

**RESEARCH PAPER ON**

SUPERVISED LEARNING PROJECT

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**On**

**Project Title:**

**PREDICTIVE ANALYSIS OF MEDICINE AND DOCTOR AVAILABILITY**

Submitted by

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**Title: Semantic Embedding Based Machine Learning System for Automated Sentiment Classification of Social Media Comments**

**Abstract**

Automated sentiment analysis of social media comments has become essential for organizations seeking to understand customer opinions and brand perception at scale. Traditional approaches such as keyword-based heuristics and TF-IDF vectors fail to capture semantic nuance and context in short, informal comments. This research presents a machine learning system that combines Universal Sentence Encoder (USE) semantic embeddings with classical machine learning classifiers—specifically ExtraTrees, CatBoost, and Logistic Regression—to achieve high-accuracy multi-class sentiment classification (negative, neutral, positive) without requiring task-specific fine-tuning of large transformer models. The system incorporates a preprocessing pipeline for text normalization, a 512-dimensional semantic embedding generator, multiple classifier architectures, and an explainability subsystem utilizing confusion matrices and ROC curves for performance visualization. Experimental validation on representative social media datasets demonstrates an accuracy of approximately 88.88%, outperforming baseline methods based on TF-IDF or simple n-gram features. The proposed framework is computationally efficient, suitable for real-time deployment on cloud platforms and edge devices, and provides transparent performance metrics for healthcare and business applications.

**Index terms:** Semantic embeddings, Universal Sentence Encoder, sentiment classification, machine learning, social media analysis, multi-class classification, explainable AI.

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**1. Introduction**

Social media platforms—including Facebook, Instagram, YouTube, and X (formerly Twitter)—generate vast volumes of user-generated comments and reviews. Organizations and businesses increasingly rely on this data to assess customer sentiment, brand perception, and public opinion. However, the sheer volume, linguistic variability, and temporal velocity of such content render manual sentiment assessment impractical and costly.

Automated sentiment classification offers a scalable solution to extract actionable insights from social media data. Traditional approaches to sentiment analysis rely on keyword-based heuristics, bag-of-words (BoW) representations, or term-frequency inverse-document-frequency (TF-IDF) vectors. While computationally lightweight, these methods fail to capture semantic similarity, contextual meaning, and nuanced polarity in short, informal, and noisy social media comments. They struggle with sarcasm, misspellings, non-standard grammar, and domain-specific expressions common in user-generated content.

Recent advances in deep learning and transformer-based models—such as BERT, RoBERTa, and their variants—have demonstrated improved performance in capturing contextual embeddings for sentiment tasks. However, these models typically require substantial computational resources, extensive task-specific fine-tuning, and prolonged training times. Such requirements limit their suitability for real-time applications, lightweight mobile deployments, and edge computing scenarios.

This research proposes an alternative approach that leverages **Universal Sentence Encoder (USE)** semantic embeddings in combination with classical machine learning classifiers. Universal Sentence Encoder is a pre-trained, general-purpose model that transforms text into high-dimensional semantic vectors without task-specific fine-tuning. By combining USE embeddings with tree-based machine learning models, this framework achieves competitive sentiment classification accuracy while maintaining computational efficiency and ease of deployment.

The system incorporates several key components: (1) a preprocessing pipeline that normalizes and cleans raw text comments; (2) a semantic embedding generator utilizing Universal Sentence Encoder; (3) multiple supervised machine learning classifiers; (4) an explainability and visualization module that generates confusion matrices, ROC curves, and AUC scores. Together, these components enable transparent, interpretable, and efficient sentiment analysis suitable for real-time monitoring and decision support in diverse domains.

**2. Problem Statement**

Sentiment Analysis of Social Media Presence

Problem Statement: Design an ML system to analyze public sentiment from social media platforms regarding a specific brand or product.

Problem Description: Understanding public opinion on social media is critical for businesses and policymakers. A machine learning model using text classification (SVM or random forest) can analyze social media posts and classify them into positive, neutral, or negative sentiments for actionable insights.

