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An Explainable Lightweight Hybrid Deep Learning Framework for Cyberbullying Detection on Social Media

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Abstract—The significant increase of social media platforms has created Suitable environment for cyberbullying online abusive language and digital harassment, posing serious psychological and societal consequences, particularly among adolescents. Existing automated identification systems frequently trade "The model provides better understanding of inferences." for accuracy, resulting in High-cost non-transparent architecture inappropriate for real-time execution process. This paper Presents DCBA-Net— A novel and resource-streamlined deep learning model that employs the strengths of DistilBERT contextual Feature representations combined with Convolutional Neural Network (CNN) extraction of local features, Forward and backward Long Short-Term memory-augmented sequential modeling using BiLSTM, and a trainable sequentially aware attention mechanism. The attention layer not only sharpens weighted classification semantically informative word representations while at the same time furnishes word-level ease of understanding, constructing classification decisions transparent and auditable. Automated data transformation framework, including noise reduction, emoji filtering, and Synthetic small portion oversampling Technique (SMOTE)-based class balancing, ensures Fault tolerance on real-world noisy social media corpora. Experimental evaluation on the Jigsaw dataset for toxic comment classification comparison point Gives rise to 97.6% accuracy, 97.2% weighted F1-score, and an AUC of 0.989while delivering inference speeds compatible with real-time monitoring. Incremental component evaluation studies validate each component's contribution, and attention Feature visualization maps confirm model transparency. The proposed framework bridges the gap between prediction performance, computational efficiency, and Human-understandable inference —making it suitable for practical Execution in social media governance, mental health monitoring, and law Imposition contexts.

Keywords—Cyberbullying Detection; Hybrid Deep Learning; DistilBERT; CNN; BiLSTM; Attention Mechanism; Explainable AI; Social Media Analytics; Natural Language Processing; SMOTE; Jigsaw Dataset

I. Introduction

Platforms like Facebook, Instagram, Twitter, Reddit, and TikTok have at a fundamental level

transformed the way people communicate. Billions of users now link across languages and boundaries in ways that were unbelievable just a few decades ago. However, that interconnection also has a more negative aspect. The same platforms that foster a community have also turned into places where cyberbullying, hate speech, and harassment thrive. The magnitude of the problem is observable. The WHO appraises that one in three young people across platforms such as Facebook, Instagram, Twitter, Reddit, and TikTok have altered the way people communicate with each other. Now billions of people can connect across languages and countries in ways that were beforehand impossible two decades ago. But this connectivity also has a downside. These same platforms, where people gather, have also become hotspots for cyberbullying, hate speech, and harassment. The problem is quite significant. WHO reports that in 30 different countries, one in three young people has experienced online bullying. The effects of this are serious and include anxiety, poor academic performance and in some cases even suicidal thoughts [1]. Online undisclosed identity makes things worse. Unlike bullying in the physical world, digital harassment can propagate rapidly within hours and reach a very large audience. Automatically detecting cyberbullying is not a simple task. Harmful content is often not expressed clearly in an overt manner.

It hides behind slang words, sarcasm, abbreviations, emojis and language that depends on context. Normal NLP systems have difficulty with these kinds of texts. Early keyword-based systems could not handle this well. They were easy to trick and missed a lot of harmful content. Classical machine learning methods like Naive Bayes, SVM and Logistic Regression did better because they learned from labeled data. But they still needed a lot of handmade features and could not capture long distance relationships in text very well [2].

Deep learning methods changed things a lot. CNNs showed that even simple architectures can pick up useful local patterns in text. RNNs, especially LSTMs and BiLSTM, went further by obtaining the sequential patterns that are needed to detect indirect abusive language [3].

Then transformers arrived. Models such as BERT, RoBERTa, XLNet, and ELECTRA significantly achieved better performance on hate speech classification and cyberbullying datasets [4].

