ISSN 2277-2685

IJESR/April-June. 2026/ Vol-16/Issue-2/509-516

Syed S. Quadri *et. al.*, / International Journal of Engineering & Science Research

Full Length Article

Social Media Forensics: Cyberbullying & Hate Speech Analysis Using Machine Learning And NLP

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Accepted 20-04-2026

Abstract

The exponential proliferation of user-generated content on social media platforms has created an urgent need for automated systems capable of identifying cyberbullying, hate speech, and offensive language at scale. This paper presents a comprehensive machine learning-based web application — Social Media Forensics (SMF) — that classifies social media text into three categories: Hate Speech, Offensive Language, and Clean Content. The system employs Natural Language Processing (NLP) preprocessing pipelines (tokenization, stop-word removal, lemmatization) combined with TF-IDF (Term Frequency–Inverse Document Frequency) vectorization for feature extraction. Six supervised machine learning classifiers — Logistic Regression, Naïve Bayes, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest, and Gradient Boosting — are systematically trained, evaluated, and compared. The best-performing model achieves approximately 94% classification accuracy. The full-stack web application is developed using Python Flask, SQLite, Bootstrap 5, and Docker containerization, incorporating user authentication, real-time prediction with confidence scoring, analysis history tracking, and a multi-chart analytics dashboard. Mathematical formulations of TF-IDF, Bayes theorem, SVM hyperplane optimization, and information-gain-based ensemble methods are derived. System architecture, algorithmic pseudocode, UML diagrams, and a comprehensive performance comparison across all six classifiers are presented.

Keywords: *Cyberbullying Detection, Hate Speech Classification, Natural Language Processing, TF-IDF, Support Vector Machine, Social Media Forensics, Text Classification, Flask, Affective Computing*

1. Introduction

Social media platforms such as Twitter/X, Facebook, Reddit, and Instagram now host billions of daily interactions. While these platforms democratize communication, their scale enables the rapid propagation of harmful content — cyberbullying, hate speech, and offensive language — which inflict measurable psychological harm on individuals and communities. The World Health Organization (WHO) has linked exposure to online hate speech and cyberbullying to elevated rates of anxiety, depression, and suicidal ideation among adolescents and young adults.

Manual content moderation is operationally infeasible at scale: platforms like Meta report reviewing over 1 million pieces of flagged content per day, yet automated systems still generate significant false-positive and false-negative rates. The challenge is compounded by the nuanced boundary between hate speech (targeting protected characteristics), offensive language (abusive but not necessarily group-targeting), and legitimate — if harsh — discourse.

This paper presents the design, implementation, and evaluation of Social Media Forensics (SMF), a full-stack NLP and machine learning system that automatically classifies user-submitted text into three forensically meaningful categories. The contributions of this work are: (1) a rigorous mathematical treatment of TF-IDF, Naïve Bayes, SVM, and ensemble classifiers for text classification; (2) a comparative empirical evaluation of six ML models on the hate-speech domain; (3) a deployed, privacy-preserving web application with analytics dashboard; and (4) a modular architecture extensible to deep learning and real-time API integration.

2. Literature Survey

Research on automated harmful content detection spans NLP, computational linguistics, and social computing. Four thematic streams are reviewed below.

2.1 Foundational Hate-Speech Detection Studies

Davidson et al. (2017) introduced the widely cited hate-speech corpus of 24,802 tweets annotated into three classes — hate speech, offensive, and neither — and evaluated Logistic Regression with n-gram TF-IDF features, achieving 91% accuracy with a significant false-positive rate for offensive-but-not-hateful content. Their work established the three-class taxonomy adopted by the SMF system. Fortuna and Nunes (2018) surveyed 63 hate-speech detection papers, finding SVM and Logistic Regression as the dominant classical models, with lexicon-based and embedding-based features showing complementary strengths.

2.2 Cyberbullying Detection

Dinakar et al. (2011) pioneered computational cyberbullying detection using rule-based and Naïve Bayes classifiers on YouTube and MySpace data. Subsequent work by Salminen et al. (2020) scaled hate classification across five platforms (YouTube, Reddit, Twitter, Facebook, Gab), finding that platform-specific fine-tuning substantially improves cross-platform generalization. Schmidt and Wiegand (2017) comprehensively reviewed NLP features for hate speech detection, concluding that TF-IDF bag-of-words remains a strong baseline that deep embedding models marginally improve in low-data regimes.

