuracy 0.951 and0.911; F-measure 0.910 and 0.890	Only textual Twitter data; ignores multimodal content
Sanjay & Muthuram, 2025 (BERT-GPT) [28]	Social media text	Advanced NLP with BERT and GPT	Contextual embeddings and language modeling	Accuracy 92.5; precision 90.5	Multilingual support and real-time deployment not covered
Sree & Joseph, 2025 (BullyNet) [29]	Social media text	BullyNet (GNNs, transformers, attention)	Linguistic features with graph and attention	Accuracy up to 95; F1 ≈ 0.95	Temporal trends and user metadata not modeled
Khafajeh, 2024 (BERT) [30]	Social networks	BERT-based deep learning	Contextual text embeddings	Accuracy 87.3; better than CNN-LSTM baseline (86.5)	No additional cross-platform validation
Proposed DVS-TA-LSTM (this work)	YouTube, Wikipedia Talk, Twitter, Kaggle	Metaheuristic-tuned Temporal Fusion Network with DVS-TA-LSTM	Pre- processed text (token normalization, lexical correction, contextual noise removal) + BERT embeddings	Accuracy 97.28, precision 93.45, recall 95.78, F1 94.55, specificity 97.54	Primarily text-based; high computational cost; multimodal extension and real-time deployment planned for future work

Data preparation entails using a variety of cleaning and transformation approaches to enhance data quality and model performance to prepare raw text data for cyberbullying detection. Token normalization, lexical correction, and contextual noise removal are some of the preprocessing techniques used to clean and standardize the text. Table 2 displays the sample of Pre-processed Text Data for Cyberbullying Detection.

- ***Token normalization:*** Token normalization ensures consistency by converting text data into a common format. Common practices include converting to lowercase, removing special characters and punctuation, expanding contractions, and removing extra white space. It uses Unicode NFC/NFKC, maps elongated letters, normalizes repeated characters, and substitutes unique tokens for usernames and URLs.
- ***Contextual noise removal:*** Contextual noise removal is used to eliminate irrelevant or distracting elements such as URLs, emojis, non-informative symbols, and platform-specific clutter from data. Contextual noise elimination focuses on content in SM text that is deceptive or irrelevant. To recover or choose what to eliminate, use a masked language model (MLM) denoiser. This eliminates orphan noise while maintaining meaning.
- ***Lexical correction:*** Lexical correction corrects errors and colloquial words that are frequently found on SM. It makes use of libraries such as SymSpell or TextBlob. Candidates are generated using a quick non-contextual pass (SymSpell), which is then validated using a context model. Tune conservative to avoid eliminating bullying cues in low-resource or noisy language.

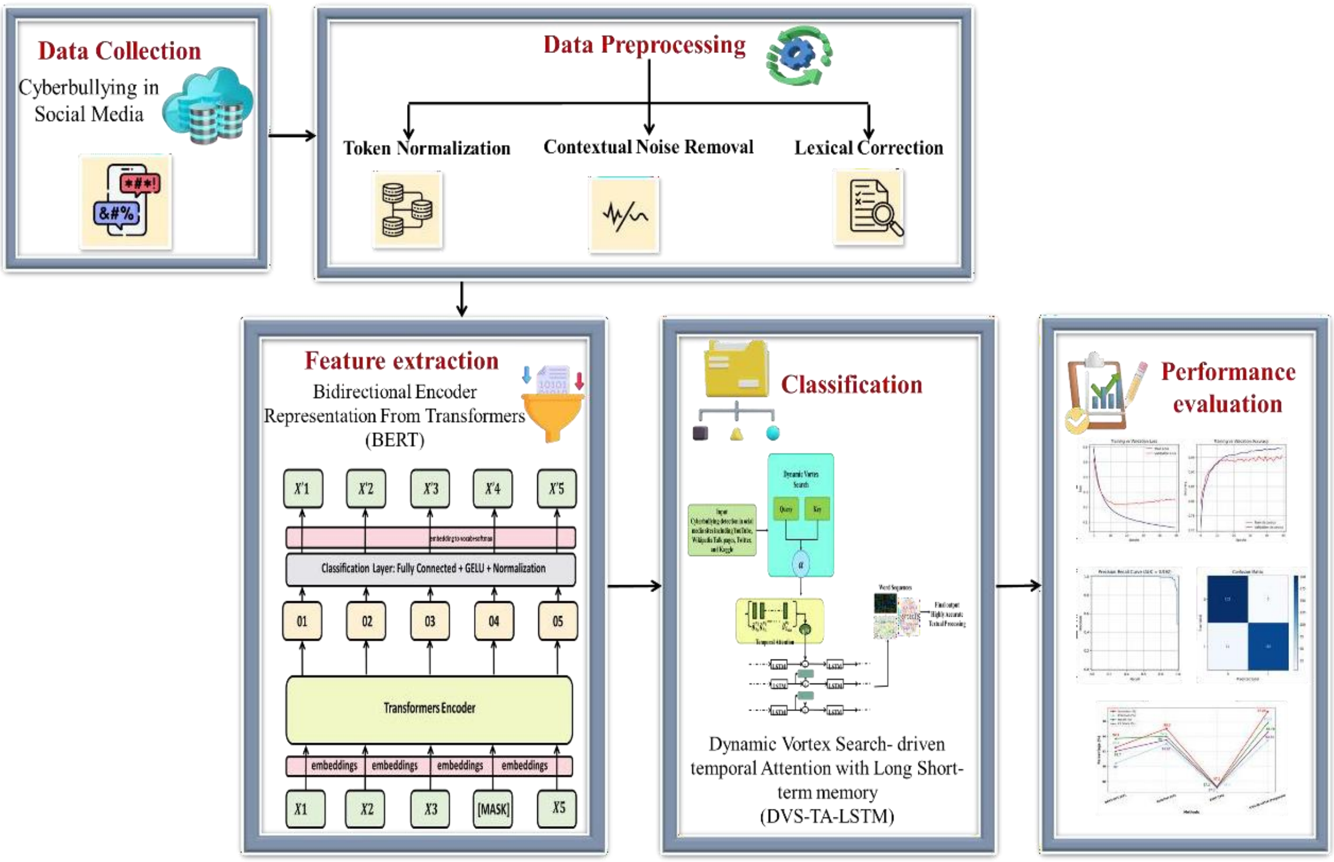

Figure 1. Overall proposed system for detecting cyberbullying in SM

Table 2. Data of Pre-processed Text Data for Cyberbullying Detection

Index	Text	label_0	label_1	oh_label	Processed_text
0	This is not ``creative``. Those are the di...	0.9	0.1	0	this is not creative those are the dictionary ...
1	: the term ``standard model`` is itself le...	1.0	0.0	0	the term standard model is itself le npov than ...
2	True or false, the situation as of March 20...	1.0	0.0	0	true or false the situation a of march wa such ...
3	Next, maybe you could work on being less cond...	0.55556	0.44444	0	next maybe you could work on being le condesce ...
4	This page will need disambiguation.	1.0	0.0	0	this page will need disambiguation