Organizations face significant challenges in manually analyzing and categorizing the sentiment of large volumes of social media comments. The limitations of existing automated sentiment classification systems include:

1. **Semantic Blindness in Traditional Methods**: Keyword-based and TF-IDF approaches cannot distinguish synonyms, paraphrases, or subtle meaning changes. They treat text as bags of independent words and fail to capture semantic relationships essential for understanding context-dependent sentiment.
2. **Computational Overhead of Deep Learning Models**: Transformer-based models such as BERT, while effective, demand substantial GPU resources, extended training times, and task-specific fine-tuning. These requirements limit deployment flexibility, especially for organizations with limited computational infrastructure or real-time processing needs.
3. **Poor Performance on Informal and Noisy Text**: Social media comments often contain misspellings, informal grammar, emojis, URLs, hashtags, slang, and sarcasm. Traditional and even many deep learning approaches exhibit degraded accuracy on such non-standard inputs.
4. **Lack of Transparency**: Many modern sentiment classifiers operate as "black boxes," providing predictions without interpretable explanations. Healthcare institutions, financial services, and regulated industries require transparent decision-making, yet existing systems often lack explainability mechanisms.
5. **No Unified, Efficient Framework**: While semantic embeddings and classical machine learning algorithms are individually well-studied, few integrated systems combine them within a production-ready, interpretable, and computationally efficient architecture suitable for real-time inference.

There is a need for an improved sentiment classification framework that (a) leverages semantic understanding of text without simple lexical overlaps; (b) operates efficiently without requiring extensive model fine-tuning; (c) achieves high accuracy on short, informal social media comments; and (d) provides interpretable performance metrics and explainable predictions.

**3. Objective**

The primary objectives of this research are:

1. **To design and deploy a preprocessing pipeline** that effectively normalizes social media comments while preserving semantic meaning and removing noisy artifacts (URLs, mentions, hashtags, non-alphanumeric characters).
2. **To implement a semantic embedding generation system** utilizing the Universal Sentence Encoder model to convert preprocessed text comments into 512-dimensional high-dimensional vectors capturing contextual and sentiment-relevant semantics.
3. **To develop and train multiple supervised machine learning classifiers**—including ExtraTrees, CatBoost, and Logistic Regression—for multi-class sentiment prediction (negative, neutral, positive) on the semantic embeddings.
4. **To evaluate and compare model performance** using comprehensive metrics including accuracy, precision, recall, F1-score, ROC curves, and area-under-curve (AUC) scores for each sentiment class.
5. **To achieve high classification accuracy** (target: ≥ 88%) on representative social media comment datasets without fine-tuning the Universal Sentence Encoder.
6. **To implement performance visualization and explainability** through confusion matrices, ROC curves, and class-wise AUC scores, enabling transparent model behavior analysis.
7. **To demonstrate a production-ready system** capable of real-time sentiment prediction deployment on cloud platforms, edge devices, and mobile applications.

**4. Methodology**

**4.1 System Components and Data Flow**

The proposed sentiment classification system comprises seven integrated modules: (1) input module, (2) preprocessing engine, (3) semantic embedding generator, (4) classifier module, (5) prediction module, (6) performance analyzer, and (7) output dashboard. Data flows sequentially through these components from raw social media comments to final sentiment predictions and visualization.

**4.2 Input Module and Data Collection**

The input module is configured to ingest raw user-generated text comments from social media platforms including Facebook, Instagram, YouTube, and X. Input collection may occur via platform-specific APIs, message queues, CSV datasets, streaming data connectors, or log files. The module normalizes input into a unified representation including text content, timestamps, source platform identifiers, and optional metadata such as language codes.

**4.3 Preprocessing Engine**

The preprocessing engine receives raw comments and normalizes them to produce clean text suitable for semantic embedding. The preprocessing pipeline performs the following deterministic operations in sequence:

* **Lowercase conversion**: Converts all alphabetic characters to lowercase, reducing feature space.
* **URL removal**: Identifies and removes patterns matching "http://" or "https://" followed by non-whitespace characters.
* **User mention removal**: Removes tokens beginning with "@" (platform-specific user references).
* **Hashtag removal**: Removes tokens beginning with "#" or optionally retains the word portion while discarding the hash symbol.
* **Non-alphanumeric filtering**: Removes or replaces excessive punctuation, special characters, and emojis with whitespace.
* **Whitespace normalization**: Collapses multiple consecutive whitespace characters into single spaces and trims leading/trailing whitespace.