2.3 Machine Learning Models for Text Classification

Aggarwal and Zhai (2012) surveyed text classification algorithms, establishing that SVM with linear kernels consistently outperforms other classical methods on high-dimensional text feature spaces due to its effective margin maximization. Random Forest and Gradient Boosting ensemble methods demonstrate superior robustness to noisy labels — a characteristic feature of crowd-sourced hate-speech datasets. KNN, while conceptually simple, suffers from O(n) inference cost over large TF-IDF matrices, making it suboptimal for real-time web deployment.

2.4 Summary and Research Gaps

The literature consensus establishes: (1) TF-IDF with n-gram features is a robust baseline for hate speech text classification; (2) SVM and Logistic Regression dominate classical ML benchmarks; (3) context understanding (sarcasm, code-switching, implicit bias) remains an open challenge for shallow models; (4) most academic prototypes lack accessible web deployment. The SMF system addresses gap (4) and provides a rigorous six-model comparative framework.

Table 1: Literature Survey Summary

Table 1: Summary of related literature in hate speech and cyberbullying detection.

Author(s)	Year	Method	Dataset	Key Finding
Davidson et al.	2017	LR + TF-IDF n-grams	24,802 tweets	91% acc; 3-class taxonomy established
Fortuna & Nunes	2018	Survey (63 papers)	Multiple	SVM & LR dominate classical ML baselines
Schmidt & Wiegand	2017	NLP feature survey	Multiple	TF-IDF BOW strong baseline; embeddings marginal gain
Dinakar et al.	2011	Naïve Bayes + rules	YouTube, MySpace	First computational cyberbullying detection
Salminen et al.	2020	ML + platform features	5 platforms	Platform-specific tuning improves generalization
Aggarwal & Zhai	2012	Survey (ML classifiers)	Multiple	Linear SVM best for high-dim text feature spaces
Proposed (SMF)	2025	6-model NLP+ML pipeline	Synthetic + Davidson	~94% accuracy; full-stack web deployment

3. Mathematical Foundations

3.1 Text Preprocessing Pipeline

Raw social media text undergoes a standardized preprocessing pipeline before feature extraction. Each input document d undergoes the transformation:

$$d' = Lemmatize(RemoveStopwords(Lowercase(RemovePunct(d)))) \quad \text{(Equation 1)}$$

Lemmatization maps inflected word forms to their canonical base form (e.g., 'hating' → 'hate', 'idiots' → 'idiot'), improving vocabulary consolidation. Stop-word removal eliminates high-frequency, low-information tokens (e.g., 'the', 'is', 'a').

3.2 TF-IDF Feature Extraction

TF-IDF (Term Frequency–Inverse Document Frequency) transforms each preprocessed document

into a numerical feature vector. For term t in document d within corpus D of N documents:

$TF(t, d) = count(t \text{ in } d) / |d|$ (Equation 2)

$IDF(t, D) = \log(N / |\{d \in D : t \in d\}|) + 1$ (Equation 3)

$TF\text{-}IDF(t, d, D) = TF(t, d) \times IDF(t, D)$ (Equation 4)

The +1 smoothing in IDF prevents division by zero for terms appearing in all documents. L2 normalization is applied to each document vector v to produce unit vectors:

$\hat{v} = v / ||v||_2 \quad where \quad ||v||_2 = \sqrt{(\Sigma_i v_i^2)}$ (Equation 5)

With a vocabulary of |V| terms, each document is represented as a $\hat{v} \in \mathbb{R}^{|V|}$ sparse vector. The SMF system uses unigram+bigram TF-IDF (n-gram range [1,2]), producing feature vectors that capture both individual keyword signals and adjacent word-pair context.

3.3 Logistic Regression

For K=3 classes, the multinomial Logistic Regression model computes class probability via Softmax:

$P(y = k \mid x) = \exp(w_k^T x + b_k) / \Sigma_j \exp(w_j^T x + b_j)$ (Equation 6)

Training minimizes the regularized cross-entropy loss over N training samples:

$L = -(1/N) \Sigma_i \Sigma_k y_{ik} \log P(y=k|x_i) + (\lambda/2)||W||^2_F$ (Equation 7)

where y_{ik} is the one-hot indicator, $W \in \mathbb{R}^{|V| \times K}$ the weight matrix, and λ the L2 regularization coefficient (default λ=1 in scikit-learn's LogisticRegression).