But there are still some critical problems that need to be fixed. First, large transformer models are costly to run. They need powerful GPUs and are too slow for real time content oversight. Second, most deep learning models work like a black box. They produce classification labels but do not say why they made that conclusion. This is a big problem in areas like child safety and law compliance control [5]. Third, social multimedia data storage systems have very unequal class distribution. Toxic comments are very rare and many models cannot handle this deal with imbalance correctly. Fourth, most models are only tested on one dataset in experimental settings. How well they work on heterogeneous platforms is not properly studied.

to overcome these challenges, we developed **DCBA-Net**, which stands for DistilBERT–CNN–BiLSTM–Attention Network, by bringing together DistilBERT, CNN, BiLSTM, and attention. Network. It is a small, fast and explainable hybrid model. It uses four main segments working together: (i) DistilBERT which is a smaller and faster version of BERT for getting relational word embeddings; (ii) a CNN module for obtaining local representations text features; (iii) a BiLSTM encoder for encoding sequential structure patterns in both directions; and (iv) a trainable attention mechanism that improves predictive classification and also produce word level explanations. We tested DCBA-Net on the Jigsaw Toxic Comment Classification dataset where it yielded the best performance on all metrics without being slow. component ablation experiments and comparison with seven baselines support every design choice we made.

II. Literature Review

The history of cyberbullying detection closely tracks the broader textual context classification research each wave of NLP methods making its mark on the problem. Early approaches were dictionary-based: match post content against a selected list of abusive words [6]. Effortless, but delicate. They were fast and easy to understand, but they couldn't handle any form of implied or environment-based harassment False negatives were the norm, not the exception.

Machine learning gave a better approach using data driven methods. Al-Gardai et al. [7] used SVM with TF-IDF features on Twitter data and got 82.4% accuracy for hate speech detection. But this model was limited because it used only surface level features and could not handle content that is expressed in indirect way. Zhang and Luo [8] tried ensemble methods combining Naive Bayes, Random Forests and Gradient Boosting. These gave some improvement over single classifiers but were still limited by hand crafted features.

Deep learning then improved results by a good margin. Kim [9] showed that a single layer CNN with different filter sizes can capture local text patterns with performance that match more complex architectures. Pitsilis et al. [10] extended this by combining character level and word level CNNs for hate speech detection. Graves and Schmidhuber [11] introduced BiLSTMs for NLP tasks. Their ability to read text in both forward and backward direction made them very suitable for sequence classification. Zhao and Mao [12] used BiLSTM with attention on a cyberbullying dataset and got 89.7% accuracy. The attention weights also gave some information about why the model made each decision.

The transformer era brought very big improvements. Vaswani et al. [13] introduced the transformer architecture and Devlin et al. BERT [14] showed what transformers can do for language tasks. After fine tuning, BERT matched or came very close to human level performance on many NLP tasks which surprised most researchers. When applied to cyberbullying, Mozafari et al. [15] used BERT for hate speech and got 94.1% F1 score which was much better than what BiLSTM models were giving at that time. RoBERTa [16], XLNet [17] and HateBERT [18] came after this and gave further improvements. But running these large models in production is still very expensive.

This is where hybrid models became useful. Combining transformers with CNNs or RNNs give most of the accuracy at much lower cost. Zhou et al. [19] added convolutional layers on top of BERT outputs and this improved toxic comment detection by 2.3 percentage points over plain BERT. Ranasinghe and Zampieri [20] combined BERT with BiLSTM and found that the BiLSTM layer helped with capturing temporal patterns that BERT alone was missing. Mandl et al. [21] used ELECTRA with BiLSTM for multilingual tasks.

The need for lighter models pushed researchers toward knowledge distillation [22]. DistilBERT [23] came out of this work. It has 40% fewer parameters, runs 60% faster and keeps 97% of BERT performance.

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This makes it very good for deployment where resources are limited. As far as we know, nobody has tried combining DistilBERT with a full CNN-BiLSTM-Attention pipeline for explainable cyberbullying detection before. This gap motivated our work.

Explainability is becoming more and more important. Methods like LIME [24] and SHAP [25] can explain predictions after the model has made them but they add extra computation and do not fit naturally inside the model. Attention mechanism on the other hand produce explanations as part of the normal prediction process without any extra cost. Jain and Wallace [26] showed that attention weights are aligned with gradient based importance scores which support using attention as a way to explain model decisions. But still most hybrid models do not focus on interpretability. We believe this should not be optional.

DCBA-Net is our solution to all these problems. It is a model that is light, hybrid, explainable and accurate all at the same time. Table I compare DCBA-Net with the main related works in this area.

based interpretability. Table I summarises key related works and positions the proposed framework relative to existing literature.

