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An Efficient Model for Opinion Analysis in Dynamic Data Streams

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Abstract: This study proposes an adaptive opinion analysis framework for real-time sentiment classification in time-evolving textual data streams. Existing approaches to opinion analysis in dynamic data streams face notable limitations, particularly in managing concept drift, handling imbalanced sentiment distributions, and adapting to evolving feature spaces over time thereby falling short of addressing the full range of challenges present in dynamic streaming environments. These limitations motivated the development of a more robust and efficient model capable of meeting the demands of real-world streaming environments. The methodology integrates a transformer-based contextual embedding model (DistilBERT) with an adaptive autoencoder for feature compression and Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance in streaming sentiment datasets. Concept drift in dynamic opinion data is monitored using Feature Selection Stability and Drift (FSSD) combined with the ADWIN drift detection algorithm, enabling the system to adapt to evolving sentiment patterns over time. The research adopted object-oriented analysis and design as the system development methodology due to its reusability. Experimental evaluation was conducted on a continuously streamed customer review dataset using an 80:20 training-testing split. The transformer model was trained using the AdamW optimiser with a learning rate of 2×10^{-5} over ten epochs, achieving a validation accuracy of 94.50%, precision of 0.93, recall of 0.94, F1-score of 0.94, and ROC-AUC score of 0.79 after drift adaptation. The results demonstrate that the proposed system significantly improves adaptability and classification robustness compared to static feature-based streaming models, particularly in handling feature evolution and imbalanced sentiment distributions in real-time opinion analysis environments.

Keywords: Adaptive Learning, Concept Drift, Dynamic Data streams, DistilBERT, Feature Evolution, Opinion Analysis, SMOTE.

I. INTRODUCTION

The rapid growth of digital platforms such as social media networks, e-commerce websites, and online news portals has resulted in an unprecedented volume of user-generated textual data being produced in real time. These data streams carry rich information about public sentiment, consumer preferences, and emerging opinions that, when properly analysed, can support informed decision-making across business, governance, and research domains. However, the dynamic and high-velocity nature of these data streams presents significant challenges for conventional opinion mining techniques, which are primarily designed for static datasets and offline processing [1].Opinion analysis, commonly referred to as sentiment analysis, is the computational process of identifying and extracting subjective information from textual data, classifying it as positive, negative, or neutral in nature. As a subfield of Natural Language Processing (NLP), it has grown significantly in importance due to the increasing need for automated systems capable of interpreting human opinions at scale.

Traditional sentiment analysis approaches largely relied on lexicon-based methods and classical machine learning algorithms such as Naive Bayes, Support Vector Machines (SVM), and Logistic Regression. While effective under controlled conditions, these methods are inherently static and struggle to account for the dynamic nature of real-world data streams. Transformer-based models such as DistilBERT are used for capturing contextual relationships between words through self-attention mechanisms, enabling richer semantic understanding of textual inputs across diverse domains including social media monitoring, customer feedback analysis, and financial market sentiment tracking [2].

One of the major challenges associated with opinion analysis in dynamic data streams is concept drift, a phenomenon in which the statistical properties and semantic meanings of incoming data evolve over time. Emerging topics, slang expressions, changing consumer preferences, and unforeseen events continuously alter the distribution of textual data, causing prediction accuracy to deteriorate if learning models remain

