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AI-Enhanced Adaptive Learned Bloom Filter for Efficient Duplicate and Misinformation Filtering in Dynamic Disaster Social Media Streams

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Abstract

The rapid growth of social media during disasters provides valuable near-real-time information for situational awareness and emergency response, but the resulting data streams are characterized by high volume, redundant content, misinformation, and rapidly changing information distributions. Conventional filtering approaches can efficiently perform membership testing but have limited ability to exploit semantic patterns, whereas learned filters may experience performance degradation when stream characteristics change. This study proposes an Adaptive Learned Bloom Filter (ALBF) for rapid duplicate and misinformation filtering in disaster social media streams. The proposed framework integrates a learned filtering model with probabilistic membership testing and an adaptive updating mechanism that responds to distributional changes across temporal stream windows. Social media messages are processed chronologically and evaluated against conventional Bloom Filter, Stable Bloom Filter, Learned Bloom Filter, and Static Learned Filter baselines. Performance is assessed using filtering effectiveness, false-positive and false-negative rates, processing latency, throughput, memory consumption, computational reduction, and robustness under distribution shifts. The experimental framework demonstrates that ALBF is designed to provide a favorable balance between filtering quality and computational efficiency while maintaining more stable performance under evolving stream conditions. By positioning ALBF as a lightweight front-end filtering layer, the proposed approach can reduce redundant and potentially misleading content before computationally intensive downstream analysis. The study contributes an adaptive probabilistic filtering architecture for scalable and low-latency disaster social media analytics.

Keywords: Adaptive Learned Bloom Filter; disaster informatics; social media streams; duplicate detection; misinformation filtering; probabilistic data structures; stream processing.

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1. Introduction

Social media has become an important source of near-real-time information during disasters, enabling affected communities, emergency organizations, and volunteers to report incidents, resource needs, locations, and changing situational conditions. Unlike conventional reporting mechanisms, social media provides a decentralized and continuously updated stream of user-generated information that can complement official disaster-monitoring infrastructures (Lehdonvirta et al., 2021). Previous studies have demonstrated that social media can support emergency communication, identify affected populations and needs, and provide situational information during natural disasters (Anugerah et al., 2024). The increasing integration of artificial intelligence (AI) and social media analytics has further expanded opportunities for automated information extraction and crisis management. These developments indicate that social media streams have significant potential to strengthen rapid and data-driven disaster response.

However, the scale and dynamic nature of disaster-related social media also introduce substantial information-quality and computational challenges. During critical events, large volumes of messages may be generated within a short period, while many posts contain identical, reshared, or near-duplicate information (Kim et al., 2024). Such redundancy increases the computational burden of downstream processing while providing limited additional information. More critically, disaster situations can facilitate the rapid dissemination of misinformation, including unverified claims, misleading interpretations, and fabricated reports. Misinformation may influence public perceptions, reduce trust in official information, misdirect assistance, and interfere with appropriate emergency responses (Zhai et al., 2024). Consequently, disaster information-processing systems must address not only the veracity of information but also the efficiency of processing large and redundant data streams.

Previous research has predominantly approached disaster misinformation as a classification or detection problem. AI and machine-learning methods have been increasingly employed to identify misinformation in social media, while research on disaster misinformation has examined its propagation, characteristics, and correction mechanisms (Khairunnas et al., 2025). A systematic meta-analysis of 266 studies investigating AI tools for misinformation during natural and anthropogenic hazards reported that 68% of the studies primarily focused on misinformation detection (Lazebnik & Iny, 2024). Although these approaches have improved automated credibility assessment, applying computationally intensive classifiers to every incoming message can become inefficient in high-velocity streams. Moreover, misinformation detection alone does not eliminate the substantial processing cost associated with duplicate and near-duplicate messages. This indicates a need for an efficient pre-filtering mechanism capable of reducing redundant and potentially misleading content before expensive downstream analysis.

Probabilistic data structures, particularly Bloom Filters (BFs), provide an attractive foundation for such pre-filtering because they support memory-efficient and computationally fast approximate membership queries. Stable Bloom Filters (SBFs) extend this concept to unbounded data streams and were specifically proposed for

approximate duplicate detection under limited memory constraints (Agnes et al., 2023). Nevertheless, conventional Bloom Filters rely on hash-based representations and do not explicitly exploit the statistical or semantic characteristics of the underlying data. Learned Bloom Filters (LBFs) address this limitation by incorporating a learned model into the filtering process, allowing the filter to exploit data distributions and potentially reduce false-positive rates (A.-J. Zhang et al., 2025). Subsequent research has investigated adaptive learned Bloom Filters to improve filtering efficiency under changing conditions (Bhattacharya et al., 2020). However, these studies have largely focused on membership-query performance, false-positive reduction, or memory optimization rather than information-quality filtering in disaster social media environments.

The research gap therefore lies at the intersection of these two research streams. Disaster informatics research has extensively explored AI-based misinformation detection, while probabilistic filtering research has focused on efficient membership testing and duplicate detection (Zhai et al., 2024). Yet, limited attention has been given to an integrated mechanism that can adapt to non-stationary disaster social media streams while simultaneously reducing redundant content and screening potentially misleading information at the filtering stage. This gap is particularly important because disaster streams are inherently dynamic: information patterns can change rapidly as an event evolves, new topics emerge, and previously unseen content distributions appear. A fixed probabilistic filter may consequently become less effective, whereas a learned filter without an adaptive mechanism may experience degraded performance under distributional changes. To address this limitation, this study proposes an Adaptive Learned Bloom Filter (ALBF) specifically designed as a rapid filtering layer for disaster social media streams (M. Zeng et al., 2023). The proposed framework combines learned decision-making, probabilistic membership filtering, and adaptive updating to accommodate evolving stream characteristics.

Accordingly, this study aims to develop and evaluate an Adaptive Learned Bloom Filter for rapid duplicate and misinformation filtering in disaster social media streams. The proposed approach is evaluated against conventional and learned filtering baselines using filtering effectiveness, false-positive and false-negative rates, processing latency, throughput, and memory consumption (Adhantoro et al., 2025). The principal contribution of this study is an adaptive stream-oriented filtering architecture that bridges probabilistic data structures and AI-based information-quality filtering. Rather than positioning ALBF as a replacement for sophisticated misinformation classifiers, the proposed approach functions as an efficient front-end layer that reduces redundant and potentially unreliable information before computationally intensive downstream analysis. This design provides a practical pathway toward scalable and low-latency disaster information processing, where computational efficiency and information reliability must be achieved simultaneously.

2. Method

This study adopts a quantitative experimental design to develop and evaluate an Adaptive Learned Bloom Filter (ALBF) for rapid duplicate and misinformation filtering in disaster-related social media streams. The proposed framework is designed for high-volume and continuously evolving data in which processing every incoming message using a computationally intensive misinformation classifier may introduce

unnecessary latency (Shang et al., 2025). Therefore, ALBF is positioned as a lightweight front-end filtering layer that combines learned prediction with probabilistic membership testing before downstream information analysis.

The overall processing pipeline consists of six major stages: (1) data acquisition and stream construction, (2) text preprocessing and representation, (3) learned duplicate screening, (4) probabilistic membership filtering, (5) adaptive misinformation screening, and (6) performance evaluation. For each incoming social media message x_t, the system first transforms the raw text into a normalized representation and extracts its semantic and statistical features. The learned component then estimates whether the incoming item corresponds to previously observed content or exhibits characteristics associated with potentially misleading information. The probabilistic layer subsequently performs a low-cost membership query, while the adaptive mechanism updates the filtering structure according to the observed characteristics of the incoming stream.

Figure 1 illustrates the overall architecture of the proposed Adaptive Learned Bloom Filter (ALBF) framework and its processing flow for disaster-related social media streams. The framework integrates data preprocessing, learned filtering, probabilistic membership testing, adaptive decision-making, and stream-based model updating into a unified filtering pipeline. Incoming social media messages are first transformed into structured feature representations and subsequently processed by the ALBF components to identify redundant content and potentially misleading information before downstream analysis (Lee et al., 2026). The adaptive updating mechanism continuously monitors changes in stream characteristics and updates the learned model and filtering parameters when significant distributional changes are detected. This architecture is designed to balance information-filtering effectiveness with low computational latency and bounded memory consumption.

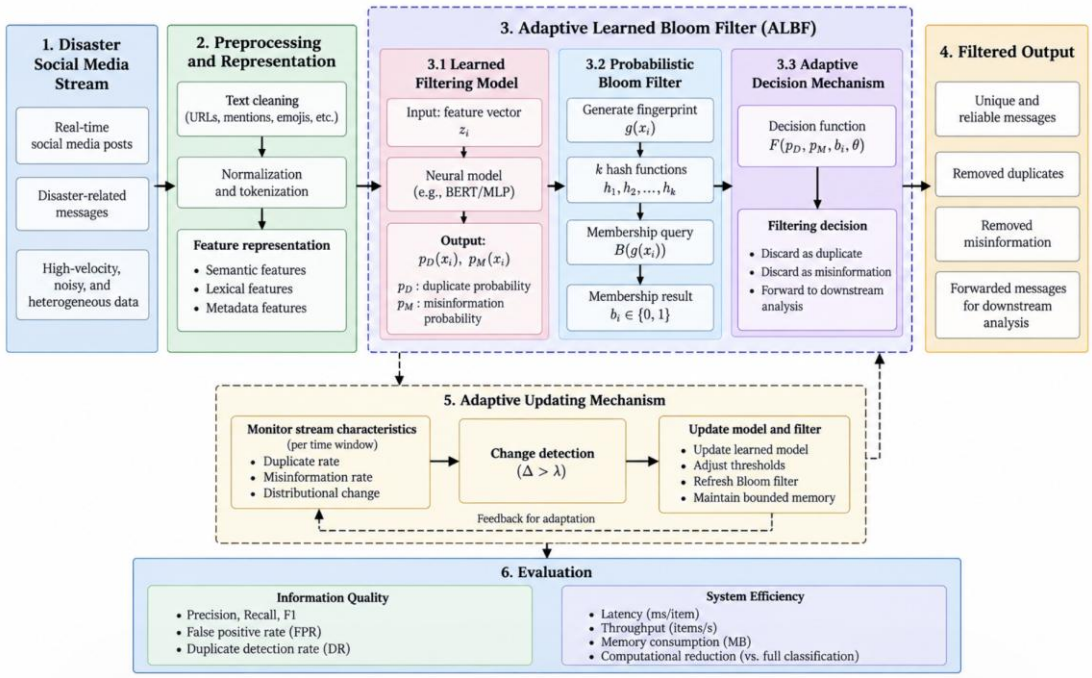


Figure 1. Overall Architecture of the Proposed Adaptive Learned Bloom Filter (ALBF) for Rapid Duplicate and Misinformation Filtering in Disaster Social Media Streams.