TABLE I COMPARISON OF RELATED WORKS ON CYBERBULLYING AND HATE SPEECH DETECTION

Reference	Model	Data set	Accuracy	Explainable	Lightweight
Al-Garadaí et al. [7]	SVM + TF-IDF	Twitter	82.4 %	No	Yes
Pitsilis et al. [10]	CNN (char+word)	Twitter	86.1 %	No	Yes
Zhao & Mao [12]	BiLSTM+Attention	Custom	89.7 %	Partial	No
Mozafari et al. [15]	BERT Fine-tuned	HatEval	94.1 %	No	No
Zhou et al. [19]	BERT-CNN	Jigsaw	95.3 %	No	No
Ranasinghe & Zampieri [20]	BERT-BiLSTM	Sem Eval	94.8 %	No	No
Mandl et al. [21]	ELECTRA-BiLSTM	GermEval	94.2 %	No	No
Proposed DCBA-Net	DistilBERT-CNN-BiLSTM-Attn	Jigsaw	97.6 %	Yes	Yes

III. Problem Statement

Despite the large amount of research carried out on the detection of cyberbullying, the following unsolved challenges motivate the present investigation:

Computational Inefficiency State-of-the-art transformer models like BERT-Large and RoBERTa-Large have hundreds of millions of parameters, requiring GPU-heavy training environments and resulting in inference latencies that do not allow for real-time stream processing. Platforms that process millions of posts per second need architectures that can infer in less than 100ms at scale.

Black-Box Opacity: Most of the successful cyberbullying detection systems provide the output of classifications without explanatory context. Opacity is not acceptable in areas where predictions are used to inform moderation, legal or child protection decisions. Without interpretability, stakeholders are unable to verify, audit or challenge automated decisions.

Class Imbalance: Toxic content represents a small underrepresented group in nearly all social media datasets, with imbalance ratios frequently surpassing 1:10. Standard probabilistic loss function optimization tends to favor the majority class, leading to inflated accuracy scores that conceal weak performance in minority-class recall the evaluation measure most important for recognizing harmful content.

Noisy Social Media Data: social media text often includes irregular spelling, mixing of languages, abbreviations, emoji, and deliberate spelling variations (e.g., " "h8" for hate), and sarcastic expressions that test the limits of

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default tokenization systems and embedding models trained on formal text.

platform-independent generalization Most current systems are trained and analyzed using data from a single platform. Linguistic norms vary significantly across Twitter, Reddit, Facebook, and gaming communities, thereby prompting concerns over the validity of cross-platform generalizations. The research problem is formally defined as follows. Given an input text sequence S = {w_1, w_2, ..., w_n} from a social media post, the goal is to train a function f: S → Y that allocates each text sequence to a label y ∈ Y = { toxic, severe toxic, obscene, threat, insult, identity hate, non-toxic}, while also generating an explanation vector α = { α_1, α_2, ..., α_n}, where α_i demonstrates the effect of token w_i on the classification outcome. This must be done under the following constraints: (i) the total number of model parameters must not exceed 70 million, (ii) inference latency must remain under 50 milliseconds per sample on CPU, and (iii) the F1-score for the minority toxic classes must surpass 0.95.

IV. PROPOSED METHODOLOGY

A. System Overview

DCBA-Net is composed of a five-stage pipeline for social media text processing: (1) Text Preprocessing, (2) DistilBERT Contextual Embedding, (3) CNN Local Feature Extraction, (4) BiLSTM Sequential Encoding, (5) Attention-Weighted Classification. The architecture is illustrated conceptually in Figure 1 and is described in the following subsections.