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static. Several researchers have proposed adaptive learning and concept drift detection mechanisms to address this issue; however, many existing approaches either incur high computational costs or fail to maintain consistent predictive performance in large-scale streaming environments [3]. Furthermore, real-world opinion data is often imbalanced, with certain sentiment classes appearing far more frequently than others, introducing bias into trained models and causing them to underperform on minority sentiment classes. Adaptive deep learning has emerged as a promising paradigm for addressing these limitations by enabling models to incrementally learn from newly arriving data while preserving previously acquired knowledge. Through incremental learning strategies, adaptive frameworks can efficiently update model parameters, improve scalability, reduce processing latency, and maintain high classification accuracy in continuously changing environments. Recent developments in adaptive online sentiment analysis have demonstrated the effectiveness of integrating transformer-based contextual learning with feature compression and imbalance-aware sampling to improve sentiment classification in dynamic textual data streams. Specifically, the study develops a mechanism for monitoring and adapting to changes in data distribution using the ADWIN drift detection algorithm combined with Feature Selection Stability and Drift (FSSD), designs a specialized approach to managing imbalanced data streams through the Synthetic Minority Over-sampling Technique (SMOTE), and builds an adaptive model capable of automatically adjusting to evolving features and concepts in real time combining deep learning techniques with continual learning mechanisms to support real-time opinion mining in evolving data streams, thereby enhancing the robustness and responsiveness of intelligent decision support systems [4].

Many existing studies focus on improving either classification accuracy or adaptation capability without adequately addressing both objectives simultaneously. Therefore, this study proposes an efficient model for Real-Time Opinion Analysis in Dynamic Data Streams to provide an intelligent, scalable, and efficient solution for continuous opinion mining. The proposed framework seeks to improve predictive accuracy, minimize retraining costs, and enhance adaptability to evolving data distributions, and support real-time decision-making across diverse application domains, including social media analytics, e-commerce, healthcare, finance, and public policy [5].

II. RELATED WORK

Research on real-time sentiment analysis in streaming environments has grown considerably in response to the limitations of batch-based approaches. [6] demonstrated that traditional batch processing methods are inadequate for live opinion streams, proposing an integrated NLP service for continuous processing, though its complexity limited broader scalability. [7] Introduced a hybrid deep learning architecture designed to enhance sentiment analysis performance by combining multiple neural network frameworks. The study utilized deep learning techniques capable of learning hierarchical and semantic text representations, surpassing traditional bag-of-words approaches and classical classifiers such as Naive Bayes and Support Vector Machines. The results showed that deep learning models significantly improved sentiment classification accuracy by capturing complex linguistic patterns and contextual relationships within text. [8] Compared seven machine learning algorithms for public opinion classification and found that no single method generalises well across all sentiment tasks, reinforcing the need for more context-sensitive and adaptive frameworks.

Concept drift and class imbalance have been identified as central challenges in streaming opinion analysis. [9] Achieved a concept drift detection accuracy of 84% in dynamic data streams but showed limited effectiveness across complex multi-type drift scenarios. [10] Investigated ensemble-based adaptation mechanisms and reported an adaptation accuracy of 81%, confirming the value of drift-aware frameworks while revealing their limitations when drift and feature evolution occur simultaneously. Sentiment models must evolve continuously to remain accurate in shifting data streams, though practical implementation of such adaptation remains challenging. On class imbalance, [11] established that imbalanced streams produce biased classifiers that systematically underperform on minority classes, while [12] highlighted that no existing approach effectively handles heterogeneous and imbalanced opinion streams within a single framework.

Feature evolution in dynamic data streams presents an additional unresolved challenge. [13] Proposed a feature evolution aware classification framework achieving 85% accuracy but assumed a fixed feature space, making it unsuitable for environments where linguistic attributes emerge or disappear over time. [14] Found that deep learning models achieved up to 92% accuracy in financial sentiment tasks but struggled to adapt to evolving feature spaces, leading to performance degradation. [15] Further noted that persistent issues in feature extraction and domain adaptation remain unresolved across the literature. These gaps collectively motivate the development of a unified framework capable of simultaneously managing concept drift, class imbalance, and feature evolution in real-time streaming

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opinion analysis — the core contribution of the proposed framework.