- ***Topic Modeling:*** We adopt Latent Dirichlet Allocation (LDA) with collapsed Gibbs sampling to uncover latent themes within the social media streams. To determine the optimal number of topics, K , we conduct a selection procedure utilizing a grid search over K \in \{10, 20, 30, 40, 50\} using held-out perplexity and topic coherence (C_V). The C_V coherence measure evaluates the contextual similarity of the top words within each topic, with typical values in our analysis ranging between 0.45 and 0.65. To validate the semantic interpretability of these topics, two domain experts rated 50 randomly sampled top-10 word lists; 84% were judged interpretable. Furthermore, to evaluate stability, we run the topic model 5 times with different random seeds and compute the average Jaccard similarity between the top-10 words of each topic; the mean stability achieved was 0.81, indicating low variability in topic assignments.

3.3 BERT Using Feature Extraction

BERT embeddings and complex feature extraction, a dependable system for identifying cyberbullying in SM streams. It focuses on extracting sentiment cues, contextual linkages, and semantic meaning from text. A system being developed from the BERT is typically pre-trained on vast volumes of online data.

BERT embeddings and complex feature extraction, a dependable system for identifying cyberbullying in SM streams. It focuses on extracting sentiment cues, contextual linkages, and semantic meaning from text. A system being developed from the BERT is typically pre-trained on vast volumes of online data. The incoming text is encoded into a high-level semantic space using a multi-layer bidirectional transformer encoder.

In this scenario, both left (before) and right (following) are successfully captured by a pretrained "bert-base-uncovered" model with transformer layers. As shown in Figure 2, the transformer Encoder architecture for Masked Language Modelling classification. The Transformer creates contextual embeddings by masking and processing the input sequence tokens. These are given to a sigmoid classifier and a dense layer after being averaged.

The Transformer models sequential relationships via self-attention. Equation (1) illustrates how query key and value projections are used to calculate the attention score between tokens. The identical transformer design is used by each self-attention layer to calculate attention ratings using scaled dots to measure attention:

$$B = Softmax\left(\frac{RL^S}{\sqrt{c_1}}\right) U \qquad (1)$$

Where, B is the output attention matrix, and R is the query matrix (learned projection of input tokens);

RL^S is the key matrix (sequence-level key representation); cl is the scaling factor equal to the dimensionality of the key vectors. U is the value matrix (transformed token representations);

$softmax(.)$ Normalization function that converts attention scores into probability weights. The BERT model generates contextualized representations of the input text by utilizing bidirectional attention.

3.4 DVS-TA-LSTM improved SM cyberbullying detection for high-performance Textual Analysis

Cyberbullying detection combining DVS-TA-LSTM of the method improves time-series prediction. It focuses on capturing complex sequencing data's temporal connections and pertinent feature structures. The DVS optimizes model performance through metaheuristic-driven hyper-tune and temporal attention to record the purpose of significance in context over a word sequence. Ultimately, LSTM aims to improve prediction accuracy and robustness in dynamic environments. Figure 3 depicts the DVS-TA-LSTM to detect cyberbullying for high-performance text processing.

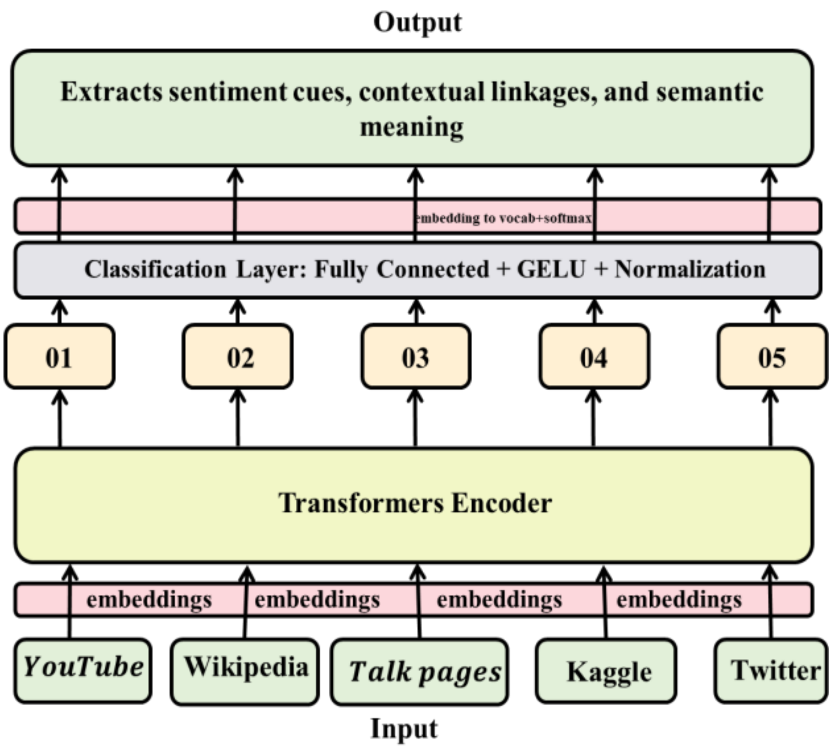

Figure 2. BERT-Based Transformer Encoder Architecture for Masked Language Modelling