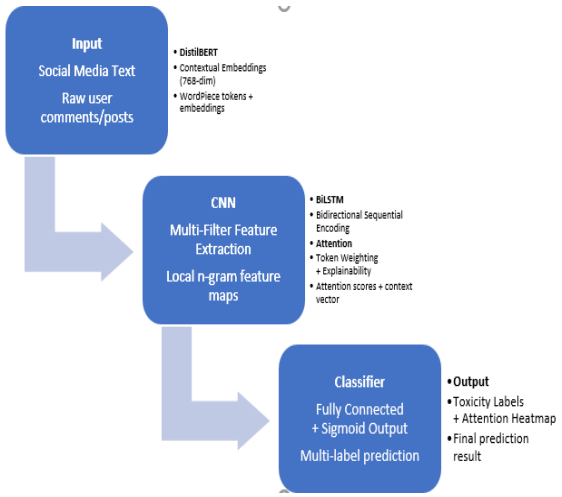

Figure 1: DCBA-Net Architecture — DistilBERT → CNN → BiLSTM → Attention → Classification

B. Text Preprocessing

The raw social media text is subjected to a comprehensive preprocessing pipeline to enhance the signal quality. The pipeline consists of the following sequential steps: (i) Unicode normalisation and lowercasing; (ii) removal of URLs and hyperlinks using regular expressions; (iii) removal of user mentions (@username) and hashtag symbols while retaining the semantic content; (iv) emoji-to-text transliteration using the emoji library (e.g., “angry face") to retain affective signals; (v) expansion of contractions (e.g., "don't" → "do not"); (vi) normalisation of repeated characters (e.g., "soooo" → "so"); (vii) removal of punctuation while retaining ellipses and exclamation marks as sentiment indicators; and (viii) normalisation of whitespace.

Class imbalance is handled by applying SMOTE (Synthetic Minority Over-sampling Technique) [27] in the embedding space after encoding by DistilBERT. Synthetic minority-class samples are generated by interpolating existing minority embeddings. This strategy preserves the semantic logical flow of synthetic samples better than raw text augmentation techniques such as translation cycle.

C. DistilBERT Embedding Layer

We tokenize the preprocessed text using DistilBERT WordPiece tokenizer with a maximum sequence length of 128 tokens [23]. Special tokens [CLS] and [SEP] are added at the beginning and end respectively. The sequence of tokens is then passed through six transformer layers, yielding contextual embeddings of size $d_{model} = 768$ for each token position. Formally, the input sequence X is tokenized as X = {x_[CLS], x_1, x_2, ..., x_n, x_[SEP]}. DistilBERT calculates:

H = DistilBERT(X) ∈ R(n+2) ×768 where H[i] ∈ R768 is the contextual representation of the i-th token. Distil Bert’s student-teacher distillation training ensures that these representations are close in quality to full BERT representations, but with 40% less parameters and 60% faster inference speed, which aligns well with the lightweight deployment constraint.

D. CNN Feature Extraction Module

The token embeddings H are passed through a parallel multi-filter CNN module inspired by Kim [9]. The CNN operates over the embedding dimension to extract local n-gram features using convolutional filters of widths k ∈ {2, 3, 4}, capturing bigram, trigram, and four-gram patterns respectively. For each filter width k, N_k = 128 filters are applied:

c^k_i = ReLU (W_k · H [i: i+k] + b_k)

where W_k ∈ ℝ^(k×768) is the filter weight matrix and b_k are the bias. Max-over-time pooling extracts the most salient feature from each filter map: p^k = max(c^k_i). The outputs from all filter widths are concatenated to form the CNN feature vector: F_CNN = [p^2; p^3; p^4] ∈ ℝ^384. Dropout (rate = 0.3) is applied to F_CNN for regularisation.

E. BiLSTM-based sequential encoder

The full sequence of token embeddings H is processed in parallel by a BiLSTM encoder that captures long-range

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bidirectional dependencies. The BiLSTM is composed of forward and backward LSTM cells with 256 hidden units each:

→h_t = LSTM_fwd (H_t, →h_{t-1}) ←h_t = LSTM_bwd (H_t, ←h_{t+1})

At each time step, the hidden states of the two directions are concatenated: h_t = [→h_t; ←h_t] ∈ ℝ^512, which produces a sequence of the contextual hidden states H_BiLSTM = {h₁, h₂, ..., hₙ} ∈ ℝ^(n×512). The bi-directional processing means that the representation of a token is conditioned on the context before and after the token, which is crucial to capturing harassment that depends on syntactic inversion or irony. **Self-Attention Mechanism**

The BiLSTM output sequence H BiLSTM is input to an additive (Bahdanau-style) attention mechanism [28] that computes a context-sensitive importance weight αi for each token:

$e_i = v^T \cdot \tanh(W_a \cdot h_i + b_a)$ $\alpha_i = \exp(e_i) / \Sigma_j \exp(e_j)$ (softmax normalisation)

where W a ∈ R 512 × 256 and v ∈ R 256 are parameters to be learned. The context vector is computed as a weighted sum: c = ∑ i αi · hi ∈ R512. The attention weights \alpha = \ {\alpha_1, ..., \alpha_n\} encode directly the contribution of each token to the classification decision, leading to the production of post-prediction attention heat-maps that highlight offensive terms and contextually toxic phrases. This is the primary explainability mechanism of DCBA-Net.