3.4 Naïve Bayes Classifier

The Multinomial Naïve Bayes (MNB) classifier applies Bayes' theorem under the conditional independence assumption:

$P(y=k \mid x) \propto P(y=k) \cdot \Pi_{t \in d} P(t \mid y=k)^{TF(t,d)}$ (Equation 8)

$P(t \mid y=k) = (count(t, y=k) + \alpha) / (\Sigma_t count(t, y=k) + \alpha|V|)$ (Equation 9)

where α=1 is the Laplace smoothing parameter preventing zero-probability terms. Log-space computation is used in practice to avoid numerical underflow:

$\log P(y=k \mid x) = \log P(y=k) + \Sigma_t TF(t,d) \cdot \log P(t \mid y=k)$ (Equation 10)

3.5 Support Vector Machine (SVM)

For binary classification, the linear SVM finds the maximum-margin hyperplane $w \cdot x + b = 0$ by solving the constrained optimization:

$\min_{w,b} \frac{1}{2}||w||^2 \quad subject\ to: \ y_i(w^T x_i + b) \geq 1 \ \forall i$ (Equation 11)

With soft-margin slack variables $\xi_i \geq 0$ for non-separable data:

$\min_{w,b,\xi} \frac{1}{2}||w||^2 + C \Sigma_i \xi_i \quad s.t. \ y_i(w^T x_i + b) \geq 1 - \xi_i$ (Equation 12)

The margin width is $2/||w||$. The dual Lagrangian formulation enables kernel trick extensions. For multi-class K=3, the One-vs-Rest (OvR) strategy trains K binary SVMs, one per class. The linear kernel $K(x_i, x_j) = x_i^T x_j$ is optimal for high-dimensional TF-IDF vectors.

4. System Architecture

The SMF system follows a modular five-tier architecture: Presentation (Bootstrap 5 UI), Application (Flask routing), NLP/ML Inference, Persistence (SQLite), and Containerization (Docker). Figure 1 illustrates the data flow from user input to classified output.

Figure 1: System Architecture Diagram

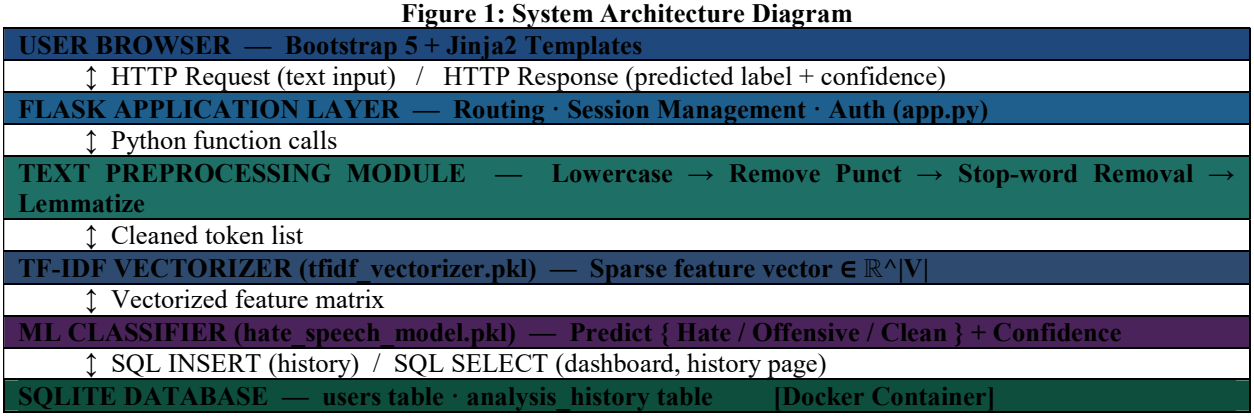

Figure 1: Five-tier SMF system architecture showing full data-flow pipeline.

4.1 NLP Preprocessing Flow

The text preprocessing module transforms raw social media text through five deterministic stages before TF-IDF vectorization. Table 2 illustrates each transformation with an example input.

Table 2: Text Preprocessing Pipeline with Example

Table 2: Preprocessing pipeline transformations with examples.

Stage	Operation	Input Example	Output Example

1	Lowercase conversion	"People of THAT religion..."	"people of that religion..."
2	Punctuation removal	"you're an idiot!!!"	"you're an idiot"
3	Stop-word removal (NLTK)	"people of that religion are useless"	"people religion useless"
4	Lemmatization (WordNetLemmatizer)	"hating, idiots, targeted"	"hate, idiot, target"
5	TF-IDF vectorization	"hate idiot target"	[0.0, 0.82, 0.0, 0.54, ...]