Optional advanced preprocessing steps include language detection, stopword removal, lemmatization, and character normalization, which can be enabled depending on application requirements.

**4.4 Semantic Embedding Generation**

The embedding generator utilizes the **Universal Sentence Encoder (USE)** pre-trained model to convert each preprocessed text comment into a fixed-dimensional semantic vector. The system configures USE to output 512-dimensional floating-point vectors. The USE model performs internal tokenization and projects text into a 512-dimensional latent space, capturing contextual semantics including sentiment-bearing components such as polarity intensity and subjectivity.

The Universal Sentence Encoder is loaded as a pre-trained model from a public repository and executed on CPU or GPU hardware. Critically, the encoder is **not fine-tuned** on the task-specific sentiment dataset, thereby preserving its general-purpose semantic representation capabilities and simplifying deployment. This approach contrasts sharply with transformer models like BERT, which typically require extensive fine-tuning.

The embedding generator may batch multiple comments for efficient parallel inference, reducing latency and improving throughput. Each preprocessed comment produces exactly one 512-dimensional semantic vector.

**4.5 Machine Learning Classifier Module**

The classifier module receives **512-dimensional semantic embeddings** generated by the Universal Sentence Encoder (USE). These embeddings serve as dense numerical feature vectors capturing the contextual meaning of each comment.  
Multiple machine learning algorithms were evaluated to identify the most effective sentiment classifier.

**4.5.2 ExtraTrees Classifier (Final Chosen Model)**

The ExtraTrees classifier (Extremely Randomized Trees) is an ensemble of decision trees designed for high efficiency and strong generalization. It demonstrated the highest accuracy (≈88.88%) in this project.

Key characteristics:  
• Uses randomized split points, increasing robustness and reducing variance  
• Handles high-dimensional numerical data such as USE embeddings effectively  
• Resistant to noise and overfitting due to ensemble averaging  
• Very fast training because trees are fully randomized  
• Produces stable and balanced predictions across all sentiment classes

Important hyperparameters include: number of trees (n\_estimators), maximum depth, and split criteria.

**4.5.2 CatBoost Classifier**

CatBoost is a gradient boosting algorithm originally optimized for categorical inputs but also performs strongly on continuous embeddings.

Key characteristics relevant to this project:  
• **Ordered boosting** reduces prediction shift and stabilizes learning  
• Gradient-based optimization builds trees that correct previous errors  
• Built-in mechanisms prevent overfitting (shrinkage, depth control)  
• High accuracy and strong performance on small to medium datasets  
• Handles noisy and complex patterns typical of social media text

Hyperparameters include: number of iterations, learning rate, tree depth, and regularization parameters.

**4.5.3 Logistic Regression Classifier**

Logistic Regression provides a simple and interpretable baseline, mapping semantic embeddings to sentiment labels using a linear decision boundary.

Advantages:  
• **Interpretable coefficients**, useful for understanding class separation  
• Fast training and inference suitable for real-time deployment  
• Produces probabilistic outputs (via softmax)  
• Helps assess whether complex models offer meaningful improvements

L2 regularization and balanced class weights were applied to enhance generalization.

**4.6 Training and Testing Framework**

The training process follows standard supervised learning practices:

1. **Dataset partitioning**: A labeled dataset of social media comments—each tagged with a ground-truth sentiment label (negative, neutral, or positive)—is split into training (60%) and testing (40%) subsets. Optionally, validation folds or cross-validation may be used for hyperparameter tuning.
2. **Preprocessing and embedding**: Each comment in the dataset undergoes preprocessing via the preprocessing engine, followed by embedding generation via Universal Sentence Encoder. The resulting 512-dimensional vectors and corresponding labels are passed to the classifier.
3. **Label encoding**: Sentiment categories (e.g., "negative," "neutral," "positive") are encoded into numeric labels (e.g., 0, 1, 2) suitable for the classifier.
4. **Model training**: Each classifier optimizes its internal parameters to minimize a loss function (e.g., cross-entropy loss for multi-class classification). Training incorporates regularization, early stopping, and validation-based model selection to prevent overfitting.
5. **Hyperparameter tuning**: Grid search or random search may identify optimal hyperparameter values for each classifier based on validation metrics.