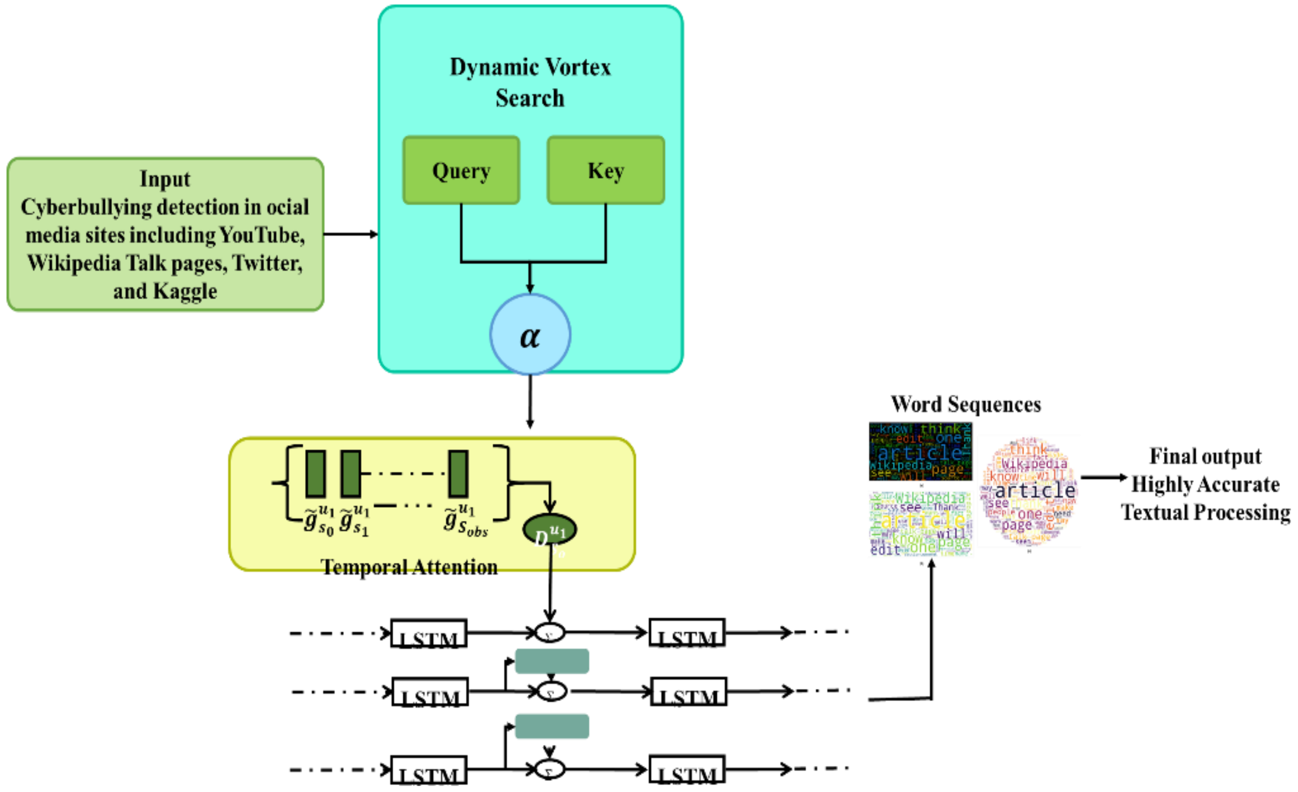

Figure 3. DVS-TA-LSTM to detect cyberbullying for high-performance text processing

3.4.1 LSTM for classifying the cyberbullying detection

Sequential word associations can be effectively interpreted by using the LSTM network to capture contextual patterns and long-range dependencies in SM material. Its memory cells enhance the precision and dependability of cyberbullying classification by identifying minor indicators, emotional changes, and recurring abusive patterns over time.

LSTM is a recurrent neural network with feedback connections, and feed-forward neural networks are well known for their ability to retain patterns over extended periods of time. Every cell in an LSTM unit has its own input gate, output gate, and forget gate. To solve the vanishing gradient problem that often occurs during the training of conventional RNN models. Equations (2) through (7) address the set of formulas that determine the functional variables. Here, O, r, q, f, D, l stand for the input, forget, output gates, and cell activation vectors, updated cell state, and output vector. tan is the tangent function, and σ represents the logistic sigmoid function. (s) is the prior time step and concealed condition Ls−1, ws, Vo, Vr, Vq, Vh, Xo, Xr, Xq, Xh are the learnable weight matrices for respective gates and cell updates. The LSTM layer is designed as follows: Global Max Pool, Dropout Dense, Softmax, and Embedding.

$$O_s = \sigma(w_s V^o + L_{s-1} X^o) \tag{2}$$

$$r_s = \sigma(w_s V^r + L_{s-1} X^r) \tag{3}$$

$$q_s = \sigma(w_s V^q + L_{s-1} X^q) \tag{4}$$

$$f_s = tang(w_s V^h + L_{s-1} X^h) \tag{5}$$

$$D_s = \sigma(r_s * D_{s-1} + O_s * f_s) \tag{6}$$

$$l_s = tang(D_s) * q_s \tag{7}$$

The LSTM model has a 128-unit LSTM layer, a sequential data input layer, and a recurrent_dropout to reduce overfitting. An LSTM layer with neurons is used to capture non-linear relationships via ReLU activation. During binary classification, an individual neuron and sigmoid activation are used in a dense output layer. The Adam optimizer with a training rate and binary cross-entropy as the loss function is used in its construction. If val_loss does not improve, early stopping is utilized to terminate training early. The LSTM-based sequential text processing for feature encoding and classification is shown in Figure 4.

Long-range relationships and contextual patterns in SM language are efficiently captured by the LSTM network, improving the identification of subtle signs and recurrent abusive conduct. Because of its gated construction, which reduces vanishing gradients, the classification of cyberbullying is more reliable. The model produces reliable and accurate binary classification when dropout and early stopping are used.