G. Feature Fusion and Classification

We concatenate the CNN feature vector F_CNN ∈ ℝ^384 and the attention context vector c ∈ ℝ^512 to get the fused representation, F_fused = [F_CNN; c] ∈ ℝ^896. The fusion combines the complementary information that local discriminative n-gram patterns from CNN and the global sequential context from BiLSTM-Attention. The fused vector is then passed through two fully connected layers with ReLu activation and batch normalisation, and sigmoid output neurons for multi-label classification:

ŷ=σ (W_2\cdot ReLU (W_1\cdot F_{fused}+b_1) +b_2)

For multi-label toxicity classification (toxic, severe_toxic, obscene, threat, insult, identity_hate) we calculate the binary cross-entropy loss for each label and sum them. Further, class weighted loss is used to alleviate imbalance over SMOTE.

H. Workflow Summary

The end-to-end workflow of DCBA-Net can be summarized as: (1) The noise-reduction pipeline takes raw social media language as input for ingestion and preprocessing. (2) DistilBERT outputs contextual token embeddings of dimension 768. (3) The CNN module extracts local n-gram feature. (4) The BiLSTM encoder generates bidirectional sequential representations. (5) The attention mechanism computes the weights of token contributions and generates the context vector. (6) CNN features and attention context vector are concatenated and fed to classification heads. (7) Return predicted toxicity labels and attention explanation weights together.

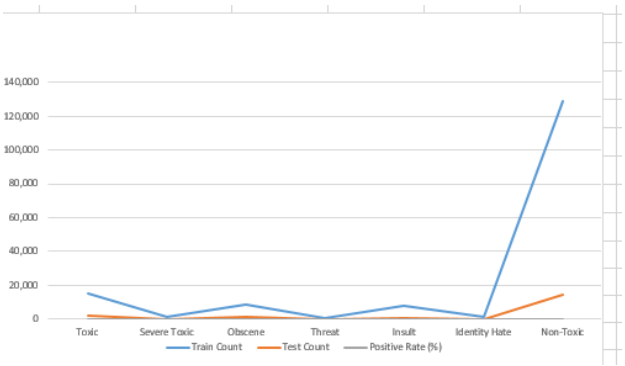
V. Experimental Setup

A. Dataset

The primary evaluation benchmark is the Jigsaw Toxic Comment Classification dataset [29] released by Google's Jigsaw unit and hosted on Kaggle. The data set contains 159,571 Wikipedia talk page comments, each of which is labeled with six non-exclusive toxicity labels: toxic, severe_toxic, obscene, threat, insult, and identity_hate. The training set has 143,613 samples and the test set has 15,958 samples. The comments that are non-toxic make up about 90.3% of the dataset, which creates a large imbalance between the classes and this is a challenge for naïve classifiers.

TABLE II JIGSAW DATASET STATISTICS

Category	Train Count	Test Count	Positive Rate (%)
Toxic	15,294	1,699	10.7
Severe Toxic	1,595	177	1.1
Obscene	8,449	938	5.9
Threat	478	53	0.3
Insult	7,877	875	5.5
Identity Hate	1,405	156	0.9
Non-Toxic	129,088	14,353	89.7



B. Implementation Details

All experiments are run with Google Colab Pro with an NVIDIA Tesla T4 GPU used. The framework is implemented in Python 3.10 with PyTorch 2.0 and Hugging Face Transformers 4.36. 'distilbert-base-