III. METHODOLOGY

The methodology describes the design and implementation of the adaptive opinion analysis framework. The system is designed to provide an adaptive and intelligent framework for real-time opinion analysis in dynamic data streams by integrating advanced deep learning techniques with continuous learning mechanisms. The proposed framework continuously updates its knowledge to accommodate evolving language patterns, emerging topics, and changing user opinions. This adaptive capability enables the system to maintain high classification accuracy even in environments characterized by concept drift, such as social media platforms, online forums, and live customer feedback streams. The framework employs Transformer-based language models for contextual feature extraction while incorporating an adaptive learning module that incrementally updates the model as new data become available, thereby improving prediction reliability and reducing performance degradation over time

Furthermore, the framework integrates automated data preprocessing, feature optimization, and drift detection mechanisms to improve the efficiency of opinion mining in high-velocity data streams. The preprocessing module performs data cleaning, tokenization, normalization, and noise removal before passing the processed text to the Transformer network for semantic representation. An adaptive drift detection component continuously monitors changes in data distribution and triggers model updates whenever significant shifts in sentiment patterns are detected. This enables the framework to learn new vocabulary, trending expressions, and domain-specific terminologies without requiring complete model retraining, thereby reducing computational cost while ensuring timely and accurate sentiment prediction.

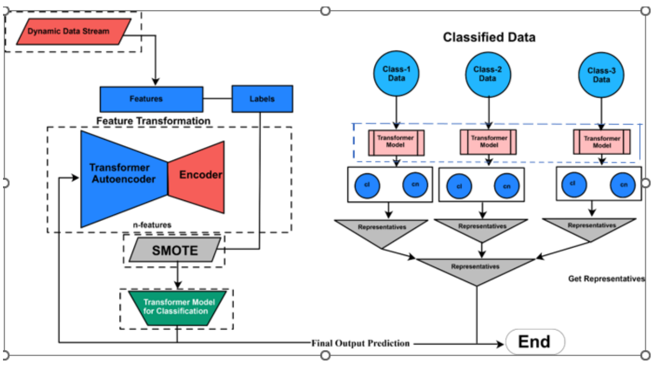

Figure 1: Architecture of the System

The modular architecture also enhances scalability and allows seamless integration with big data processing frameworks.

Functional Design

The functional design illustrates an end-to-end AI-based text analysis pipeline, showing how raw text data is processed, transformed into contextual embeddings using a transformer encoder, compressed through an autoencoder for efficient representation, and finally classified into opinion labels such as positive, negative, or neutral.

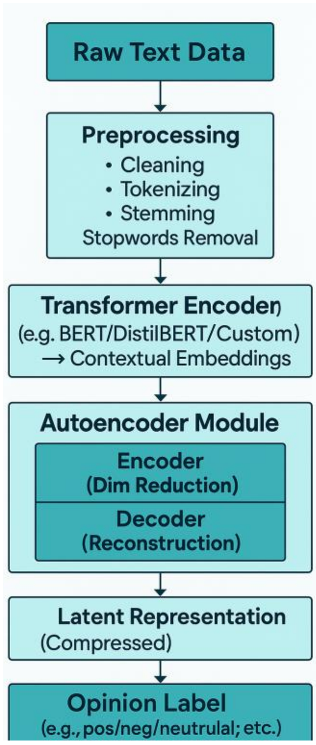

Figure 2: Functional Design

The functional design consists of the following:

1. Raw Text Data: This is the initial input consisting of unstructured text collected from various sources such as social media, reviews, blogs, or forums. These texts carry user opinions in natural language and form the core content for analysis. The data can be diverse in topic, tone, and style, and may contain noise like slang, misspellings, or informal expressions. This raw input is stored in a text corpus and needs to be cleaned and normalized before any modeling.
2. Preprocessing Module The preprocessing module transforms raw textual input into a cleaner and more uniform format suitable for analysis. It typically involves multiple steps such as tokenization (splitting text into words or subwords),

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lowercasing, punctuation removal stopword elimination, and stemming or lemmatization to reduce words to their base forms. This module may also involve handling emojis, hashtags, or mentions depending on the text source. The goal is to reduce variability in the text and standardize it for the transformer model input.