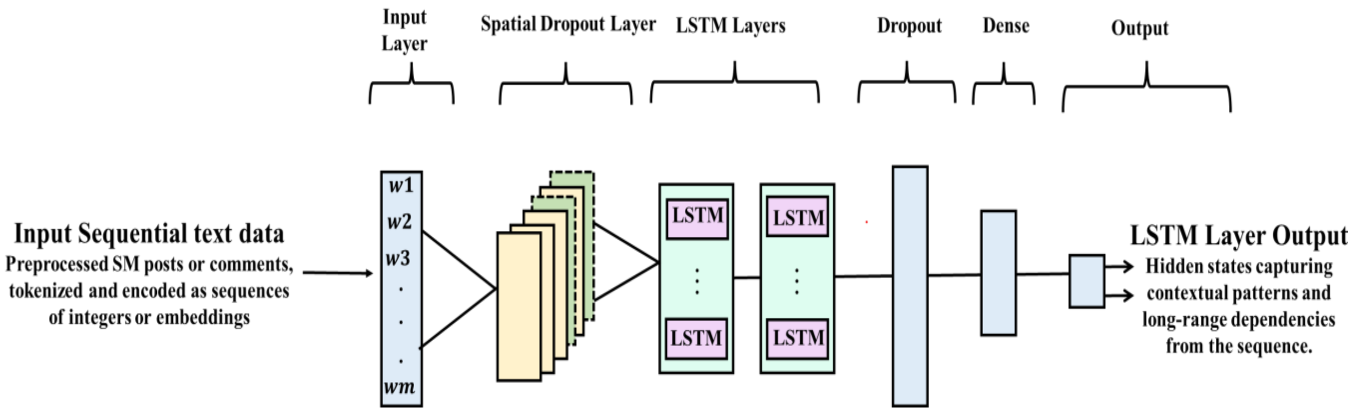

Figure 4. LSTM-based sequential text processing for feature encoding and classification

3.4.2 Temporal attention identifies time-dependent features in SM cyberbullying

Temporal attention is used to detect and draw attention to time-dependent trends in SM activity that point to cyberbullying. It aids the model in identifying when detrimental behavior takes place and how it changes over time. This enables the identification of abusive content more quickly and accurately.

By successfully capturing important temporal patterns, TA improves model performance. Temporal Mechanisms for enhanced sequential features in cyberbullying detection are shown in Figure 5. The anticipated time is so at each time step. At each time step so in the forecasting process in equation (8), the LSTM associated with u computes a vector of context, D^u_{so} is the concealed states scaling average from observing moment.

$$D^u_{s_o} = \sum_{s_t=s_p}^{S_{obs}} = \alpha s_o \tilde{g}^u_{st} \quad (8)$$

Here, αso denoted by the attention weight at the prediction time step S_o g^u_{st} Spatially-weighted hidden State of user $u$at observed time step (s_t) in the input sequence; s_p and S_{obs} is the start and last of the prediction sequence.

The aligned vector (αso) wherein $\sum t\,'$ prime is equal to the quantity of time steps in the detected pattern as seen in equation (9). The current vertically-balanced concealment $\tilde{g}^o_{st}$ with each separated Concealed condition $\tilde{g}^o$ from the detected pattern:

$$\alpha s_o = align(\tilde{g}^u_{st}, \tilde{g}^u_{s_o}) = \frac{score\,(\tilde{g}^u_{st}, \tilde{g}^u_{so})}{\sum_t{}'exp\,(score(\tilde{g}^u_{st}, \tilde{g}^u_{so}))} \quad (9)$$

A score called a content-based function is used to determine how comparable an initial concealed condition and a target secret region appear. Equation (10) uses the dot product to calculate the score, potentially assigning a larger value to similar observed experiences. These two concealed conditions under contrast are "equal," the dot product achieves its maximum, indicating that the two spatially loaded concealed states under contrast are summing the same spatial contexts.

$$Score(\tilde{g}^u_{st}, \tilde{g}^u_{s_o}) = \tilde{g}^u_{st}.\tilde{g}^u_{s_o} \quad (10)$$

At each soft attention context vector, D^u is calculated. The decoding system's concealed state at the next timestep, $s_o + 1$, $g^u_{so} + 1$, is the updated concatenating, and the computed regionally averaged concealed position, g^u_{so} , is at each time step. The most recent concealed state is transformed towards an anticipated planned for u_1 at $s_o + 1$ is using a fully connected linear layer in equations (11) and (12).

$$\tilde{g}^u_{s_o} = concat\,(D^u_{s_o}, \tilde{g}^u_{s_o}) \quad (11)$$

$$W^u_{s_o+1} = linear(g^u_{s_o+1}) \quad (12)$$

Where, $W^u_{so+1}$is the anticipated position or intent u for is denoted by s_{o+1} Cyberbullying can be detected more precisely and prompt the temporal attention's ability to record time-dependent patterns in SM. The approach highlights crucial instances of abusive behavior by aligning and weighting subsequent user activities. This improves the model's capacity to monitor changing detrimental behavior over time and increases prediction accuracy.

3.4.3 DVS fine-tunes the hyper parameters in SM cyberbullying detection

Optimizing model hyperparameters for increased precision and the purposes of DVS fine-tuning identify cyberbullying in SM. It guarantees that the model minimizes overfitting while efficiently capturing pertinent patterns.

The vortex rotation form of liquids serves as the idea for the DVS algorithm. In order to obtain the global optimum more quickly, the algorithm uses the inverse incomplete gamma function to reduce the search space and iterations. Furthermore, there are no user-tuning parameters in SM. Figure 6 depicts the workflow of the DVS to identify cyberbullying.