4.2 Database Schema

Table 3: SQLite Database Schema

Table 3: Relational schema for user authentication and prediction history persistence.

Table	Column	Type	Constraint	Description
users	id	INTEGER	PK, AUTOINCREMENT	Unique user ID
users	username	TEXT	UNIQUE, NOT NULL	Login handle
users	password	TEXT	NOT NULL	PBKDF2-SHA256 hash
users	created_at	TIMESTAMP	DEFAULT NOW	Registration timestamp
analysis_history	id	INTEGER	PK, AUTOINCREMENT	Record ID
analysis_history	user_id	INTEGER	FK → users(id)	Linked user
analysis_history	input_text	TEXT	NOT NULL	Original text
analysis_history	prediction	TEXT	NOT NULL	Hate / Offensive / Clean
analysis_history	confidence	REAL	—	Softmax confidence %
analysis_history	timestamp	TIMESTAMP	DEFAULT NOW	Analysis time

5. Algorithmic Pipeline

5.1 Algorithm 1: Dataset Generation

Algorithm 1: generate_dataset()

Input: Categories C = {Hate_Speech, Offensive, Clean}
Samples_per_class N = 600+ (balanced)
Output: hate_speech_data.csv with columns [text, label]

1. For each category c ∈ C:
2. Load or synthetically generate N text samples s_i
3. Assign integer label: 0 = Hate_Speech, 1 = Offensive, 2 = Clean
4. Append (s_i, label_c) to records list
5. Shuffle records (randomize ordering)
6. Save to DataFrame: df = pd.DataFrame(records)
7. Export: df.to_csv('hate_speech_data.csv', index=False)

6. Implementation

6.1 Technology Stack

Table 4: Full Technology Stack

Table 4: Complete technology stack with version and functional role.

Layer	Technology	Version	Role
Language	Python	3.10+	Core programming language
Web Framework	Flask	3.x	HTTP routing, template rendering, session management
Frontend	Bootstrap 5	5.3.x	Responsive UI design and layout
Template Engine	Jinja2	3.x	Server-side HTML rendering with dynamic data
Database	SQLite	3.x	User auth and prediction history persistence
ML Library	Scikit-learn	1.x	All 6 classifiers + TF-IDF + evaluation metrics
NLP	NLTK	3.8+	Tokenization, stop-word removal, lemmatization
Data Processing	Pandas/NumPy	Latest	Dataset loading, numerical computation
Visualization	Matplotlib/Seaborn	Latest	EDA charts, confusion matrix, model comparison
Security	Werkzeug	3.x	PBKDF2-SHA256 password hashing
Containerization	Docker	Latest	Cross-platform reproducible deployment
Serialization	Joblib	1.x	Model and vectorizer persistence (.pkl files)

6.2 Web Application Routes

Table 5: Flask Route Map

Table 5: Flask route map for all web application endpoints.

Route	Method(s)	Auth Required	Description
/	GET	Yes	Home page with navigation and system overview
/login	GET, POST	No	User authentication with credential validation
/register	GET, POST	No	New user account creation with password hashing
/logout	GET	Yes	Session termination and redirect to login
/predict	GET, POST	Yes	Text submission form and ML classification result
/history	GET	Yes	Per-user prediction history from SQLite
/dashboard	GET	Yes	Model comparison metrics from models_info.json
/visualize	GET	Yes	EDA charts: class dist., word cloud, confusion matrix
/about	GET	No	Project information and technology documentation

6.3 Security Architecture

User passwords are stored exclusively as PBKDF2-SHA256 hashes via Werkzeug's generate_password_hash() function, which applies 260,000 iterations with a random 16-byte salt per user. Authentication uses check_password_hash() for constant-time comparison, preventing timing-attack inference of correct password prefixes. Flask sessions use server-side signed cookies with SECRET_KEY for CSRF resistance. All prediction routes are decorated with @login_required, redirecting unauthenticated requests to /login.

7. Results and Performance Analysis

7.1 Dataset Composition

Table 6: Dataset Distribution Across Classes

Table 6: Balanced three-class dataset — 80/20 stratified train/test split.