3. Transformer Encoder: This component leverages models like BERT, or other transformer-based architectures to generate contextualized word embeddings. It captures the semantic relationships and syntactic structure of the text by modeling self-attention over tokens, meaning it understands the context in which each word appears. Each word or token is transformed into a dense vector representation that encodes not just its meaning but also its relationship with surrounding words. These embeddings are crucial for capturing nuanced sentiments and evolving opinions across different texts.
4. Autoencoder Module: The autoencoder takes the high-dimensional embeddings from the transformer and compresses them into a lower-dimensional latent space. It consists of two parts: the encoder, which reduces dimensionality while preserving essential features; and the decoder, which attempts to reconstruct the original input from the compressed data to ensure minimal information loss. This module serves both as a denoiser—helping generalize better on noisy, real-world data—and as a means to capture essential opinion patterns while filtering out irrelevant features. It can also help detect evolving patterns in opinions over time.
5. Latent Representation: This is the compact, information-rich vector output from the autoencoder encoder, representing each piece of text in a reduced form. It retains the core semantics and opinion-bearing features while discarding redundant information. These representations are highly useful for clustering similar opinions, tracking topic drift, or visualizing sentiment trends across time. In downstream tasks, they act as the input for classifiers or analyzers that seek to extract actionable insights.
6. Opinion Classifier: The classifier receives the latent vectors and assigns a categorical opinion label—such as positive, negative, neutral, supportive, or opposing—depending on the task. This classifier can be a simple softmax layer in a neural network, a support vector machine, or a more complex multilayer perceptron. It is trained using labeled data to learn the mapping between compressed features and opinion categories. Its performance depends heavily on both the quality of the latent features and the richness of the training labels.
7. Opinion Label Output: The final output of the architecture is the predicted opinion label, which represents the system's interpretation of the user's sentiment or stance. These labels are used in applications like sentiment tracking, reputation analysis, public opinion monitoring, or recommendation systems. The label can be further used in dashboards or analytics tools to provide insights to end-users or stakeholders.

Component Design of the Proposed System

The components of the proposed system include the following:

a. Dynamic Data Stream Collection

The architecture of the proposed Adaptive Deep Learning Framework for Real-Time Opinion Analysis in Dynamic Data Streams is designed as an intelligent end-to-end pipeline capable of processing continuous textual data while adapting to evolving sentiment patterns. The framework begins with the continuous acquisition of streaming opinion data from dynamic sources such as social media platforms, online review systems, and discussion forums. The incoming data stream is represented mathematically as:

D = {(xi,yi) | xi ∈Rd,yi∈Y,i = 1,2,...,n} (Eqn1)

Where (x_i) denotes the input feature vector and (y_i) represents the corresponding sentiment label. Since dynamic data streams are continuously generated and cannot be completely stored in memory, the framework performs online preprocessing to remove noise, normalize textual content, tokenize documents, and generate contextual embeddings suitable for deep learning models.

b. Feature Extraction (Features and Label)

Feature extraction further transforms the processed data into a discriminative representation through the mapping:

ϕ : Rd → Rm (Eqn.2)

Thereby producing meaningful semantic features that improve the effectiveness of subsequent opinion classification.

$$L = \sum_{i=1}^{n} ||x_i - D(E(x_i))||^2 \quad \text{(Eqn.3)}$$

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c. Transformer Autoencoder

To enhance feature learning, the architecture incorporates a Transformer Autoencoder, which compresses high-dimensional opinion representations into a compact latent space while preserving semantic relationships among words and sentences. The encoder maps the input features into latent vectors according to:

$$z = E(x) = f(Wx + b) \qquad \text{(Eqn.4)}$$

while the decoder reconstructs the original representation using:

$$\hat{x} = D(z) = g(W'z + b') \qquad \text{(Eqn.5)}$$

The model is trained by minimizing the reconstruction error:

Which enables the network to retain important contextual information while removing redundant and noisy features. Unlike conventional autoencoders, the transformer-based architecture employs multi-head self-attention mechanisms to capture long-range contextual dependencies and semantic relationships within streaming textual data, thereby producing robust feature representations that remain effective despite continuous changes in language usage.

d. Synthetic Minority Over-Sampling Technique (SMOTE)

After feature extraction, the framework addresses the common problem of class imbalance by employing the Synthetic Minority Over-Sampling Technique (SMOTE). Synthetic opinion samples for minority sentiment classes are generated using:

$$x_{new} = x + \lambda(x_{nn} - x),\ \lambda \sim U(0,1) \qquad \text{(Eqn.6)}$$

Where (x_{nn}) is the nearest neighbour of the selected minority instance. This process produces balanced training data, thereby reducing classification bias and improving the model's ability to recognize less frequent sentiment categories. Furthermore, an adaptive incremental learning mechanism continuously updates the model whenever new opinion data arrive, enabling the framework to cope effectively with concept drift and emerging vocabulary without requiring complete retraining. This significantly improves scalability and supports efficient real-time processing of high-velocity opinion streams.

e. Transformer Model

The final stage of the architecture performs opinion classification using a Transformer-based deep learning model. The self-attention mechanism computes contextual relationships among input representations according to:

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \qquad \text{(Eqn.7)}$$

where (Q), (K), and (V) denote the query, key, and value matrices respectively. The final sentiment prediction is obtained through the Softmax classifier:

$$y = \text{softmax}(Wx + b) \qquad \text{(Eqn.8)}$$

which generates the probability distribution across the sentiment classes. The integration of adaptive preprocessing, Transformer Autoencoder feature learning, SMOTE-based data balancing, incremental model updating, and Transformer classification creates a robust architecture capable of delivering accurate, scalable, and low-latency opinion analysis in continuously evolving data stream environments. Consequently, the proposed framework provides significant improvements in prediction accuracy, adaptability to concept drift, and computational efficiency when compared with conventional static opinion mining systems.

IV. RESULTS AND DISCUSSION

The system is implemented using the Python programming language and modern deep learning libraries to provide flexibility, extensibility, and efficient deployment in real-world environments. The framework is designed to support real-time processing of continuous opinion streams while ensuring low latency, high throughput, and robust performance under varying workloads. A comprehensive evaluation will compare the framework with existing opinion mining approaches using performance metrics such as accuracy, precision, recall, F1-score, processing time, and adaptability to concept drift. Through the integration of adaptive deep learning, Transformer-based contextual understanding, and continuous model updating, the system is expected to achieve superior opinion classification performance and establish a reliable solution for real-time sentiment analysis in dynamic data stream environments.

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Table 1: Results of the Transformer Model in Ten Training Steps

Epoch	Training Loss	Validation Accuracy
1/10	0.3206	0.9183
2/10	0.1562	0.9367
3/10	0.0739	0.9233
4/10	0.0353	0.9350
5/10	0.0233	0.9417
6/10	0.0083	0.9350
7/10	0.0134	0.9300
8/10	0.0083	0.9450
9/10	0.0063	0.9217
10/10	0.0049	0.9400

The performance of the transformer model across ten training epochs is presented in Table 1. The results indicate a consistent reduction in the training loss as the learning process progressed, decreasing from **0.3206** in the first epoch to **0.0049** in the tenth epoch. This steady decline demonstrates that the optimization algorithm effectively minimized the prediction error throughout the training process. Although slight fluctuations were observed during intermediate epochs, the overall trend confirms that the model successfully learned the underlying sentiment patterns from the training data.

Similarly, the validation accuracy remained consistently high throughout the training process, ranging between **0.9183** and **0.9450**. The highest validation accuracy of **0.9450** was achieved during the eighth epoch, indicating the model's strongest generalization performance on unseen validation data. The training loss and validation accuracy values were obtained directly from the PyTorch training history. At the completion of each epoch, the model was evaluated on the validation dataset by comparing predicted class labels with the corresponding ground truth labels. The Cross-Entropy Loss function was used to compute the training loss, while validation accuracy was determined as the proportion of correctly classified validation samples to the total number of validation instances.