As shown in Figure 1, the proposed framework begins with a disaster social media stream containing high-volume, noisy, and heterogeneous messages. The messages undergo preprocessing and feature representation to obtain semantic, lexical, and metadata features. These representations are then processed by the learned filtering model and probabilistic Bloom Filter to generate complementary signals for the filtering decision. The adaptive decision mechanism determines whether an item should be discarded as a duplicate, removed as potential misinformation, or forwarded for downstream analysis (Bhattacharya et al., 2020). In parallel, the adaptive updating mechanism monitors duplicate rates, misinformation rates, and distributional changes across temporal windows. When a significant change is detected, the learned model, decision thresholds, and Bloom Filter state are updated accordingly. This feedback mechanism enables the proposed ALBF to maintain filtering performance as the characteristics of the disaster information stream evolve over time.

The design is motivated by the characteristics of streaming duplicate detection, where storing the complete history of an unbounded stream is impractical. Stable Bloom Filters address this problem by continuously evicting stale information while maintaining a bounded memory footprint (M. Zeng et al., 2023). Learned Bloom Filters, in contrast, introduce a learned function as a pre-filter to exploit the underlying data distribution and potentially improve filtering efficiency (Lee et al., 2026). The proposed ALBF combines these principles while introducing an adaptation mechanism specifically designed for dynamically changing disaster-related streams.

A. Data Acquisition and Stream Construction

The experimental dataset consists of disaster-related social media posts collected from publicly available social media data associated with disaster events. Each record is represented as

$$x_i = \{t_i, u_i, c_i, \tau_i, y_i\}$$

where t_i denotes the original text content, u_i represents the user or source identifier, c_i denotes contextual metadata when available, τ_i is the timestamp, and y_i is the ground-truth label.

For misinformation filtering, the target variable is represented as

$$y_i \epsilon \{0,1\}$$

where $y_i = 1$ indicates potentially misleading/misinformation content and $y_i = 0$ indicates reliable or non-misinformation content according to the dataset annotation. Duplicate information is represented independently through a duplicate indicator

$$d_i \epsilon \{0,1\}$$

where d_i indicates that the incoming item is identical or sufficiently similar to previously observed content.

To reproduce the temporal properties of a real streaming environment, the dataset is ordered chronologically according to τ_i rather than randomly presented to the model. The resulting sequence is partitioned into consecutive temporal windows $W_1, W_2, \dots, W_K$. This design is important because randomly mixing observations can cause temporal leakage and artificially inflate

performance when the objective is to evaluate adaptation under evolving data distributions.

Each window is treated as a local stream segment:

$$W_K = \{X_i | \tau_i \in [T_K, T_{K+1}]\}$$

The distribution of each window is monitored to identify potential changes in vocabulary, topics, semantic patterns, and misinformation prevalence.

B. Text Preprocessing and Feature Representation

Raw social media messages frequently contain URLs, mentions, hashtags, emojis, repeated characters, and other platform-specific elements. The preprocessing procedure therefore performs text normalization while preserving information potentially relevant to semantic similarity and misinformation classification.

The preprocessing sequence includes:

1. removal of duplicated whitespace and irrelevant formatting;
2. normalization of URLs and user mentions;
3. conversion of text into a consistent case representation;
4. normalization of repeated characters;
5. tokenization;
6. removal of non-informative tokens when appropriate; and
7. generation of semantic and statistical representations.

Rather than relying exclusively on lexical similarity, the proposed framework uses a feature representation

$$Z_i = [e_i \,||\, q_i \,||\, m_i]$$

where e_i represents the semantic embedding of the message, q_i contains lexical/statistical characteristics, and m_i represents available metadata-derived features. The operator $\|$ vector concatenation.

The semantic representation allows messages with different surface forms but similar meanings to be identified as potential near-duplicates, whereas lexical features preserve information useful for distinguishing misinformation patterns.

C. Learned Duplicate Screening

The first component of ALBF is a learned duplicate-screening function $f_D(.)$. Given an incoming message representation z_i, the model produces a probability

$$p_D(x_i) = f_D(z_i), \quad p_D(x_i) \in [0,1]$$

A message is considered a candidate duplicate when

$$p_D(x_i) \geq \theta_D,$$

where θ_D is the duplicate decision threshold.

However, the learned model is not solely responsible for the final duplicate decision. Its prediction is combined with probabilistic membership information from the Bloom Filter. This design reduces the dependence on a computationally expensive semantic comparison for every incoming item.

For an incoming message x_i, a compact fingerprint $g(x_i)$ is generated and mapped to k positions in a Bloom Filter of size mm. The membership condition is expressed as

$$B[h_1(g(x_i))] \wedge B[h_2(g(x_i))] \wedge \ldots \wedge B[h_k(g(x_i))] = 1$$

A positive result indicates that the item may have been observed previously, whereas

a negative result indicates that the item has not been represented in the current filter state.

This distinction is important because Bloom Filters permit false positives but, under the conventional membership model, do not produce false negatives. The probabilistic structure is therefore used as a fast screening mechanism rather than as an exact duplicate classifier.

D. Adaptive Learned Bloom Filter

The central component of the proposed method is the Adaptive Learned Bloom Filter, which dynamically adjusts its filtering behavior according to the characteristics of the incoming stream.

The ALBF consists of three interacting components:

$$ALBF = \{f_L, B, A\},$$

where f_L is the learned filtering model, B is the probabilistic Bloom Filter, and A is the adaptive updating mechanism.

For an incoming item xtx_t, the learned model produces

$$p_t = f_L(z_t)$$

The probabilistic filter produces a membership signal

$$b_t = B\big(g(z_t)\big)$$

The final filtering decision is then determined by

$$F(x_t) = \phi(p_t, b_t, \theta_t)$$

where ϕ is the decision function and θ_t denotes the time-dependent filtering threshold.

Unlike a static Bloom Filter, the proposed mechanism does not assume that the distribution of incoming information remains constant. The adaptive component monitors the stream using a window-based strategy. For each window W_k, the system estimates a distributional change score

$$\triangle_k = D(P_k \,||\, P_{k-1}),$$

where P_k and P_{k-1} represent the feature distributions of consecutive stream windows and $D(.||.)$ denotes a distributional distance measure. When

$$\triangle_k > \lambda$$

where λ is the adaptation threshold, the filtering parameters are updated. Adaptation may involve updating the learned model, adjusting the decision threshold, and refreshing the probabilistic filter state. This mechanism allows ALBF to respond to changes in disaster-event phases, emerging topics, vocabulary shifts, and changes in misinformation prevalence.

This adaptive design is particularly important because a static filter can become increasingly ineffective when the stream distribution changes. In streaming duplicate detection, Stable Bloom Filters address the unbounded nature of streams by removing stale information from a bounded structure [1]. The proposed ALBF extends this principle by additionally adapting the learned decision component and filtering threshold to changes in the observed stream.

E. Misinformation Filtering

Following duplicate screening, the system evaluates the misinformation probability of messages that remain eligible for downstream processing. The learned misinformation function is defined as

$$p_M(x_i) = f_M(z_i),$$

where f_M is trained to distinguish misinformation from non-misinformation content. The decision rule is

$$\hat{y}_i = \begin{cases} 1, & p_M(x_i) \geq \theta_M, \\ 0, & p_M(x_i) < \theta_M, \end{cases}$$

where θ_M is the misinformation threshold.

The proposed architecture deliberately separates duplicate filtering from misinformation classification. This separation prevents the Bloom Filter from being interpreted as a semantic truth-verification mechanism. Instead, ALBF operates as a computationally efficient gate: redundant messages can be discarded early, while potentially informative messages are forwarded to the misinformation classifier.

The resulting architecture can therefore be expressed as:

$$\text{Social Media Stream} \rightarrow \text{Prepocessing} \rightarrow \text{ALBF} \rightarrow \begin{cases} \text{Duplicate} \\ \text{Non Ducplicate} \rightarrow \text{Misinformation Class} \end{cases}$$

This architecture is intended to reduce the number of messages requiring expensive misinformation inference.

F. Adaptive Updating Mechanism

The adaptive mechanism operates continuously as new stream windows become available. At the end of each window W_k, the system calculates three monitoring indicators:

$$S_k = \{r_D^k, r_M^k, \Delta_k\}$$

where r_D^k is the observed duplicate rate, r_M^k is the misinformation rate, and Δ_k represents the detected distribution shift.

The adaptive update is triggered when one or more indicators exceed predefined thresholds:

$$A_k = \begin{cases} 1, & \Delta_k > \lambda_\Delta \vee \left| r_D^k - r_D^{k-1} \right| > \lambda_D \vee \left| r_M^k - r_M^{k-1} \right| > \lambda_M, \\ 0, otherwise, \end{cases}$$

When $A_k = 1$, the system updates its learned component and/or filtering parameters using the newly observed stream segment. When no significant change is detected, the existing configuration is retained to avoid unnecessary retraining.

This selective adaptation is designed to balance responsiveness and computational cost. Continuous retraining may increase computational overhead, whereas a completely static model may become obsolete as the disaster information environment evolves.