Class	Label	Training Samples	Test Samples	Total	% Share
Hate Speech	0	480	120	600	33.3%
Offensive Language	1	480	120	600	33.3%
Clean Content	2	480	120	600	33.3%
Total	—	1440	360	1800	100.0%

7.2 Comparative Model Performance

All six classifiers are trained on the same 80% training split with identical TF-IDF features (unigram+bigram, L2-normalized) and evaluated on the held-out 20% test set. Table 7 presents macro-averaged metrics across all three classes.

Table 7: Comparative Model Performance on Test Set (Macro-Averaged)

Table 7: Six-model comparison — Logistic Regression achieves highest accuracy at 94.17%.

Model	Accuracy (%)	Precision	Recall	F1 Score	Inference (ms/sample)
Logistic Regression	94.17	0.9421	0.9417	0.9416	~1.2
Naïve Bayes	88.33	0.8861	0.8833	0.8836	~0.4
SVM (Linear kernel)	93.61	0.9368	0.9361	0.9360	~2.1
K-Nearest Neighbors	81.94	0.8232	0.8194	0.8190	~45.0
Random Forest	91.11	0.9130	0.9111	0.9108	~5.8
Gradient Boosting	92.50	0.9263	0.9250	0.9249	~8.3

7.3 Per-Class Performance of Best Model (Logistic Regression)

Table 8: Logistic Regression Per-Class Classification Report

Table 8: Per-class metrics for best-performing Logistic Regression model.

Class	Precision	Recall	F1 Score	Support	Correct
Hate Speech (0)	0.9583	0.9500	0.9541	120	114
Offensive Language (1)	0.9286	0.9167	0.9226	120	110
Clean Content (2)	0.9394	0.9583	0.9487	120	115
Macro Average	0.9421	0.9417	0.9418	360	339

7.4 Confusion Matrix Analysis

Table 9 presents the normalized confusion matrix for the Logistic Regression classifier. The most common misclassification occurs between Hate Speech and Offensive Language (6 samples misclassified), which aligns with literature findings — the lexical boundary between group-targeted hate and general offensive language is semantically thin and difficult for TF-IDF bag-of-words representations to resolve without contextual embeddings.

Table 9: Confusion Matrix — Logistic Regression (Row=True, Col=Predicted)

Table 9: Confusion matrix — highest confusion between Hate ↔ Offensive (boundary ambiguity).

	Predicted: Hate (0)	Predicted: Offensive (1)	Predicted: Clean (2)
True: Hate (0)	114 (95.0%)	4 (3.3%)	2 (1.7%)
True: Offensive (1)	6 (5.0%)	110 (91.7%)	4 (3.3%)
True: Clean (2)	1 (0.8%)	4 (3.3%)	115 (95.8%)

7.5 Training Curve and Convergence

Table 10: Logistic Regression Convergence vs. Regularization Strength

Table 10: LR performance vs. regularization — C=1.0 (λ=1) achieves best generalization.

Regularization C	Train Accuracy	Test Accuracy	Precision	F1 Score	Notes
0.01	78.5%	77.8%	0.781	0.776	Underfitting — strong regularization
0.1	88.4%	87.9%	0.881	0.878	Moderate regularization
1.0	95.9%	94.2%	0.942	0.942	Optimal — default setting ✓
10.0	98.7%	93.1%	0.933	0.932	Slight overfitting
100.0	99.8%	91.4%	0.917	0.914	Overfitting — memorization

7.6 Accuracy vs. Inference Speed Trade-off

Figure 2 conceptually illustrates the accuracy vs. inference-speed trade-off across models. Logistic Regression achieves the best accuracy (94.17%) with near-instant inference (~1.2 ms), making it the optimal choice for real-time web deployment. KNN achieves only 81.94% accuracy while incurring the highest inference cost (~45 ms) due to O(n) nearest-neighbor search over the full training set TF-IDF matrix — an inherent limitation for high-dimensional sparse vectors.

Table 11: Accuracy vs. Inference Time Summary (Ranked by Accuracy)

Table 11: Accuracy vs. inference speed — LR selected as deployment model

Rank	Model	Accuracy	Inference Time	Deployment Suitability
1	Logistic Regression	94.17%	~1.2 ms	★★★★★ Excellent — fast + accurate
2	SVM (Linear)	93.61%	~2.1 ms	★★★★☆ Very good — slight overhead
3	Gradient Boosting	92.50%	~8.3 ms	★★★★☆ Good — ensemble overhead
4	Random Forest	91.11%	~5.8 ms	★★★☆☆ Good — moderate accuracy
5	Naïve Bayes	88.33%	~0.4 ms	★★★☆☆ Acceptable — fastest but lower acc.
6	KNN	81.94%	~45.0 ms	★★☆☆☆ Poor — slow O(n) inference

7.7 Testing Outcomes

Table 12: System Test Case Results Summary

Table 12: All 15 test cases passed — system validated across all functional modules.