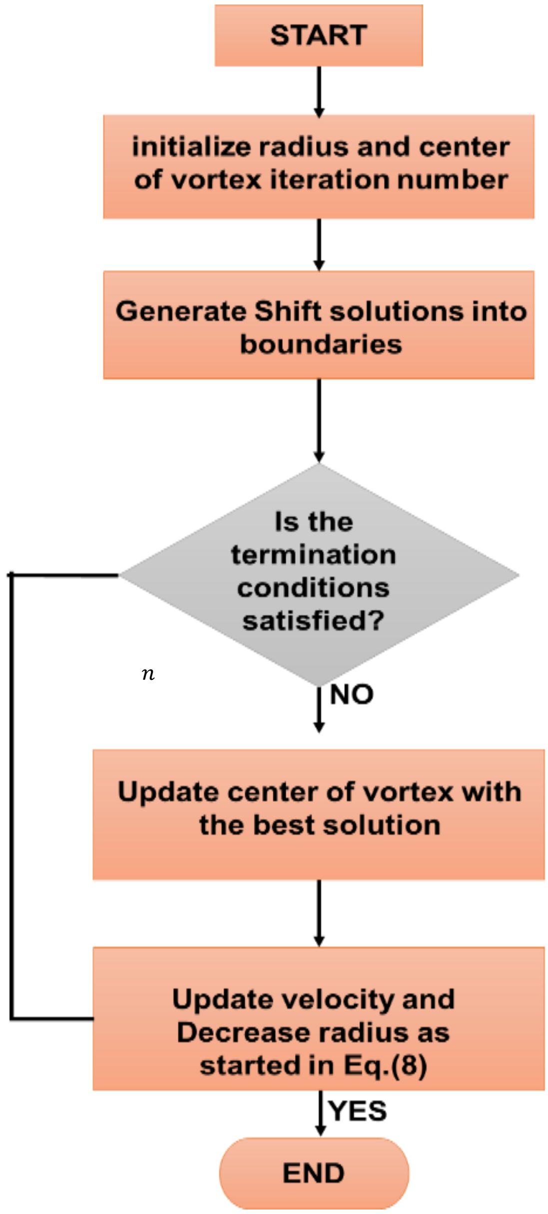

Figure 6. Workflow of the DVS to identify cyberbullying in SM

Considering a two-dimensional optimal issue, the schema of a vortex is a series of stacked circles. In the initial stage, the exact center of the largest circle for each dimension is found using equation (13).

$$\mu_0 = \frac{UpLimit + LowLimit}{2} \tag{13}$$

Where, the choice variables' upper and lower bounds arise are denoted by $UpLimit + LowLimit$, respectively. Additionally, Equation (14) determines the initial radius μ_0. Since, the outer circle must completely encompass the search area, a big value for q_0 is initially chosen.

$$q_0 = \sigma_0 = \frac{(UpLimit) - min\ (LowLimit)}{2} \tag{14}$$

Next, inside the d-dimensional searching space, a defined circle σ_0 is the potential solutions that are produced at random using a Gaussian distribution. Equation (15) provides the Gaussian distribution formulation.

$$O(w|\mu, \Sigma) = \frac{1}{\sqrt{(2\Pi)^c|\Sigma|}} exp\left\{-\frac{1}{2}(w-\mu)^S \Sigma^{-1}(w-\mu)\right\} \Sigma = \sigma^2 . [J]_{cwc} \tag{15}$$

Where, Σ is the covariance matrix, and w is a random variable's $cw1$-dimensional vector. μ is the mean of the Gaussian distribution, and σ^2 displays the distribution's variance. The CWC equivalent matrix is shown by J. After potential solutions are generated, parametric values of alternatives outside of the boundaries are dragged into the bounds. (w I μ, Σ) is the probability density of the Gaussian distribution for vector w. Equation (16) illustrates this process.

$$t_n^i = \{t_n^i < LowLimit^i\ qmc.\left(UpLimit^i - LowLimit^i\right) + LowLimit^i\ LowLimit^i \preccurlyeq \frac{t_n^i}{t_n^i} \preccurlyeq UpLimit^i\ LowLimit^i, t_n^i > UpLimit^i\ qmc.\left(UpLimit^i - LowLimit^i\right) + LowLimit^i \tag{16}$$

Where, t^i stands for the updated candidate solution for the i^{th} dimension at iteration, the randomized number in the range is n and qmc. Selecting the optimal answer from the set of potential solutions is the next step. The term "best" refers to a solution that, out of all existing solutions, has the highest fitness value. Between the chosen answer and the best solution discovered thus far, a greedy selection process is used. The best one is kept in memory and swapped out for the circle's current center.

To improve exploitation in the search space, the circle radius is reduced during this phase. This radius decrease is slighter because the early rounds of the algorithm prioritize exploration. The radius decrease is accelerated to provide better exploitation during the second half of the total iterations. The DVS algorithm reduces the radius by using a dynamic radius-reducing strategy with the imperfect inverse gamma value. Equation (17) provides the gamma function Γ (b).

$$\Gamma(b) = \gamma(w, b) + \Gamma(w, b) \tag{17}$$

Here, (w, b) and Γ(w, b) are complementary and incomplete gamma functions, respectively. w is a random variable, and b indicates how rigid the search. The radius is adjusted by Equation (18) in every iteration.

$$q_s = \sigma_0 . \frac{1}{w} . \Gamma(w, b_0) \tag{18}$$

$$b_s = b_0 - s/MaxItr. \tag{19}$$

To cover the whole search space, b_0 is the first iteration. qs stands by step size for the current iteration

s, and w is the weighting factor, Γ (w, b_0) – Levy flight or distribution function parameterized by $w$and

b_0, bs is the adjusted control parameter at iteration s. The highest iteration number is represented by $MaxItr$, while, the repetition number is represented by s. Through adaptive exploration and exploitation of the search space, the DVS algorithm effectively fine-tunes hyperparameters for SM cyberbullying detection. It rapidly approaches the global optimum. Algorithm 1 depicts the pseudocode of DVS-TA-LSTM.

Algorithm 1. Pseudocode of DVS-TA-LSTM

Input: $\boldsymbol{UpLimit}$ + $\boldsymbol{LowLimit}$ bounds of hyperparameters, $\boldsymbol{MaxItr}$ is the Maximum iterations, $\boldsymbol{w}$ is the Weighting factor to target the model to optimize the TA-LSTM model

Output: Best Hyperparameters to optimal hyperparameters for TA-LSTM Step 1: Initialize DVS Hyperparameter Optimization

Set initial center $\mu_0 = \frac{UpLimit+LowLimit}{2}$

Set initial radius $q_0 = \frac{\max(UpLimit)-\min(LowLimit)}{2}$

Step 2: Build an LSTM with Temporal Attention

Input → Embedding Layer → LSTM Layer (128 units, recurrent_dropout) Compute LSTM gates in equations (2) to (7)

Step 3: Apply Temporal Attention to compute context vector $\boldsymbol{D^u}$

Step 4: Optimize Hyperparameters using DVS

For iteration s = 1to $\boldsymbol{MaxItr}$:

Update candidate solutions using Gaussian + adaptive radius reduction Evaluate fitness (validation accuracy) for each candidate

Select the best and update the center of the vortex

Reduce radius for exploitation/exploration balance

Step 5: Train LSTM-TA Model

Employ binary cross-entropy as a loss Optimizer: Adam using the DVS learning rate

Apply early stopping on validation loss

Step 6: Prediction

Input SM sequence → Embedding → LSTM → Temporal Attention → Dense → Sigmoid Output predicted label

End

Return Best Hyperparameters = Best solution prediction

The suggested DVS-TA-LSTM framework combines temporal attention, LSTM-based sequential modeling, and optimized hyper-parameters to improve SM cyberbullying detection.