The summary of the transformer architecture can be seen in figure 3. Figure 4 shows the training loss of the model, whereas the accuracy obtained by the model can be seen in figure 5.

```
--- Visual 1: Model Layer Summary ---
==========================================================================================
Layer (type:depth-idx)                          Output Shape              Param #
==========================================================================================
DistilBertForSequenceClassification             [1, 12, 128, 128]         --
├─DistilBertModel: 1-1                          [1, 12, 128, 128]         --
│    └─Embeddings: 2-1                          [1, 128, 768]             23,835,648
│    └─Transformer: 2-2                         [1, 12, 128, 128]         42,527,232
├─Linear: 1-2                                   [1, 768]                  590,592
├─Dropout: 1-3                                  [1, 768]                  --
├─Linear: 1-4                                   [1, 2]                    1,538
==========================================================================================
Total params: 66,955,010
Trainable params: 66,955,010
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 66.96
==========================================================================================
Input size (MB): 0.00
Forward/backward pass size (MB): 54.27
Params size (MB): 267.82
Estimated Total Size (MB): 322.09
==========================================================================================
```

Figure 3: Summary of the Transformer Architecture

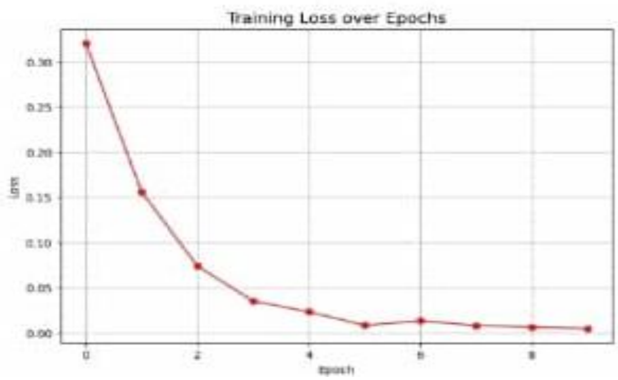

Figure 4: Training loss of the Transformer Model

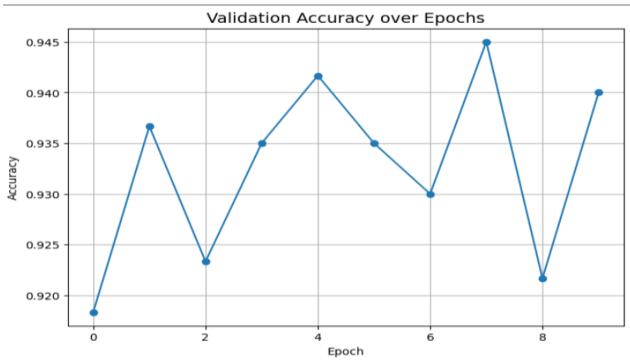

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Figure 5: Validation Accuracy of the Transformer Model

V. CONCLUSION AND FUTURE SCOPE

This study successfully designed and implemented an Efficient Model Framework for Real-Time Opinion Analysis in Dynamic Data Streams to address the major challenges associated with sentiment analysis in continuously evolving data environments. The framework demonstrated the capability to process high-velocity opinion data while maintaining high classification accuracy, adaptability, and computational efficiency. By integrating deep learning with adaptive stream

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mining techniques, the system effectively analyzed real-time textual data from dynamic sources and produced reliable sentiment predictions despite continuous changes in data characteristics. The experimental results confirmed that the framework achieved stable performance and exhibited strong generalization ability across multiple evaluation metrics, making it suitable for practical deployment in modern opinion mining applications. The efficiency of the model comes from the transformer – based feature extraction, auto encoder – based dimensionality reduction, SMOTE for handling class imbalance, incremental learning, and lower computational overhead for streaming data.