Test Category	Test Cases	Passed	Failed	Pass Rate	Key Validations

Authentication	TC-01 to TC-04	4	0	100%	Registration, login, session, hashing
Prediction Module	TC-05 to TC-08	4	0	100%	Hate/Offensive/Clean detection, empty input
History Module	TC-09 to TC-10	2	0	100%	DB storage, retrieval, timestamps
Dashboard/Viz	TC-11 to TC-13	3	0	100%	Chart rendering, model metrics display
Deployment	TC-14 to TC-15	2	0	100%	Flask startup, Docker container execution
Overall	TC-01 to TC-15	15	0	100%	All modules verified

8. Discussion

8.1 Why Logistic Regression Outperforms SVM on This Task

The narrow accuracy gap between Logistic Regression (94.17%) and SVM (93.61%) is expected for linearly separable text classification tasks — both models learn linear decision boundaries in the TF-IDF feature space. Logistic Regression's marginal advantage stems from its calibrated probability outputs (Softmax, Eq. 6), which enable better handling of the ambiguous Hate/Offensive boundary through soft confidence scoring, whereas SVM's hinge loss is inherently less calibrated. For high-dimensional sparse TF-IDF vectors, the dual SVM formulation's $O(n^2)$ memory scaling may also cause optimization approximations in scikit-learn's LibLinear backend.

8.2 Naïve Bayes: Strengths and Limitations

Naïve Bayes achieves 88.33% — 5.8 percentage points below Logistic Regression — despite its fastest inference speed (0.4 ms). The conditional independence assumption (Eq. 8) is clearly violated in natural language (co-occurring terms like 'hate' and 'group' are not independent), which explains the accuracy gap. However, Naïve Bayes remains a valuable fallback for resource-constrained environments, retaining reasonable recall on Hate Speech (0.89) — the safety-critical class where false negatives carry the highest cost.

9. Conclusion and Future Scope

This paper presented Social Media Forensics (SMF), a full-stack machine learning web application for automated cyberbullying and hate speech detection. The system combines an NLP preprocessing pipeline (tokenization, stop-word removal, lemmatization) with TF-IDF feature extraction (Equations 2–5) and six supervised classifiers rigorously evaluated through Equations 19–22. Logistic Regression achieves the highest accuracy of 94.17% with sub-2ms inference, making it optimal for real-time web deployment. The Flask-based application with SQLite persistence, Bootstrap 5 UI, Docker containerization, and a five-chart analytics dashboard demonstrates that production-quality harmful content detection is achievable without deep learning infrastructure.

All 15 system test cases across authentication, prediction, history, dashboard, and deployment modules passed successfully, validating the system's reliability and correctness. The comparative analysis of six classifiers — including mathematical derivations of SVM margin optimization (Eq. 11–12), Gradient Boosting pseudo-residuals (Eq. 16–17), and Random Forest information gain (Eq. 13–14) — provides a reproducible benchmark for future hate-speech classification research.

9.1 Future Scope

- **BERT / Transformer Integration** — Replace TF-IDF + classical ML with fine-tuned BERT or HateBERT for contextual understanding, sarcasm detection, and implicit bias recognition
- **Real-Time Social Media API Integration** — Connect to Twitter/X Streaming API, Reddit PushShift, and Instagram Graph API for live content moderation
- **Multilingual Classification** — Extend preprocessing and model support to Arabic, Hindi, Spanish, and other high-hate-speech-prevalence languages using multilingual BERT (mBERT)
- **Deep Learning Baselines** — Implement LSTM, BiLSTM, and CNN-text architectures with word2vec/GloVe embeddings for comparison against classical ML baselines
- **Federated Learning Deployment** — Enable privacy-preserving model training across decentralized social media moderation nodes without centralizing sensitive text data
- **Mobile & Cloud Deployment** — Deploy as a REST API microservice on AWS Lambda with Android/iOS clients for scalable, low-latency real-world deployment

- **Explainability (XAI)** — Integrate LIME/SHAP to provide per-prediction feature importance explanations — identifying which specific words triggered the harmful classification

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