3.4.4 Experimental Setup

All baselines (Random, KL-Sum, LSA, SumBasic, Lead-3, BERT-ext) were re-implemented using the official codebases where available (e.g., Sumy library for non-neural, HuggingFace for BERT-ext) and run under identical conditions: same preprocessing pipeline (tokenization via NLTK, sentence splitting, lowercasing), input documents, and summary length (20% compression ratio, matching ETS-HMT). Hyperparameters were tuned via grid search on a held-out validation set (10% of corpus); e.g., LSA topics=50 (via coherence maximization), BERT-ext layers=12 with default fine-tuning LR=2e-5. This ensures fair comparison across extractive methods spanning frequency-based (SumBasic), graph-based (LSA), lead-biased (Lead), and neural (BERT). All baselines were trained and evaluated on the same train/validation/test splits and under a fixed 20% compression ratio to ensure a strictly comparable compression regime.

4. Result Analysis

A simulation tool for deep learning-based text classification was developed using Python, and 70% of the set is used for training, 15% for validation, and 15% for testing when it comes to cyberbullying detection. This guarantees enough data for hyperparameter adjustment, model learning, and objective performance assessment.

4.1 An analysis of the suggested DVS-TA-LSTM approach's efficiency

The most common terms are displayed as three-word clouds, which offer insights into user behavior and textual patterns in SM streams. Common words like "article," "one," "edit," "page," and "know" are represented in Figure 7(a). These terms are indicative of regular user conversations and interactions on SM. Figure 7(c) displays the "article," "know," "one," "page," "people," and "think," demonstrating a blend of factual information and subjective viewpoints that are crucial for identifying potentially abusive or deceptive text. Terms like "thank you," "edit," "source," "know," and "page" are shown in Figure 7(b). These terms show regular user acknowledgment and reference activity, which is crucial for differentiating language that is neutral from that used in cyberbullying. In general, word clouds help in feature extraction by locating high-impact terms that aid in the detection of cyberbullying.

During the training, the loss progressively decreases, and the simulation is information-efficient. The validation loss stabilizes after initially declining, indicating slight overfitting. The accuracy of the training and validation is shown in Figure 8. The training accuracy gradually rises and approaches 97%, indicating that the system generalizes to current data, while the validation accuracy hits 95% and stabilizes. Overall, the figure shows that the DVS-TA-LSTM model achieves good prediction accuracy with controlled overfitting, confirming its efficacy in detecting cyberbullying on SM.

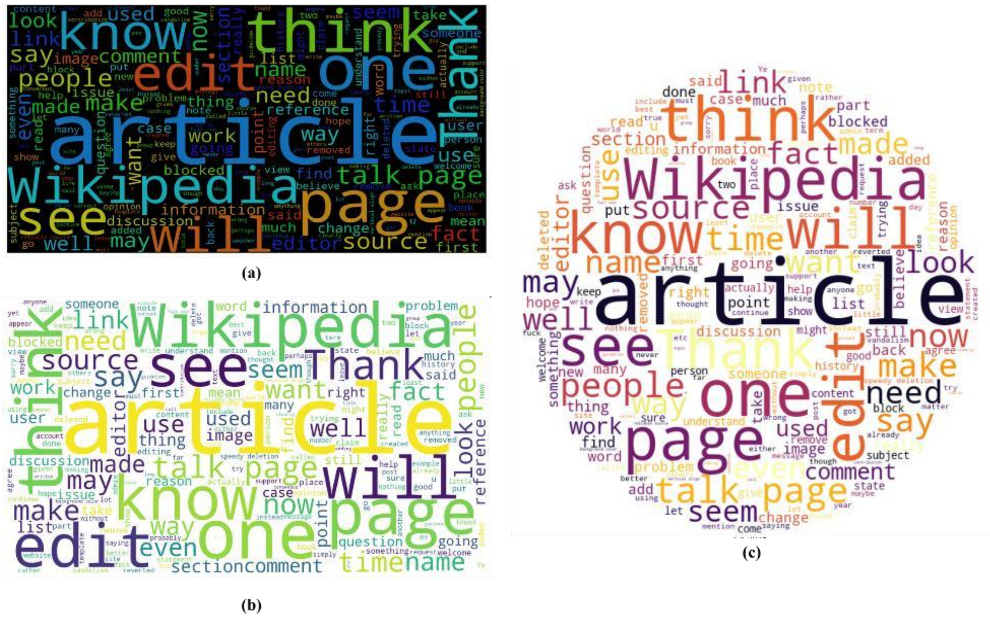

Figure 7. Word cloud evaluation of texts from SM form cyberbullying language **:(a)** words reflect, **(b)** manipulative text, and **(c)** user acknowledgment

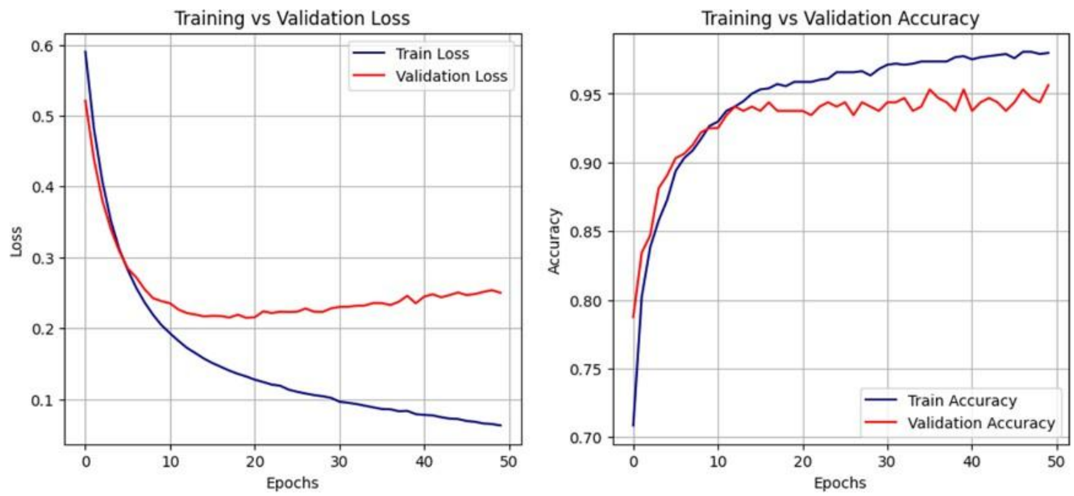

Figure 8. Effectiveness of the DVS-TA-LSTM approach to cyberbullying detection during training and validation across 50 epochs