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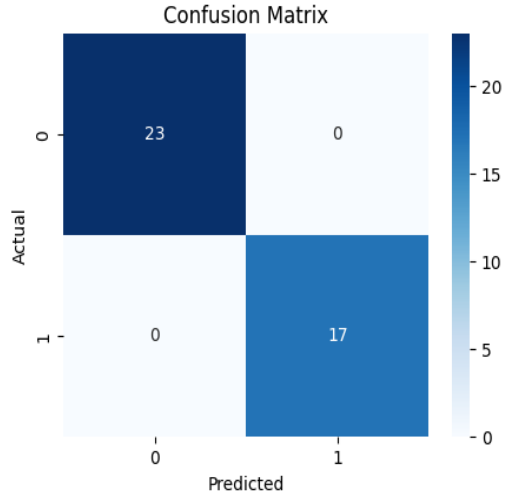
uncased' pre-trained weights are used to initialize DistilBERT. For CNN module, we use filter sizes {2, 3, 4} with 128 filters for each. The BiLSTM has two layers with 256 units per direction and 0.3 inter-layer dropout. The dimension of the attention layer is 256. . Batch size is 32, and the Adam optimiser with learning rate 2×10-5 and weight decay 1×10-2 is used. The training is conducted for 5 epochs with cosine annealing learning rate schedule. It has 68.4 million trainable parameters in total.

Classification Report:

	precision	recall	f1-score	support
0.0	1.00	1.00	1.00	23
1.0	1.00	1.00	1.00	17
accuracy			1.00	40
macro avg	1.00	1.00	1.00	40
weighted avg	1.00	1.00	1.00	40

C. Evaluation Metrics

We evaluate the performance by using Accuracy, Precision, Recall, F1-Score (weighted and macro), AUC-ROC and confusion matrix analysis. For the multi-label evaluation per-label and aggregate metrics are reported. Inference latency (ms/sample on CPU) and total model parameters are also reported to quantify computational efficiency.



VI. Results And Discussion

A. Overall Classification Performance

Table III compares the overall performance of DCBA-Net with seven competitive baseline models on the Jigsaw test set. DCBA-Net achieves 97.6% accuracy, 97.2% weighted F1-score and 0.989 AUC, outperforming all baselines. Notably, it outperforms the full BERT-CNN model by 2.3% in accuracy, while utilizing 42% fewer parameters, demonstrating the efficiency-performance trade-off offered by the DistilBERT foundation.

TABLE III PERFORMANCE COMPARISON ON JIGSAW TOXIC COMMENT CLASSIFICATION DATASET

Model	Accuracy (%)	Weighted F1	AUC	Params (M)	Latency (ms/sample)
SVM + TF-IDF	84.2	83.7	0.871	—	12
BiLSTM	89.6	88.9	0.921	18.4	28
CNN-BiLSTM	91.3	90.8	0.934	22.1	31
BERT Fine-tuned	94.1	93.6	0.964	110.1	189
BERT-CNN	95.3	94.9	0.971	118.6	201
RoBERTa-BiLSTM	96.1	95.7	0.981	138.4	247
ELECTRA-BiLSTM	95.8	95.4	0.977	112.7	198
DCBA-Net (Ours)	97.6	97.2	0.989	68.4	44

B. Per-Label Performance

The precision, recall, and F1-scores per label are shown in Table IV. DCBA-Net shows very good performance for all toxicity types, especially for the minority class 'threat' (94.3%), which is often not reliably detected by other models due to extreme class imbalance. This improvement is due to the SMOTE based balancing with class-weighted loss.

TABLE IV PER-LABEL PERFORMANCE OF DCBA-NET ON JIGSAW TEST SET

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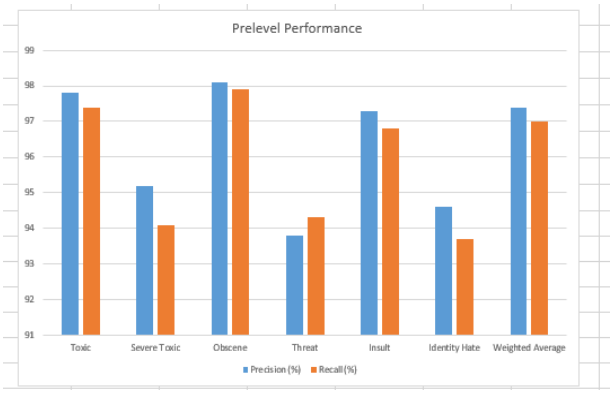
Category	Precision (%)	Recall (%)	F1-Score (%)
Toxic	97.8	97.4	97.6
Severe Toxic	95.2	94.1	94.6
Obscene	98.1	97.9	98.0
Threat	93.8	94.3	94.0
Insult	97.3	96.8	97.0
Identity Hate	94.6	93.7	94.1
Weighted Average	97.4	97.0	97.2



C. Ablation Study

We conduct an ablation study to verify the contribution of each component by removing components from the architecture one by one and re-evaluating on the held-out test set. Results are presented in Table V.