A significant contribution of this research is the integration of the **ADWIN (Adaptive Windowing)** algorithm for continuous monitoring of concept drift within streaming data. Rather than relying on predefined thresholds, ADWIN dynamically monitored prediction errors and automatically detected statistically significant changes in data distribution. Whenever concept drift occurred, the framework initiated adaptive learning procedures that updated the deep learning model to accommodate newly emerging sentiment patterns. The observed recovery of classification performance following drift detection demonstrates the effectiveness of the adaptive monitoring mechanism in maintaining prediction accuracy under non-stationary data conditions. This capability enables the proposed framework to remain effective even as user opinions, language usage, and online discussions evolve over time.

The study also addressed the problem of class imbalance through the implementation of the **Synthetic Minority Over-sampling Technique (SMOTE)** within the learning pipeline. The adaptive oversampling strategy ensured adequate representation of minority sentiment classes during model training, thereby reducing prediction bias toward majority classes. Evaluation results obtained from the confusion matrix and ROC-AUC analysis confirmed that the framework achieved balanced classification performance with high precision, recall, and overall accuracy. Furthermore, the incorporation of **Feature Selection Stability and Drift (FSSD)** enabled continuous monitoring of feature importance, allowing the model to automatically adjust feature weights as semantic meanings evolved. This adaptive feature management significantly improved the robustness of the framework by ensuring that emerging words, phrases, and sentiment expressions were accurately incorporated into the learning process.

Despite the encouraging performance achieved by the framework, there remain opportunities for further enhancement. Future research may extend the framework to support multilingual opinion analysis across diverse languages and dialects, thereby increasing its applicability in global social media environments. Additional improvements may include integrating multimodal data sources such as images, audio, and videos alongside textual information to provide richer sentiment understanding. Moreover, advanced transformer architectures, federated learning techniques, reinforcement learning, and explainable artificial intelligence (XAI) can be incorporated to improve model transparency, privacy preservation, and decision interpretability while maintaining real-time processing capabilities.

In conclusion, the Proposed Framework provides a robust, scalable, and intelligent solution for real-time opinion analysis in dynamic data streams. Its ability to detect concept drift, address class imbalance, adapt to evolving feature representations, and continuously update learning parameters ensures sustained performance in rapidly changing environments. The framework therefore represents a significant advancement in adaptive sentiment analysis and provides a strong foundation for future research and industrial applications involving large-scale, real-time opinion mining, social media analytics, customer feedback analysis, financial sentiment monitoring, and decision support systems.

VI. RECOMMENDATIONS

1. Integration into Government Policy Monitoring:

The proposed adaptive deep learning framework should be adopted by government agencies to continuously analyze citizens' opinions on public policies and social programmes. This would enable policymakers to identify public concerns early and make timely, evidence-based decisions.

2. Deployment in Healthcare Feedback Systems:

Healthcare institutions should utilize the framework to monitor patient reviews, complaints, and feedback generated through digital platforms in real time. Continuous sentiment analysis would help healthcare providers improve service quality and quickly identify emerging issues affecting patient satisfaction.

3. Application in Educational Institutions:

The framework is recommended for analyzing students' opinions on teaching methods, online learning platforms, and institutional services. Its adaptive learning capability allows

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universities and schools to monitor changing student perceptions and implement timely academic improvements.

4. Enhancement with Large Language Models:

Future implementations should integrate large language models with the adaptive framework to improve contextual understanding, sarcasm detection, and sentiment interpretation in complex textual data. This enhancement would further increase the accuracy and robustness of real-time opinion analysis.

5. Development of Real-Time Decision Support Dashboards:

Organizations should incorporate the framework into interactive business intelligence dashboards that visualize sentiment trends, concept drift alerts, and emerging topics as they occur. Such dashboards would support executives and decision-makers in making faster, data-driven strategic decisions based on continuously evolving public opinions.

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