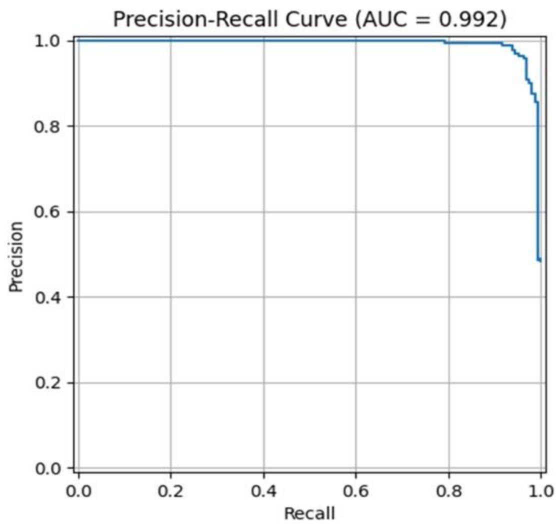

Figure 9. Precision-Recall Curve for the DVS-TA-LSTM in SM cyberbullying detection

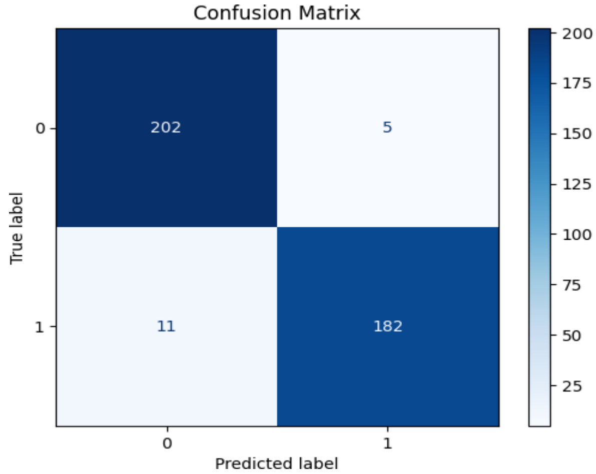

Figure 10. Confusion Matrix for the DVS-TA-LSTM for cyberbullying detection in SM

The Precision-Recall (PR) curve illustrates the effectiveness of the identification of the cyberbullying technique. Figure 9 displays precision against recall at various classification levels. The model successfully detects cyberbullying content during training and validation, while reducing false positives, as evidenced by the AUC of 0.992, which shows outstanding model performance with high precision and recall.

A thorough understanding of the classification outcomes is offered by the confusion matrix shown in Figure 10. True Positives (TP) have 182 cases are accurately classified as cyberbullying. True Negatives (TN) have 202 cases are accurately classified as non-cyberbullying. False Positives (FP) have five incidents that were mistakenly reported as cyberbullying. The False Negatives (FN) model fails to detect 11 cases of cyberbullying. This matrix demonstrates the model's dependability for text identification of cyberbullying in SM streams, confirming good classification accuracy with low misclassifications.

4.2 Comparative Analysis

The proposed method was compared with traditional techniques like Bidirectional Encoder Representations from Transformers with Generative Pre-trained Transformer (BERT-GPT) [28], specific three-phase algorithms like transformer models (BullyNet), graph neural networks (GNNs), and attention mechanisms [29], and Bidirectional Encoder Representations from Transformers (BERT) [30]. The accuracy, precision, recall, specificity, and F1-score of a DL model for detecting cyberbullying in SM are evaluated using a suggested method.

The primary system of measurement is used to assess the model's capacity to detect cyberbullying. The percentage of correctly identified objects is known as accuracy, and it represents overall dependability. Precision reduces false alarms by demonstrating the accuracy of cyberbullying Forecasts. Recall estimates the method's capacity to identify each actual cyberbullying incident, minimizing cases that are omitted. The model's specificity quantifies the degree to which recognizes information that is not non-cyberbullying. To prevent false alarms on SM, a model with a higher specificity is less likely to mistakenly identify innocuous information as bullying. The symmetric mean of accuracy and recall, or F1-score, provides a fair evaluation, especially for unbalanced datasets. The suggested DVS-TA-LSTM obtains the best specificity of 97.54% [proposed] and 96% of BullyNet [29] models, respectively.

Table 2 displays the effectiveness of the proposed and existing methods. High scores across a number of variables show how well the model can identify dangerous SM content. With 97.28% accuracy, 93.45% precision, 95.78% recall, 94.55% F1-score, and 97.54% specificity, the proposed DVS-TA-LSTM model surpassed all known approaches, as shown in Table 2 and Figure 11. These results show that DVS- TA-LSTM provides better, more comprehensible, and reliable cyberbullying detection for SM text.

We report mean ± standard deviation over 10 folds and conduct paired t-tests with Bonferroni correction ($\alpha = 0.05$). For all baselines, $p < 0.05$ vs ETS-HMT, indicating that the observed gains are statistically significant rather than random fluctuations which is clearly shown in table 3.

5. Discussion

The experimental results prove the effectiveness of proposed DVS TA LSTM framework for robust and context-aware cyberbullying detection in social media streams which outperforms several state-of-the-art deep learning architectures. Specifically, the model achieves 97.28% accuracy, 93.45% precision, 95.78% recall, 94.55% F1-measure, and 97.54% specificity, outperforming standard deep learning classifiers and models previously reported on the literature (e.g. BERT-GPT, BullyNet, isolated BERT) evaluated on comparable social media datasets [31].