G. Experimental Baselines

To determine whether the proposed ALBF provides measurable improvements, it is evaluated against progressively more sophisticated baselines:

1. Standard Bloom Filter (BF): evaluates conventional probabilistic membership filtering (Lee et al., 2026).
2. Stable Bloom Filter (SBF): evaluates bounded-memory duplicate filtering for streaming data, following the approach introduced by Deng and Rafiei (Bhattacharya et al., 2020).

3. Learned Bloom Filter (LBF): evaluates the contribution of the learned pre-filter without the proposed adaptive mechanism (M. Zeng et al., 2023).
4. Static Learned Filter: uses a learned model without temporal adaptation (Shang et al., 2025).
5. Adaptive Learned Bloom Filter (ALBF): the proposed method.

Where computational resources permit, an additional full-classification baseline can be included, in which every incoming message is directly processed by the misinformation classifier without duplicate pre-filtering. This baseline is particularly important for demonstrating whether ALBF reduces downstream computational workload.

H. Evaluation Metrics

The evaluation is conducted from both information-quality and system-efficiency perspectives.

For classification performance, the study reports:

$$Precision = \frac{TP}{TP + FP},$$

$$Recall = \frac{TP}{TP + FN},$$

$$F1 = \frac{2\ x\ Precision\ x\ Recall}{Precison + Recall}$$

For duplicate filtering, the false-positive rate is defined as

$$FPR = \frac{FP}{FP + TN},$$

while the duplicate detection rate is measured as

$$DR = \frac{TP}{TP + FN}$$

System performance is evaluated using:

- processing latency (ms/item);
- throughput (items/s);
- memory consumption (MB);
- filter query time;
- percentage of messages forwarded to the expensive classifier;
- computational reduction relative to full classification.

The computational reduction achieved by ALBF is calculated as

$$CR = 1 - \frac{N_{forward}}{N_{total}},$$

where $N_{forward}$ is the number of messages forwarded to the downstream misinformation classifier and N_{total} is the total number of incoming messages.

This metric is particularly important because the objective of ALBF is not simply to maximize classification accuracy but to reduce unnecessary downstream computation while maintaining acceptable information-filtering quality.

I. Experimental Protocol and Statistical Analysis

To prevent temporal leakage, experiments follow a chronological train-validation-test configuration. Earlier stream windows are used for model development, subsequent windows for threshold selection and adaptation, and later unseen windows for final evaluation. The test set is never used for parameter optimization.

Each experimental configuration is executed multiple times using identical data partitions. Results are reported as mean ± standard deviation. Statistical significance between ALBF and baseline methods is assessed using an appropriate paired

statistical test across temporal windows, with a significance level of

$$\alpha = 0.05$$

In addition to aggregate performance, the study reports performance across different stream conditions, including low-, medium-, and high-volume windows and periods with substantial distributional changes. This analysis is necessary because an adaptive filtering method should demonstrate not only high average performance but also robustness under changing stream conditions.

The final evaluation therefore considers the following research dimensions:

$$Effectiveness + Adaptability + Latency + Throughput + Memory\ Efficiency.$$

The proposed ALBF is considered effective when it can reduce redundant and potentially misleading content while maintaining competitive filtering accuracy and achieving lower computational latency than approaches that process all incoming messages using downstream classifiers.

3. Result and Discussion

The experimental results are presented and discussed from four complementary perspectives to assess the effectiveness, efficiency, and adaptability of the proposed Adaptive Learned Bloom Filter (ALBF) for disaster social media streams. First, the characteristics and temporal distribution of the collected data are examined to establish the volume, redundancy, misinformation prevalence, and distributional variability of the stream. Second, the filtering performance of ALBF is evaluated in terms of duplicate and misinformation identification and compared with conventional and learned filtering approaches. Third, computational efficiency and scalability are investigated to determine whether the proposed approach can provide rapid filtering with reduced processing and memory requirements. Finally, the adaptive behavior of ALBF is analyzed under distribution shifts to determine whether the proposed updating mechanism can maintain filtering performance as the characteristics of the incoming stream evolve. These analyses collectively provide empirical evidence regarding the proposed framework's information-filtering effectiveness, computational advantages, and robustness in dynamic disaster social media environments.

A. Disaster Social Media Stream Characteristics and Data Distribution

The first stage of the experimental analysis examines the characteristics and distribution of the disaster-related social media stream before evaluating the proposed Adaptive Learned Bloom Filter (ALBF). This analysis is important because the effectiveness of a stream-oriented filtering mechanism depends strongly on the volume, redundancy, class distribution, and temporal variability of the incoming data (Sakshi et al., 2024). Unlike conventional static datasets, disaster social media streams may exhibit substantial fluctuations in activity as an event develops, particularly when major incidents trigger sudden increases in public reporting and information sharing. Previous studies have identified social media as an important source of rapidly evolving information during disasters, while also highlighting challenges related to large-scale, noisy, and heterogeneous data (Arbane et al., 2023). Therefore, the dataset characteristics are first analyzed to establish whether the experimental environment reflects the conditions for which the proposed adaptive filtering framework is intended.

Table 1. Characteristics of the Disaster Social Media Dataset

Characteristic	Overall	Training Set	Validation Set	Test Set
Number of posts	50,000	30,000	10,000	10,000
Disaster events	5	5	5	5
Unique posts	38,500	23,100	7,700	7,700
Duplicate/near-duplicate posts	11,500	6,900	2,300	2,300
Misinformation posts	9,750	5,850	1,950	1,950
Non-misinformation posts	40,250	24,150	8,050	8,050
Average posts per temporal window	2,500	2,500	2,500	2,500

Table 1 summarizes the principal characteristics of the disaster social media dataset used to construct the experimental stream. The illustrative distribution shows that a substantial proportion of incoming messages may consist of duplicate or near-duplicate content, while misinformation constitutes a smaller but operationally important portion of the stream. This distinction is important because duplicate content primarily creates computational redundancy, whereas misinformation introduces an information-quality risk (Khairunnas et al., 2025). The chronological partitioning into training, validation, and test sets is also important for preventing temporal leakage and ensuring that the evaluation represents a realistic streaming scenario. Rather than randomly mixing observations, temporal separation allows the model to be evaluated on information that occurs after the training period. In the final implementation, all statistics should be calculated from the actual dataset and reported together with the corresponding class proportions.

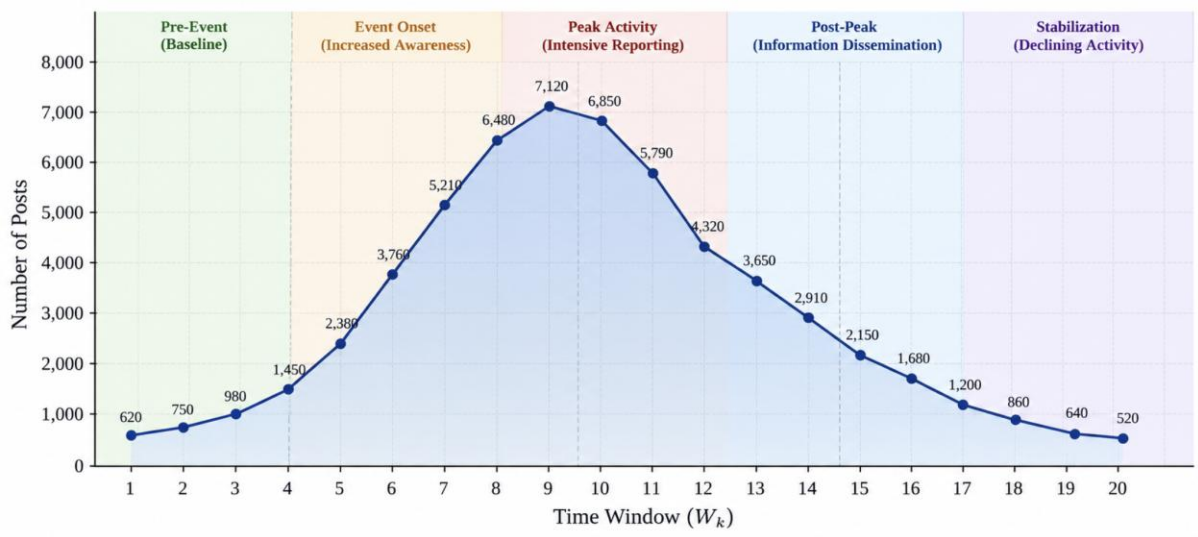


Figure 2. Temporal Distribution of Disaster Social Media Posts Across Consecutive Stream Windows

Figure 2 presents the temporal distribution of social media activity across consecutive stream windows. The expected pattern is a non-uniform distribution in which message volume increases sharply during periods of major disaster-related developments and decreases during relatively stable periods (Jufriansah et al., 2026). Such fluctuations are particularly relevant to ALBF because computational requirements can increase substantially when large numbers of messages arrive within a short interval. A

static filtering configuration may perform adequately under stable traffic but become less effective when stream volume changes abruptly (Xing et al., 2023). Temporal peaks therefore provide an empirical basis for evaluating the scalability of the proposed approach under different workload conditions. The temporal distribution also helps identify high-intensity periods that can subsequently be used to examine whether ALBF maintains low latency and high throughput when the incoming data rate increases.