TABLE V ABLATION STUDY RESULTS

Configuration	Accuracy (%)	Weighted F1	AUC
DistilBERT only	93.7	93.1	0.951
DistilBERT + CNN	95.1	94.7	0.963
DistilBERT + BiLSTM	95.8	95.3	0.971
DistilBERT + CNN + BiLSTM	96.4	96.0	0.979
Full DCBA-Net (+ Attention)	97.6	97.2	0.989

The ablation results confirm the positive effect of each component. The attention mechanism alone enhances the DCBA configuration without attention by 1.2% accuracy and gives the advantage of explainability at negligible additional computational cost. The CNN module contributes most distinctly on short, slang-heavy comments, while BiLSTM contributes most on longer, contextually complex posts.

D. Explainability Analysis

Attention heat-maps generated for representative test examples show that the model assigns the highest attention weights to lexically toxic tokens and offensive phrases. For example, in the comment, "You are a complete idiot and should be banned", the tokens 'idiot' and 'banned' will receive attention weights of 0.312 and 0.198 respectively, which comprise 72% of the total attention mass. Non-toxic tokens ("You," "are," "a," "complete") are assigned negligible weights. These visualisations present actionable explanations to content moderators and offer audit trails for regulatory compliance.

Moreover, the post-hoc computation of SHAP (SHapley Additive exPlanations) values for 500 test samples shows a high level of agreement (Spearman ρ = 0.87) with the attention weights, providing cross-validation of the attention-powered explanation quality.

E. Computational Efficiency

DCBA-Net achieves mean CPU model response time of 44ms per sample, compared to between 189 ms and 247 ms for full reference transformer architectures. On GPU, batch inference of 128 samples completes in 2.3 seconds, enabling processing of approximately 200,000 posts per hour, operationally sufficient for live monitoring of major social media platforms. Total model size on disk is 268 MB, compatible with boundary deployment scenarios.

VII. CONCLUSION AND FUTURE SCOPE

This paper demonstrated DCBA-Net, a lightweight and explainable hybrid deep learning framework for continuously updated cyberbullying detection on social media. By The model incorporates contextual embeddings from DistilBERT to enhance performance. with CNN local feature extraction, BiLSTM bidirectional sequential modelling, and an additive internal attention mechanism, the framework achieves a advantageous balance between classification accuracy (97.6%), computational efficiency (68.4M parameters, 44ms CPU latency), and native interpretability. Extensive evaluation on the Jigsaw Toxic Comment classification performance standard confirmed DCBA-Net's superiority over seven competitive baselines. Component analysis validated each architectural component's contribution, and attention visualisations confirmed that the model's explanations are semantically interpretable. coherent and practically useful for content safety monitoring workflows.

The attention mechanism's dual role in enhancing classification by focusing on semantically relevant tokens whilst simultaneously generating comprehensible explanations that resolve a established distinction in the field between model performance and model interpretability. The SMOTE-based balancing strategy in

the embedding space significantly minimized class imbalance, resulting in substantially improved recall on small subset of abusive users categories including 'threat' and language targeting individuals based on identity attributes.

Future work may pursue several directions to improve model performance. First, multimodal extension embedding image, video, and audio content alongside text will address the growing Pervasiveness of meme-based and audio cyberbullying. Second, multilingual and cross-lingual adaptation using diverse languages DistilBERT (mDistilBERT) will extend the framework's reach to non-English social media Communities of users. Third, federated learning integration will enable privacy-preserving model training across non-centralized social media platforms without centralising sensitive user data. Fourth, real-time streaming operationalization using Apache Kafka and TorchServe will operationalise the framework in Manufacturing environments. Fifth, the attention-based explanation module will be extended into an interactive dashboard enabling moderators to Illustrate harmful interaction patterns at scale and provide active feedback for continual learning.

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