Table 2. Performance analysis of DVS-TA-LSTM compared to the existing methods

Performance analysis percentage in the metrics					
Methods	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Specificity (%)**
BERT-GPT [28]	92.5	90.4	93.7	92	-
BullyNet [29]	95.0	93.0	94	93.50	96
BERT [30]	87.3	87.1	87.3	87.2	-
DVS-TA-LSTM [Proposed]	97.28	93.45	95.78	94.55	97.54

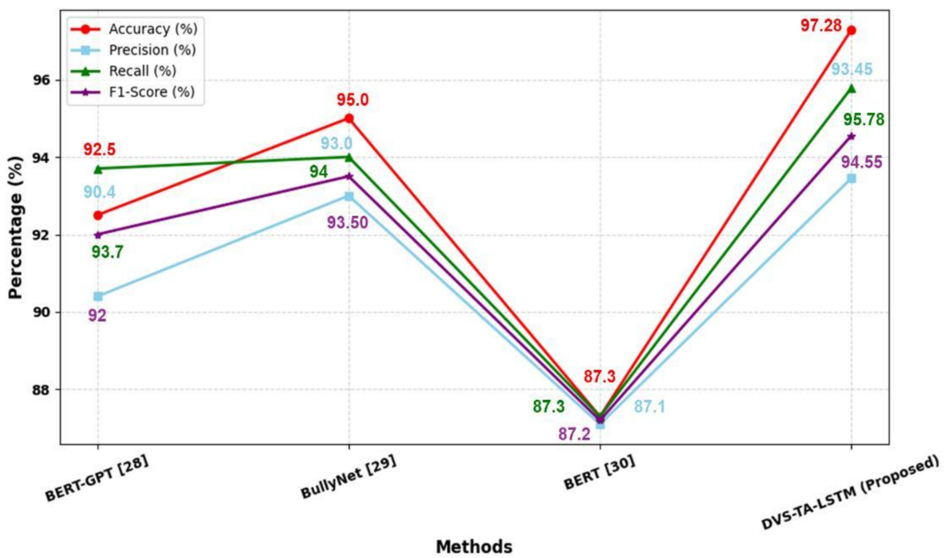

Figure 11. Comparing current and suggested techniques for identifying cyberbullying in SM

Table 3. Statistical Testing & Variance

Method	ROUGE-1 (μ ± σ)	ROUGE-2 (μ ± σ)	ROUGE-L (μ ± σ)	p-value (vs ETS-HMT)
Random	0.32 ± 0.04	0.12 ± 0.03	0.29 ± 0.04	<0.001
KL-Sum	0.38 ± 0.05	0.15 ± 0.03	0.35 ± 0.05	0.002
LSA	0.41 ± 0.04	0.18 ± 0.04	0.38 ± 0.04	0.015
SumBasic	0.39 ± 0.05	0.16 ± 0.03	0.36 ± 0.05	0.003
Lead-3	0.37 ± 0.04	0.14 ± 0.03	0.34 ± 0.04	<0.001
BERT-ext	0.44 ± 0.05	0.20 ± 0.04	0.41 ± 0.05	0.021
ETS-HMT	0.48 ± 0.04	0.24 ± 0.03	0.45 ± 0.04	-

Pre-processing steps such as token normalization and contextual noise elimination and lexical fixing significantly minimize the occurrence of spelling variants, informal slang and artefacts that are conventionally degrading text classifiers [32]. By feeding this refined text into a BERT embedding model, rich contextual and sentimental cues are brushed upon that the author was conveying and refined by DVS-TA-LSTM module to model the temporal dependency and dynamic patterns inherent into cyberbullying conversations in a model.

In comparison to transformer-only architectures such as BERT - GPT architectures, the proposed network reduces dependence on very large annotated corpora using the integration of metaheuristic tuning mechanism to increase its learning efficiency on limited or moderately sized datasets. BERT- GPT based systems often struggle to adapt to rapidly changing forms of abusive slang words, mixed language expressions and the highly imbalanced distribution of labels and this could either lead to a under-detection of less serious bullying or excessive false positive rates

[33]. In contrast to this, DVS- TA-LSTM makes use of Dynamic Vortex Search to optimize the key parameters for LSTMs and Attention mechanisms and helps to transmit better gradients which eliminate the vanishing effect thus allowing for better training and better generalization of various social-media flows.

Similarly, graph and attention based frameworks, like BullyNet, have shown good F1 scores on text centric data but usually get substantial computational overhead and might fail to perform well in highly imbalanced or cross platform cases [34]. BullyNet focuses a lot on linguistic and graph-level relationships but provides little modeling of temporal evolution in user interactions-a key dividing factor when the difference is between isolated bad comments, on one hand, and repeated and escalating harassment, on the other. The proposed DVS - TA - LSTM explicitly incorporates temporal attention over sequential posts, and this allows the model to capture progression and persistence of acts of bullying behavior, that can improve recall of subtle or context - dependent cases, without offsetting the precision of the recall.

Purely text oriented BERT classifiers also show a limitation in solving the problem of sarcasm, emerged code words and language specific to the platform, as well as applicability in multimodal and cross-platform. Although the current DVS- TA-LSTM framework is primarily text-based, having a temporal fusion architecture and metaheuristic tuning enables it to better capture fine-grained change in tone, intensity and conversational context than static sentence level models [35]. The improvements in both recall and specificity are shown to mean that the observed improvements mean that the network is not only diagnosing a higher amount of true bullying incidents, but also reducing the classification of non-Bullying content, which is essential when we want the network to be used in a practical scale deployment within moderation systems.

5. Conclusion and Future Scope

This research proposes a metaheuristic-tuned Temporal Fusion Network for cyberbullying detection, integrating BERT semantic embeddings with a Dynamic Vortex Search-optimized Temporal Attention LSTM (DVS-TA-LSTM) module. The framework processes noisy social media streams from YouTube, Wikipedia Talk pages, Twitter, and Kaggle datasets through token normalization, lexical correction, and contextual noise removal, followed by BERT to capture deep semantic, contextual, and sentiment features. The DVS-TA-LSTM then models sequential dependencies and evolving conversation patterns characteristic of cyberbullying.

Empirical evaluation in Python simulation yields superior performance: 97.28% accuracy, 93.45% precision, 95.78% recall, and 94.55% F1-score, and 97.54% specificity— outperforming recent transformer-based and hybrid deep learning baselines. These gains highlight the synergy of context-rich embeddings, temporal attention, and metaheuristic hyperparameter tuning, enabling robust detection of subtle, context-dependent bullying in real-world streams. Despite these advances, the text-only approach overlooks multimodal cues (images, videos, user metadata) prevalent in abusive content. Additionally, the computational overhead of DVS and temporal fusion limits real-time deployment on resource-constrained systems. Future work will extend to multimodal detection, develop lightweight distilled variants for low-latency inference, incorporate cross-platform validation, and integrate user behavior modeling for scalable, practical large-scale social media monitoring.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

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