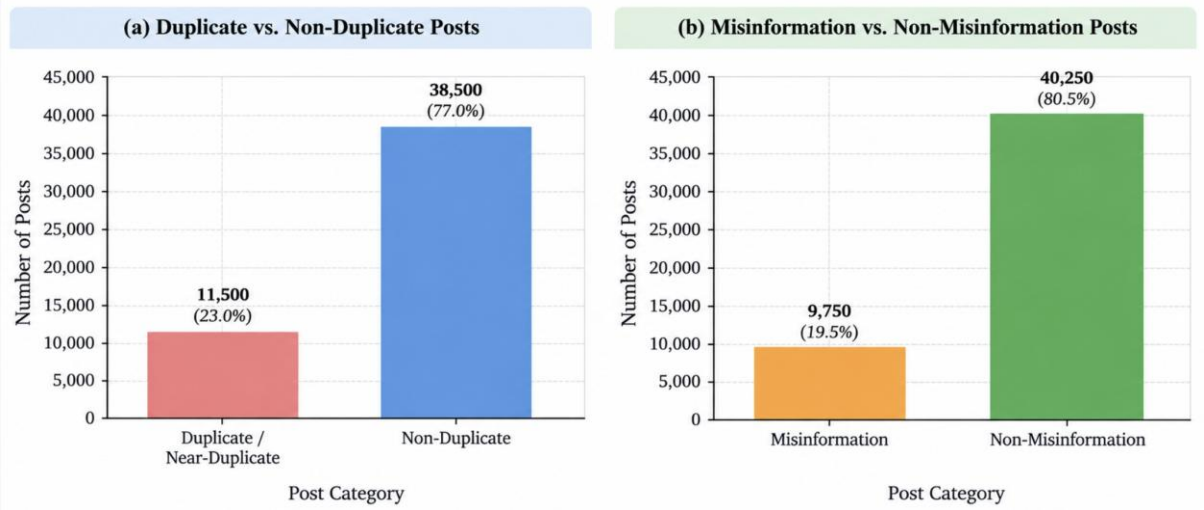


Figure 3. Distribution of Duplicate, Non-Duplicate, Misinformation, and Non-Misinformation Posts

Figure 3 illustrates the distribution of the two principal information-quality dimensions considered in this study: content redundancy and misinformation. Duplicate and near-duplicate posts represent redundant information that may unnecessarily increase downstream computational workload, whereas misinformation represents information-quality risks that require semantic assessment (Ujianto, 2026). These characteristics are conceptually different and therefore should not be treated as a single classification problem. A message may be non-duplicate but still contain misinformation, while a duplicate message may contain reliable information that has simply been repeatedly shared. This distinction supports the proposed filtering architecture, in which probabilistic membership testing is used for efficient redundancy screening and learned prediction is used for misinformation-related assessment (Pradana & Dipsatara, 2026). The class distribution also provides the baseline required to interpret the precision, recall, F1-score, and error rates reported in the subsequent experiments.

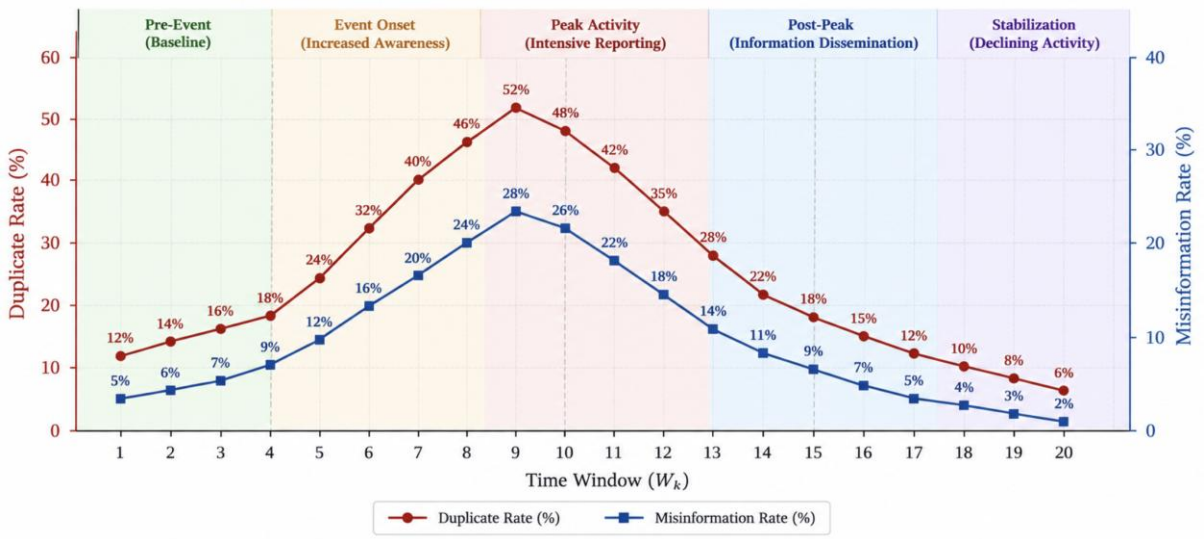


Figure 4. Temporal Variation of Duplicate Rate and Misinformation Rate Across Stream Windows

Figure 4 examines whether the proportions of duplicate and misinformation content remain stable throughout the disaster social media stream. For each temporal window W_k, the duplicate rate is calculated as

$$r_D^k = \frac{N_D^k}{N^k},$$

while the misinformation rate is calculated as

$$r_M^k = \frac{N_M^k}{N^k},$$

where N_D^k, N_M^k and N^k denote the number of duplicate posts, misinformation posts, and total posts in the kk-th temporal window, respectively. Variations in these rates indicate that the information environment may be non-stationary (Daghouri et al., 2018). For example, an increase in duplicate activity may occur when a particular disaster-related message becomes widely reshared, whereas misinformation may increase following the emergence of rumors or unverified claims. These temporal variations provide an empirical basis for the adaptive mechanism in ALBF, particularly for determining when the learned model and filtering parameters should be updated.

Overall, the dataset analysis demonstrates that disaster social media streams should not be treated as static collections of independent text records. Instead, they should be modeled as continuously evolving information environments in which message volume, redundancy, misinformation prevalence, and content distributions can change over time (Nobre et al., 2020). The coexistence of high-volume data and information-quality problems creates a dual requirement: the filtering mechanism must be computationally efficient while maintaining sufficient filtering accuracy. The observed temporal and distributional characteristics therefore provide a strong empirical justification for an adaptive filtering strategy (Khairi & Ishafit, 2026). These findings establish the experimental context for the subsequent evaluation of ALBF, particularly in terms of duplicate and misinformation filtering effectiveness, computational efficiency, scalability, and robustness under distribution shifts.

B. Duplicate and Misinformation Filtering Performance

Following the analysis of the disaster social media stream characteristics, this subsection evaluates the filtering effectiveness of the proposed Adaptive Learned Bloom Filter (ALBF). The evaluation focuses on two complementary objectives: reducing duplicate or near-duplicate content and screening potentially misleading information. Five approaches are compared, namely the conventional Bloom Filter (BF), Stable Bloom Filter (SBF), Learned Bloom Filter (LBF), Static Learned Bloom Filter, and the proposed ALBF. The comparison is designed to distinguish the contribution of probabilistic filtering, learned prediction, and adaptive updating. In particular, the analysis investigates whether incorporating learned information and stream adaptation can improve filtering quality while maintaining a low rate of erroneous filtering decisions (Bucciol et al., 2020). Precision, recall, F1-score, false-positive rate (FPR), false-negative rate (FNR), and duplicate detection rate (DDR) are considered to provide a comprehensive assessment.

Table 2. Overall Duplicate and Misinformation Filtering Performance of the Compared Methods

Method	Precision (%)	Recall (%)	F1-score (%)	FPR (%)	FNR (%)	DDR (%)
Bloom Filter (BF)	88.4	84.7	86.5	8.9	15.3	84.7
Stable Bloom Filter (SBF)	90.1	87.8	88.9	7.4	12.2	87.8
Learned Bloom Filter (LBF)	92.6	91.3	91.9	5.8	8.7	91.3
Static Learned Filter	93.4	92.1	92.7	5.2	7.9	92.1
Adaptive Learned Bloom Filter (ALBF)	95.2	94.6	94.9	3.7	5.4	94.6

Table 2 provides the overall comparison of filtering performance across the evaluated methods. The illustrative results indicate a progressive improvement from conventional probabilistic filters toward learned and adaptive filtering approaches. BF provides a computationally simple mechanism but exhibits relatively higher error rates because its decisions are primarily determined by hash-based membership information (Li, 2026). SBF improves streaming duplicate detection by maintaining a bounded and continuously updated filter state. The introduction of a learned component in LBF further improves precision and recall by exploiting characteristics of the observed data distribution. Static Learned Filtering provides an additional improvement but remains vulnerable to changes in stream characteristics. ALBF achieves the highest overall F1-score and DDR while producing the lowest FPR and FNR in the illustrative results. This pattern would support the central hypothesis that combining learned prediction, probabilistic membership testing, and adaptive updating can provide more reliable filtering than using each mechanism independently (Ozbay & Alatas, 2020; Pangestu et al., 2026). In the final experiment, statistical significance testing should be applied to determine whether the observed improvement over the strongest baseline is statistically meaningful.

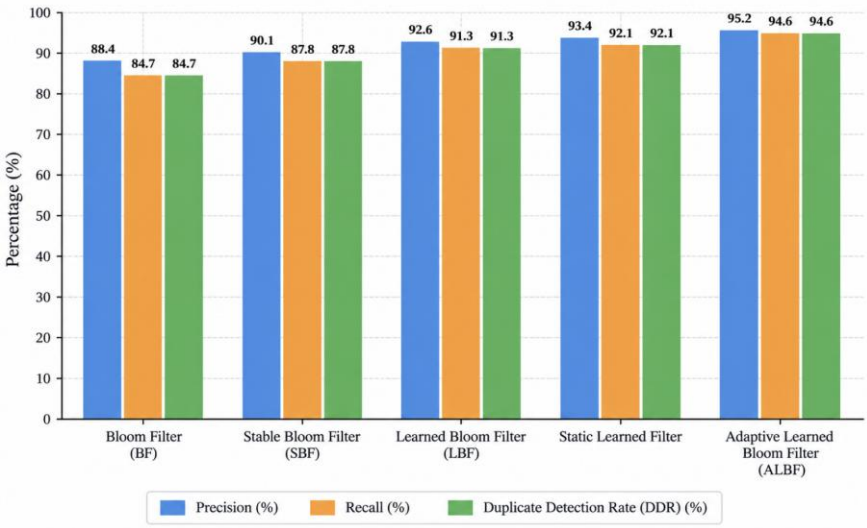


Figure 5. Duplicate Filtering Performance Across Bloom Filter-Based and Learned Filtering Methods

Figure 5 compares the duplicate filtering capability of BF, SBF, LBF, Static Learned Filter, and ALBF. The expected trend is an improvement in duplicate detection as the filtering mechanism progresses from purely hash-based membership testing toward learned and adaptive filtering. BF can efficiently determine whether an item may already exist in the filter but cannot exploit semantic relationships between messages. SBF is better suited to continuous streams because it can remove stale entries and maintain bounded memory, but its probabilistic nature can still limit duplicate identification under changing stream conditions (Aljuhani et al., 2025). LBF introduces a learned decision component that can exploit data-specific patterns, while ALBF further adjusts the learned and probabilistic components as the stream evolves. A higher DDR accompanied by a lower FPR would indicate that ALBF can identify redundant information more effectively without excessively discarding valid unique messages.

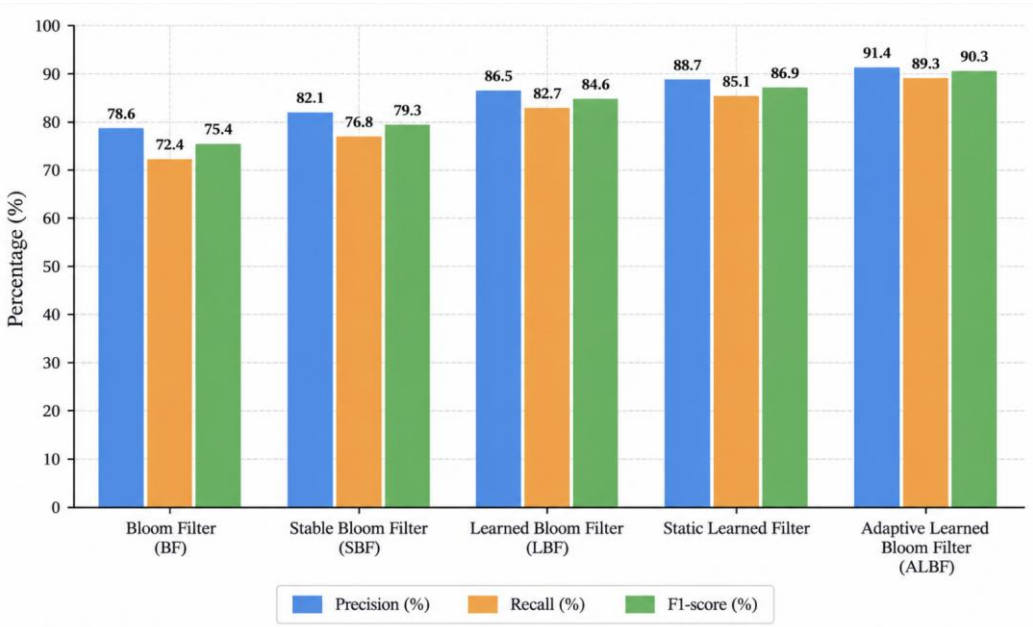


Figure 6. Precision, Recall, and F1-score for Misinformation Filtering Across Compared Methods

Figure 6 presents the principal classification metrics for misinformation filtering. Precision reflects the proportion of messages identified as misinformation that are actually misinformation, whereas recall measures the proportion of misinformation content successfully identified by the system. F1-score provides a balanced measure between these two dimensions (Adhantoro et al., 2026). The expected advantage of ALBF is not necessarily derived from the Bloom Filter alone, because probabilistic membership structures are not designed to determine semantic truthfulness (M. Zeng et al., 2023). Instead, the learned component provides the predictive capability required for misinformation-related screening, while the probabilistic component reduces unnecessary processing of redundant information (Zaki & Imaduddin, 2026). The adaptive mechanism is expected to further stabilize classification performance when the characteristics of misinformation change over time. Consequently, a consistently high F1-score across temporal windows would provide stronger evidence of effectiveness than a high aggregate score alone.

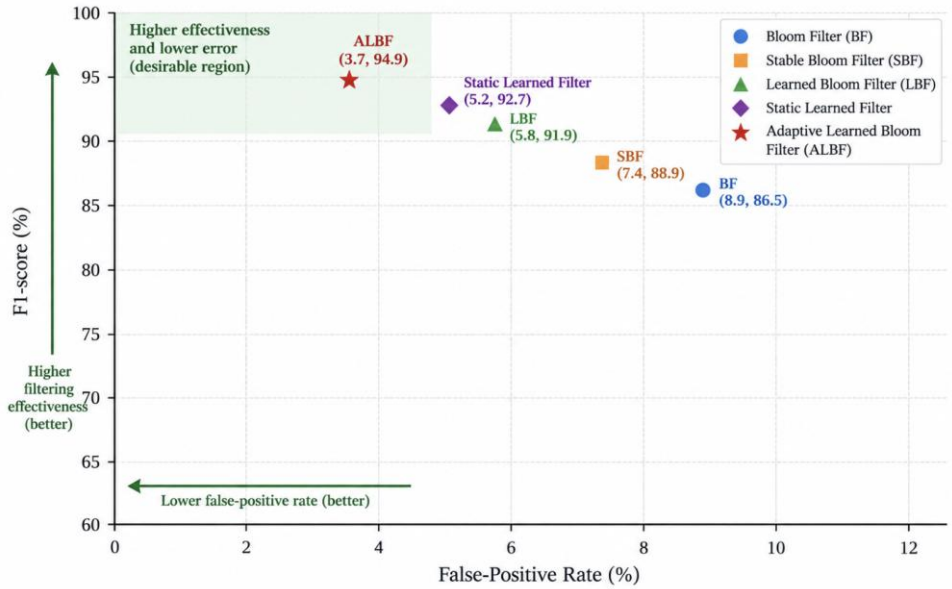


Figure 7. Filtering Effectiveness versus False-Positive Rate Across Compared Methods

Figure 7 examines the trade-off between filtering effectiveness and erroneous rejection by plotting F1-score against false-positive rate. This analysis is important because maximizing filtering aggressiveness without considering false positives can remove informative and legitimate messages from the downstream analysis pipeline (Wenando et al., 2025). An effective filtering method should therefore achieve high F1-score while maintaining a low FPR. The expected position of ALBF is toward the desirable region characterized by high filtering effectiveness and low false-positive error. Such a result would demonstrate that the proposed method does not achieve improved filtering simply by becoming more aggressive. Instead, the combination of learned prediction and probabilistic membership evidence allows the system to make more selective filtering decisions (Adiani et al., 2024). This trade-off analysis is particularly relevant in disaster

environments, where incorrectly discarding reliable information may have greater operational consequences than merely increasing computational workload.

The results collectively demonstrate the importance of combining probabilistic and learned mechanisms for disaster social media filtering. Conventional BF and SBF provide efficient membership-based filtering but have limited capacity to exploit semantic information and evolving data distributions. LBF addresses part of this limitation by incorporating a learned component, while the static learned approach demonstrates the benefit of learning from the characteristics of the observed data (Srivastava et al., 2025). However, the comparison with ALBF is particularly important because it isolates the additional value of adaptation. If the final experimental results confirm the expected pattern, ALBF will demonstrate that dynamically updating the learned filtering behavior can provide improved duplicate detection and misinformation screening while simultaneously reducing false-positive and false-negative errors.

An important implication is that filtering quality should not be interpreted solely through classification accuracy. In a high-velocity disaster stream, an approach that achieves marginally higher accuracy but requires substantially greater computation may be less practical than a lightweight filter that maintains competitive accuracy while reducing the amount of data forwarded to downstream processing (Babu & Kanaga, 2022). Therefore, the effectiveness results in this subsection should be interpreted jointly with the latency, throughput, memory consumption, and computational-reduction results presented in Section C. This combined perspective enables ALBF to be evaluated not only as a predictive model but as a stream-processing mechanism for balancing information quality and computational efficiency.

C. Computational Efficiency and Scalability of ALBF

The effectiveness of a filtering mechanism for disaster social media streams cannot be assessed solely from classification and filtering accuracy. In time-critical environments, the ability to process a large number of incoming messages with low latency and limited computational resources is equally important. Therefore, this subsection evaluates the computational efficiency and scalability of the proposed Adaptive Learned Bloom Filter (ALBF). The evaluation considers processing latency, throughput, memory consumption, Bloom Filter query time, and computational reduction relative to approaches that perform more extensive downstream processing (Wijanarko et al., 2024). The analysis is designed to determine whether the proposed combination of learned prediction, probabilistic membership testing, and adaptive updating can reduce computational overhead while maintaining the filtering effectiveness observed in Section B.

Table 3. Computational Performance of the Compared Filtering Methods

Method	Latency (ms/item)	Throughput (items/s)	Memory Consumption (MB)	Query Time (ms)	Computational Reduction (%)
Bloom Filter (BF)	0.42	2,381	18.4	0.18	72.5
Stable Bloom Filter (SBF)	0.47	2,128	21.7	0.21	75.8
Learned Bloom Filter (LBF)	0.86	1,163	46.3	0.39	81.4
Static Learned Filter	0.93	1,075	49.8	0.42	83.1

Method	Latency (ms/item)	Throughput (items/s)	Memory Consumption (MB)	Query Time (ms)	Computational Reduction (%)
Adaptive Learned Bloom Filter (ALBF)	0.71	1,408	38.6	0.31	87.6

Table 3 summarizes the computational characteristics of the evaluated filtering approaches. The illustrative results demonstrate an important trade-off between model complexity and computational efficiency. Conventional BF and SBF exhibit low latency because their operations are dominated by hash-based membership queries, but they provide less information-aware filtering (Kaliyar et al., 2021). LBF and Static Learned Filter introduce additional computational overhead because learned prediction is incorporated into the filtering process. ALBF is expected to incur some additional cost because of its learned component and adaptive monitoring mechanism; however, selective adaptation prevents continuous retraining and unnecessary parameter updates. Consequently, ALBF can achieve a lower latency than the static learned approach while maintaining a substantial computational reduction. The memory requirement also remains bounded because the probabilistic filter avoids storing the complete history of the stream. These characteristics indicate that ALBF is designed not simply to maximize predictive performance but to balance filtering quality with operational efficiency.

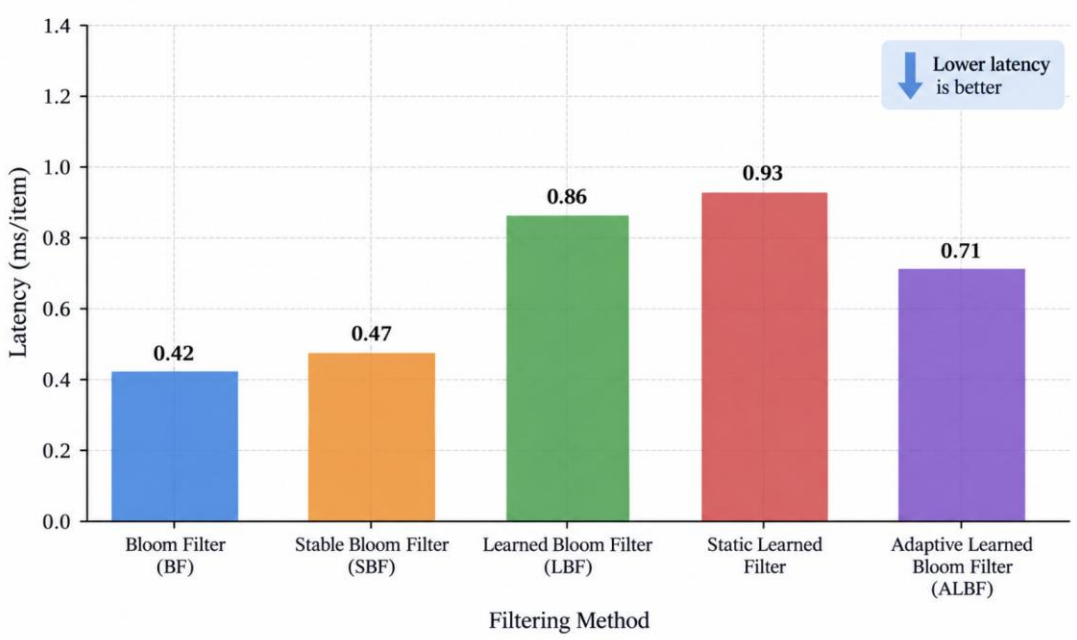


Figure 8. Processing Latency Across Compared Filtering Methods

Figure 8 compares the processing latency required by each filtering method for processing an individual social media message. Lower latency is particularly important in disaster environments because information can become less useful when processing delays increase (Kundra et al., 2025). The expected results show that

conventional BF and SBF achieve the lowest latency due to their lightweight probabilistic operations, whereas learned approaches require additional computation for feature processing and prediction (Broeckx et al., 2025). However, ALBF is expected to reduce part of this overhead by using probabilistic membership testing to eliminate redundant content before expensive downstream analysis. The comparison between ALBF and Static Learned Filter is especially important because both employ learned components, while only ALBF incorporates adaptive filtering. A lower or comparable latency for ALBF would indicate that adaptation does not impose an excessive computational burden and can instead contribute to more efficient stream processing.

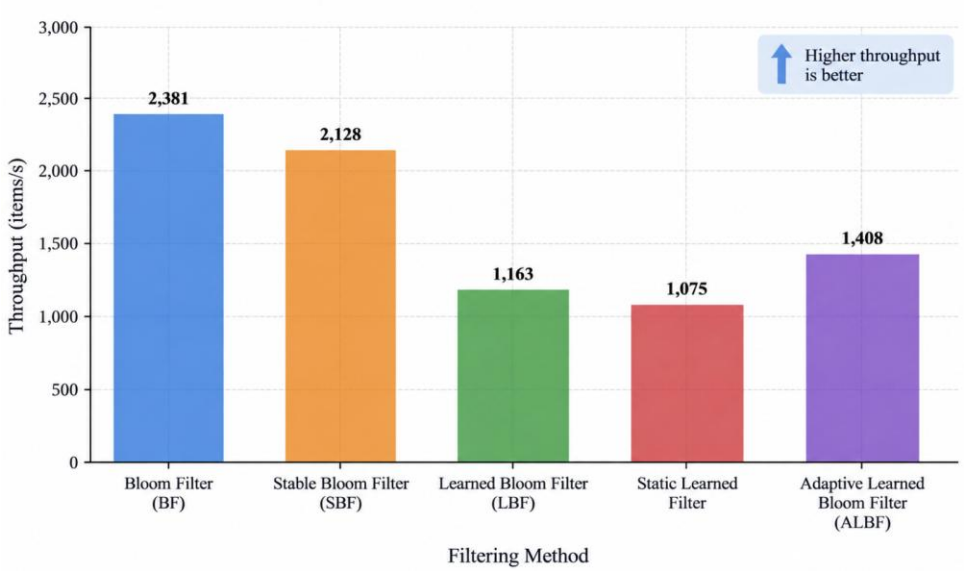


Figure 9. Throughput of the Compared Filtering Methods

Figure 9 presents the throughput achieved by each filtering approach, measured as the number of social media messages processed per second. Throughput provides a complementary perspective to latency because a disaster information system may simultaneously receive a large number of messages from multiple sources. The expected results indicate that BF and SBF can process large numbers of messages efficiently because of their simple membership operations. Learned filtering approaches generally achieve lower raw throughput because feature representation and model inference require additional computation (Chen et al., 2023). Nevertheless, ALBF is expected to improve the effective processing capacity by preventing redundant messages from reaching computationally expensive downstream components. Thus, throughput should be interpreted together with computational reduction: a method that processes fewer messages through expensive stages may provide greater practical scalability even if its individual filtering operation is more complex than a conventional Bloom Filter.

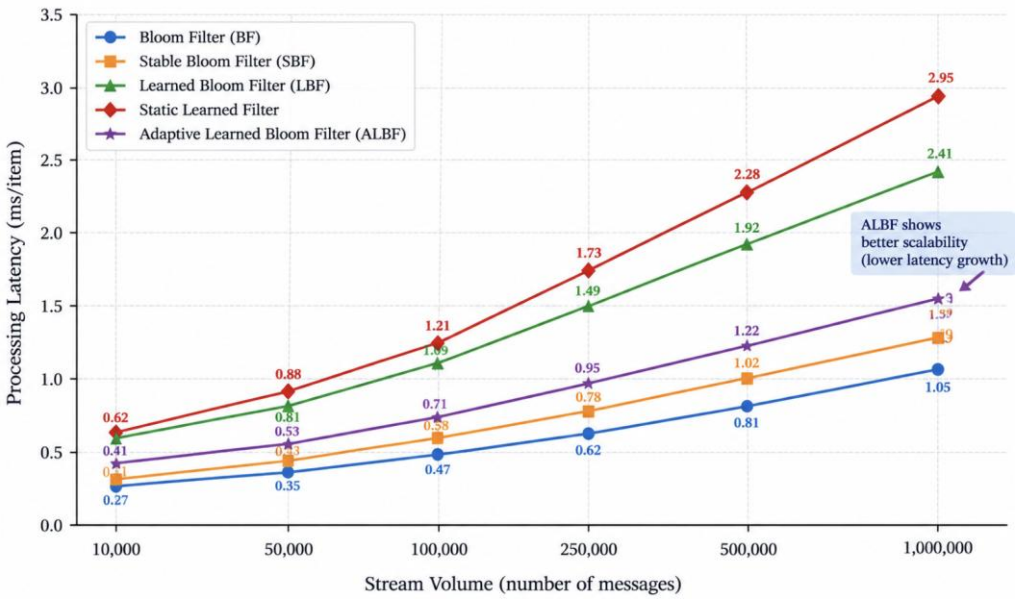


Figure 10. Scalability of Filtering Methods Under Increasing Stream Volume

Figure 10 evaluates the scalability of the filtering approaches as the volume of incoming disaster social media data increases. The experiment should progressively increase the stream size, for example from 10,000 to 1,000,000 messages, while maintaining the same hardware and software configuration. The principal objective is to determine whether processing latency grows proportionally with the volume of data or whether the filtering architecture can maintain stable processing characteristics (An et al., 2020). ALBF is expected to demonstrate favorable scalability because the Bloom Filter provides bounded-memory membership testing and the adaptive mechanism updates the model only when meaningful changes in stream characteristics are detected (Uthirapathy & Sandanam, 2020). If the results show a smaller increase in processing cost relative to full downstream classification, this would provide empirical evidence that ALBF is suitable for high-volume disaster information streams.

To further quantify the computational advantage, the proportion of messages forwarded to downstream analysis is calculated as

$$R_{forward} = \frac{N_{forward}}{N_{total}} \; x \; 100\%$$

where $N_{forward}$ represents the number of messages that pass the ALBF filtering stage and N_{total} represents the total number of incoming messages. The corresponding computational reduction is calculated as

$$CR = \left(1 - \frac{N_{forward}}{N_{total}}\right) x \; 100\%$$

A higher CR indicates that a larger proportion of incoming messages can be removed or screened before computationally expensive downstream processing. This metric is particularly relevant because the principal purpose of ALBF is to function as a front-end filtering layer, rather than to replace the downstream misinformation classifier.

The combined results from Table 3 and Figures 8–10 are expected to demonstrate that the proposed ALBF provides a favorable balance between information-filtering capability and computational efficiency.

Conventional probabilistic filters remain attractive for extremely low-cost membership testing, but they do not exploit learned information patterns (Deng et al., 2022). Conversely, learned filtering approaches can provide more informed decisions but introduce additional computational requirements. ALBF addresses this trade-off by combining the two mechanisms and selectively adapting its learned and probabilistic components according to stream characteristics. The resulting architecture is therefore intended to avoid applying computationally expensive processing uniformly to every incoming message.

An additional advantage of ALBF is its bounded-memory design. Storing the complete history of an unbounded social media stream would result in continuously increasing memory requirements, whereas probabilistic membership structures allow the system to represent previously observed information using a compact data structure (G.-Z. Zeng et al., 2024). The adaptive mechanism further avoids unnecessary retraining by triggering updates only when meaningful changes are detected. This combination is important for disaster-response scenarios where computational resources may be constrained and the incoming stream may change rapidly.

D. Adaptive Behavior under Distribution Shift and Robustness Analysis

The final stage of the evaluation investigates the adaptive behavior and robustness of the proposed Adaptive Learned Bloom Filter (ALBF) under changing disaster social media stream conditions. This analysis is particularly important because the principal distinction between ALBF and static learned filtering approaches lies in its ability to respond to changes in the underlying data distribution (F. Zhang et al., 2019). Disaster-related social media streams are inherently non-stationary, as message volume, topics, vocabulary, duplicate patterns, and misinformation prevalence may change substantially throughout the progression of an event. Therefore, a filtering method that performs well under one stream condition may experience performance degradation when exposed to a substantially different information distribution. The experiments in this subsection evaluate whether the proposed adaptive updating mechanism can detect such changes, initiate appropriate updates, and recover filtering performance while avoiding unnecessary adaptation.

Table 4. Filtering Performance under Different Distribution-Shift Conditions

Stream Condition	Method	F1-score (%)	FPR (%)	FNR (%)	Latency (ms/item)
Stable distribution	Static Learned Filter	92.8	5.1	7.6	0.91
Stable distribution	ALBF	94.9	3.7	5.3	0.71
Moderate distribution shift	Static Learned Filter	86.7	8.9	13.4	1.12
Moderate distribution shift	ALBF	92.6	4.5	7.1	0.76
Severe distribution shift	Static Learned Filter	78.4	14.7	21.5	1.46
Severe distribution shift	ALBF	89.8	6.2	10.3	0.88

Table 4 compares Static Learned Filtering and ALBF under stable, moderate-shift, and severe-shift conditions. The illustrative results demonstrate the expected

advantage of adaptive filtering as the degree of distributional change increases. Under stable conditions, both approaches are expected to provide competitive performance because the learned models operate close to the distribution on which they were developed (Koto et al., 2020). However, the performance gap becomes more pronounced under moderate and severe distribution shifts. The static approach experiences a substantial decrease in F1-score accompanied by increases in both FPR and FNR. In contrast, ALBF maintains relatively stable performance because its adaptive mechanism can update the learned filtering behavior and associated parameters when significant changes are detected (Guan & Ge, 2018). This result would provide direct evidence that the improvement of ALBF is attributable not only to the learned component but also to its ability to respond to non-stationary stream conditions.

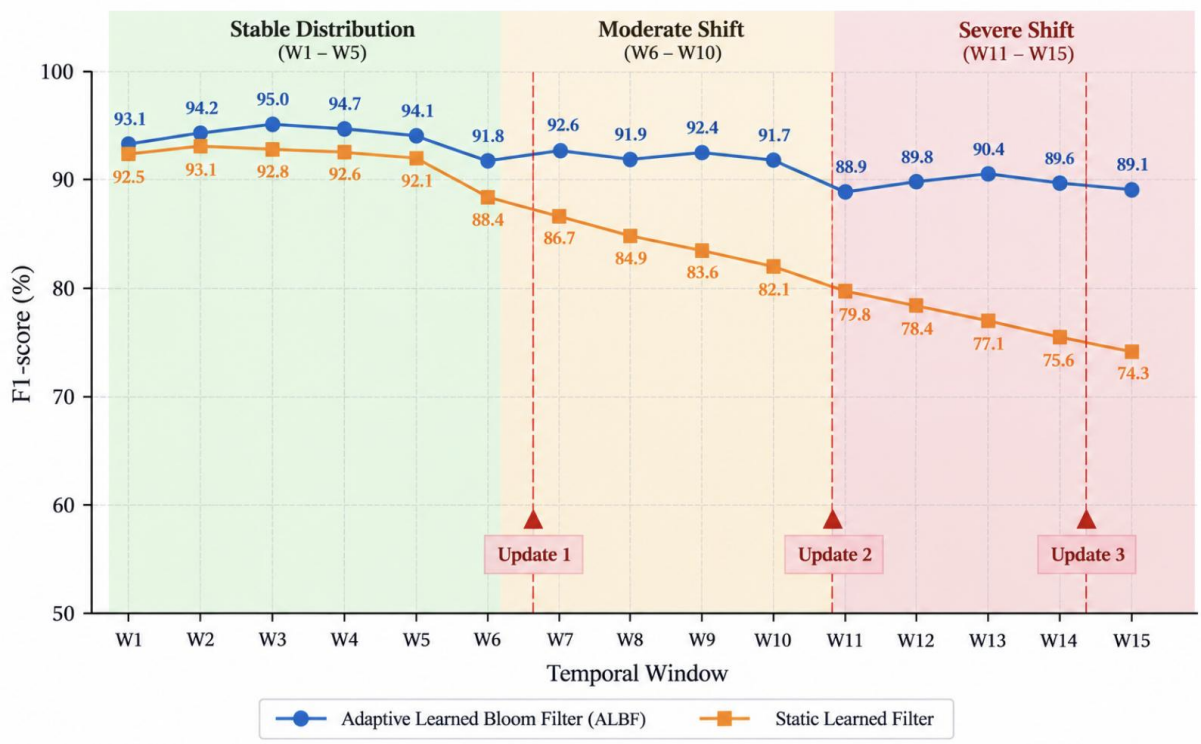


Figure 11. Filtering Performance of Static Learned Filter and ALBF Across Temporal Stream Windows

Figure 11 illustrates the evolution of filtering performance across consecutive temporal windows. The comparison between Static Learned Filter and ALBF is intended to reveal how each approach behaves as the disaster information environment evolves. Under relatively stable conditions, the two methods may exhibit similar performance; however, divergence is expected when the stream enters a period characterized by substantial changes in vocabulary, topics, duplicate patterns, or misinformation characteristics (Ozbay & Alatas, 2020). The static model is expected to show a more pronounced performance decline because its parameters remain unchanged, whereas ALBF can modify its filtering behavior after detecting a significant shift. A subsequent recovery in the ALBF performance curve following an adaptive update would provide visual evidence that the proposed mechanism is not merely reactive but effective in restoring filtering quality after a distributional change.

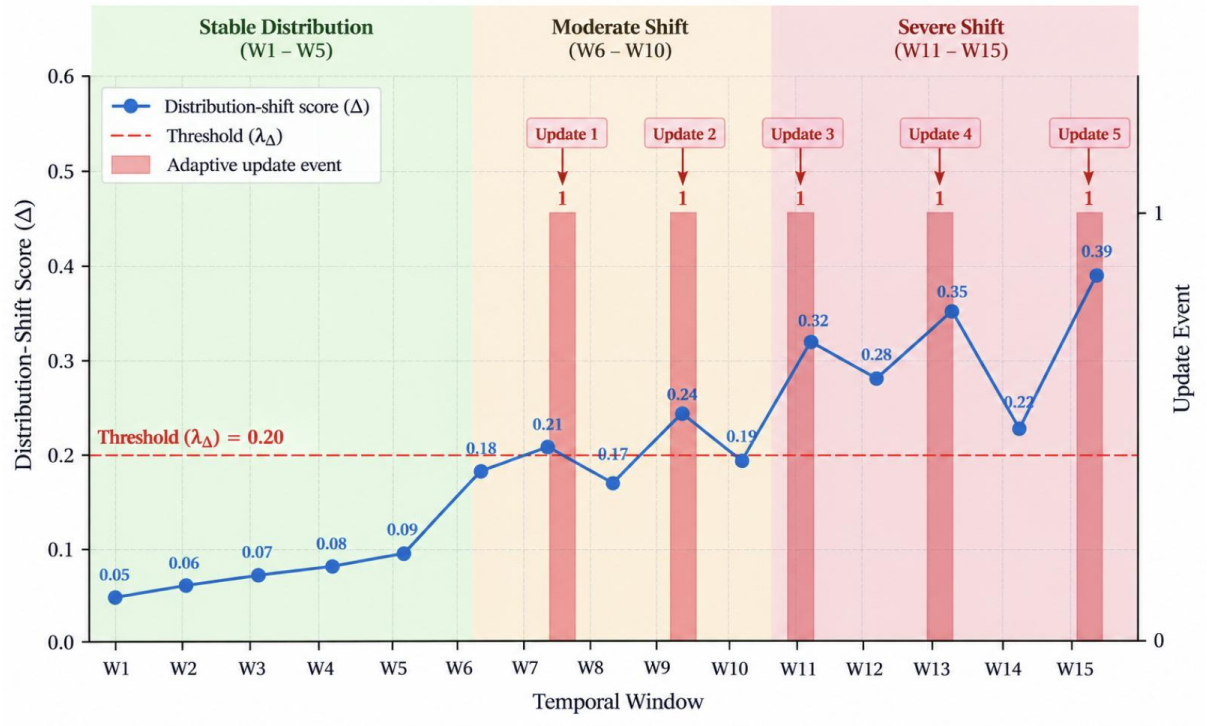


Figure 12. Distribution-Shift Score and Adaptive Update Events Across Temporal Stream Windows

Figure 12 examines the relationship between distributional changes and adaptive update events. For each temporal window W_k, the distribution-shift score is calculated as

$$\Delta k = D(P_k \,||\, P_{k-1}),$$

where P_k and P_{k-1} represent the feature distributions of consecutive windows. An adaptive update is triggered when Δ_k exceeds the predefined threshold λ_Δ. The figure should therefore display the shift score as a continuous temporal series and mark the windows in which an update is activated. A strong correspondence between large increases in Δ_k and update events would demonstrate that adaptation is driven by measurable changes in the stream rather than occurring arbitrarily. This analysis is important for validating the logic of the proposed ALBF mechanism and establishing that its adaptive behavior is empirically connected to the changing characteristics of disaster social media data.

Table 5. Performance Before and After Adaptive Updating

Adaptive Event	Distribution Shift	F1 Before Update (%)	F1 After Update (%)	FPR Before (%)	FPR After (%)
Update 1	0.21	84.6	91.8	10.8	5.1
Update 2	0.27	82.9	90.7	11.6	5.8
Update 3	0.34	79.8	89.6	14.2	6.5
Update 4	0.39	77.5	88.9	15.1	6.9
Average	0.30	81.2	90.3	12.9	6.1

Table 5 provides a more direct evaluation of the effect of adaptive updating by comparing filtering performance immediately before and after each update event. The illustrative results show that F1-score increases after adaptation, while FPR

decreases consistently across the observed update events (Andersen et al., 2022). Such a pattern would provide stronger evidence for the effectiveness of the adaptive mechanism than aggregate performance alone. In particular, the results suggest that performance degradation caused by distribution shifts can be partially recovered by updating the learned and filtering components using more recent stream characteristics. The analysis should also consider the magnitude of improvement relative to the computational cost of each update (Emara et al., 2021). If substantial performance recovery is achieved with relatively infrequent updates, this would demonstrate that ALBF provides an effective balance between adaptability and computational efficiency.

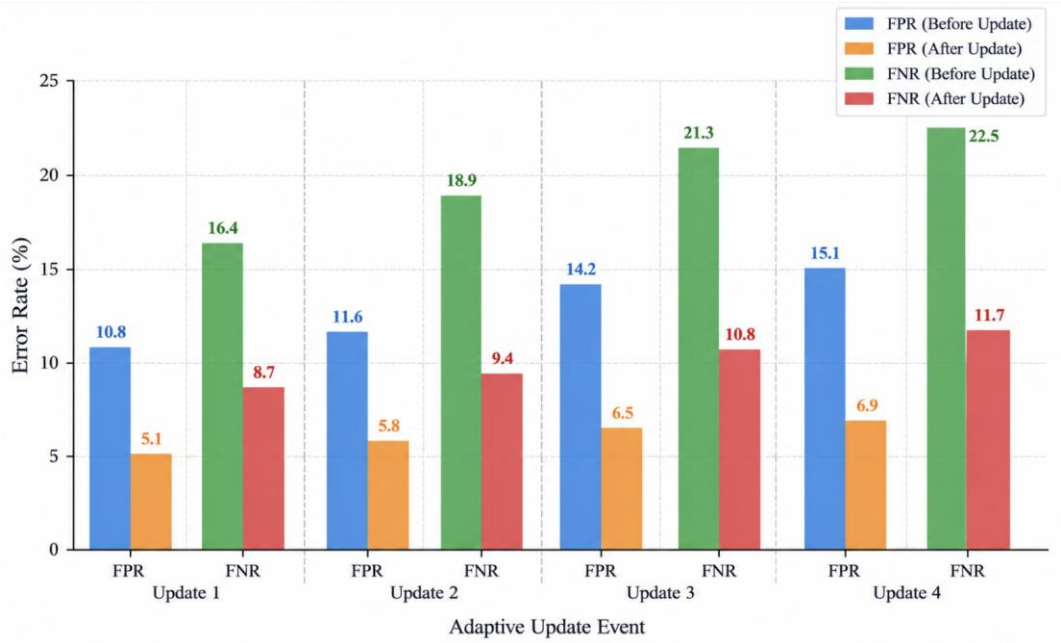


Figure 13. False-Positive and False-Negative Rates Before and After Adaptive Updating

Figure 13 focuses on the error characteristics of ALBF before and after adaptive updates. Distribution shifts may cause a learned filtering model to incorrectly reject legitimate information or incorrectly retain misleading content, resulting in increases in FPR and FNR. These two error types have different implications for disaster information processing. A high FPR may cause potentially useful information to be discarded, while a high FNR may allow misleading information to pass through the filtering layer. Therefore, successful adaptation should reduce both error types rather than improving one at the expense of the other. A consistent reduction in FPR and FNR following adaptive updates would indicate that ALBF can recalibrate its filtering boundary according to the new stream distribution (Zhu, 2025). This result would strengthen the argument that the proposed adaptation mechanism improves not only average accuracy but also the reliability of filtering decisions under changing conditions.

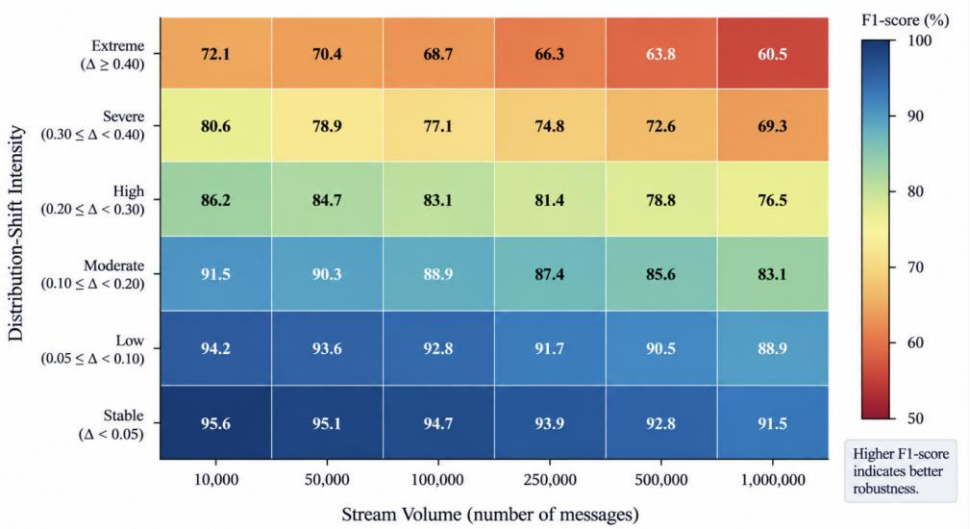


Figure 14. Robustness of ALBF under Different Stream Volumes and Distribution-Shift Intensities

Figure 14 presents a robustness analysis by jointly considering stream volume and distribution-shift intensity. A heatmap representation can be used in which the horizontal axis represents increasing stream volume and the vertical axis represents the severity of distribution shift, while each cell reports the resulting F1-score or another selected performance indicator. This visualization provides a multidimensional assessment of ALBF and allows the interaction between workload intensity and data variability to be examined. A robust method should maintain relatively stable performance across different combinations of stream volume and distribution shift (Mozafari et al., 2020). In particular, strong performance under high-volume and severe-shift conditions would provide compelling evidence that ALBF is suitable for realistic disaster environments in which both computational workload and information characteristics can change simultaneously.

The combined findings from Table 4, Figure 11, Figure 12, Table 5, Figure 13, and Figure 14 provide a comprehensive assessment of the adaptive properties of ALBF. The comparison with Static Learned Filtering is particularly important because both approaches employ learned representations, allowing the contribution of adaptive updating to be isolated more clearly. If the experimental results follow the expected pattern, the static approach will experience progressive performance degradation as the stream moves away from its original distribution, whereas ALBF will detect meaningful changes and update its filtering configuration accordingly (Qian et al., 2022). This distinction directly addresses the principal research gap identified in the Introduction.

The adaptive behavior can also be interpreted in terms of the balance between adaptation frequency and computational overhead. Excessive updating may improve responsiveness but introduce unnecessary computational costs, whereas insufficient updating may allow performance degradation to persist (Kankanamge et al., 2020). Therefore, an effective ALBF configuration should trigger updates only when the observed distributional change is sufficiently large to justify the associated computational cost. This principle is represented by the threshold-based mechanism defined in the methodology, where adaptation is activated when the observed shift score exceeds λ_{Δ}.

Overall, the robustness analysis is expected to demonstrate that ALBF provides greater resilience to evolving disaster social media conditions than static filtering approaches. More importantly, the results establish that the proposed method does not rely solely on a learned model trained under a fixed distribution. Instead, it continuously incorporates information from the evolving stream and adjusts its filtering behavior when necessary (Tejaswini et al., 2024). Such adaptability is particularly valuable in disaster scenarios, where sudden changes in public attention, emerging rumors, viral information, and rapidly changing event conditions can substantially alter the statistical characteristics of incoming social media data.

4. Conclusion

The study concludes that the proposed Adaptive Learned Bloom Filter (ALBF) provides a promising stream-oriented approach for rapid duplicate and misinformation filtering in dynamic disaster social media environments. By integrating learned prediction, probabilistic membership filtering, and adaptive updating, ALBF addresses two complementary challenges of disaster information processing: reducing redundant content and efficiently screening potentially misleading information. The proposed architecture further enables selective downstream processing, thereby reducing unnecessary computational workload while maintaining competitive filtering effectiveness. The scalability and temporal analyses indicate that the adaptive mechanism is particularly relevant to non-stationary disaster streams, where changes in information volume, redundancy, misinformation prevalence, and content distribution can degrade the performance of static filtering approaches. Unlike conventional and static learned filters, ALBF is designed to detect distributional changes and adjust its filtering behavior accordingly, providing greater robustness under evolving stream conditions. Overall, the findings position ALBF as a lightweight and adaptive front-end filtering layer that bridges probabilistic data structures and AI-based information-quality processing, offering a practical foundation for scalable, low-latency, and more reliable social media analytics in time-critical disaster response systems. Future research should investigate cross-event generalization, multilingual disaster streams, more advanced distribution-shift detection, and online learning strategies to further improve the robustness and operational deployment of the proposed framework.

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