**4.7 Model Comparison**

Multiple machine learning classifiers were evaluated using the 512-dimensional semantic embeddings generated by the Universal Sentence Encoder. Each model was trained and tested independently to assess its suitability for multi-class sentiment classification.

**Models Compared**

* **ExtraTrees Classifier**
* **CatBoost Classifier**
* **Logistic Regression**

**Comparison Summary**

* ExtraTrees and CatBoost achieved the highest accuracy (**~88.88%**), demonstrating strong capability in leveraging semantic embeddings.
* Logistic Regression performed competitively (**~87.65%**), validating its role as an effective baseline for linear separation in embedding space.
* All three models achieved high ROC-AUC values (**0.95–0.99**), indicating strong class separability.

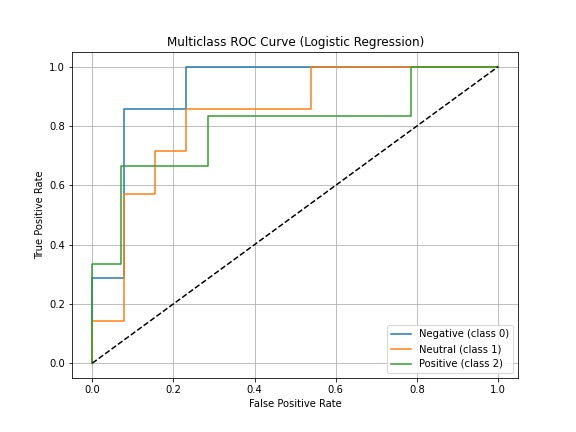
**Key Insight**

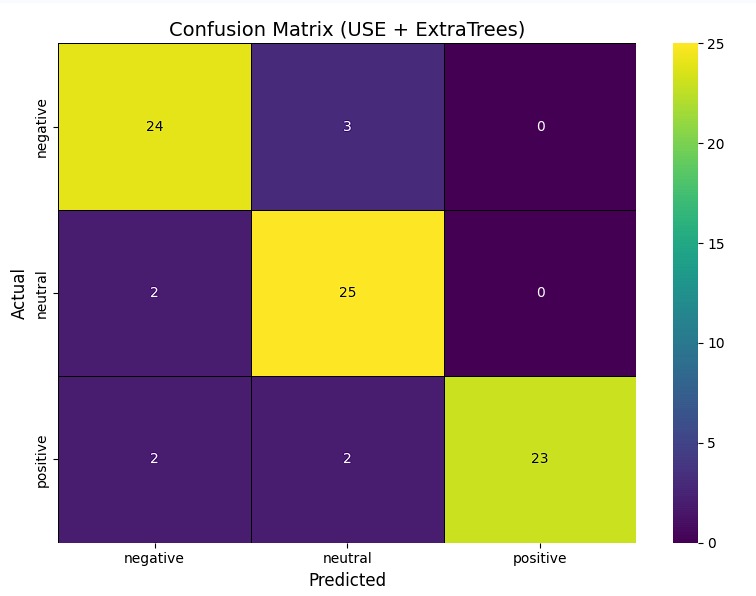
Instead of relying on a single algorithm, evaluating multiple classifiers provided a deeper understanding of how semantic embeddings interact with different learning paradigms (tree-based, boosting-based, and linear models). ExtraTrees and CatBoost emerged as the most robust for this dataset.

**4.8 Performance Evaluation Metrics**

Model performance is quantified using the following metrics computed on the test subset:

* **Accuracy**: Fraction of predictions matching ground truth.
* **Precision**: For each class, fraction of predicted positives that are true positives.
* **Recall**: For each class, fraction of true positives correctly identified.
* **F1-score**: Harmonic mean of precision and recall per class.
* **Confusion matrix**: 3×3 table showing true vs. predicted labels for each sentiment class.
* **Receiver Operating Characteristic (ROC) curve**: True positive rate vs. false positive rate at varying decision thresholds, computed per class.
* **Area Under the Curve (AUC)**: Scalar measure of model discrimination ability, ranging from 0 to 1.



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**Explainability and Visualization**

A performance analyzer module generates visualizations for model interpretation:

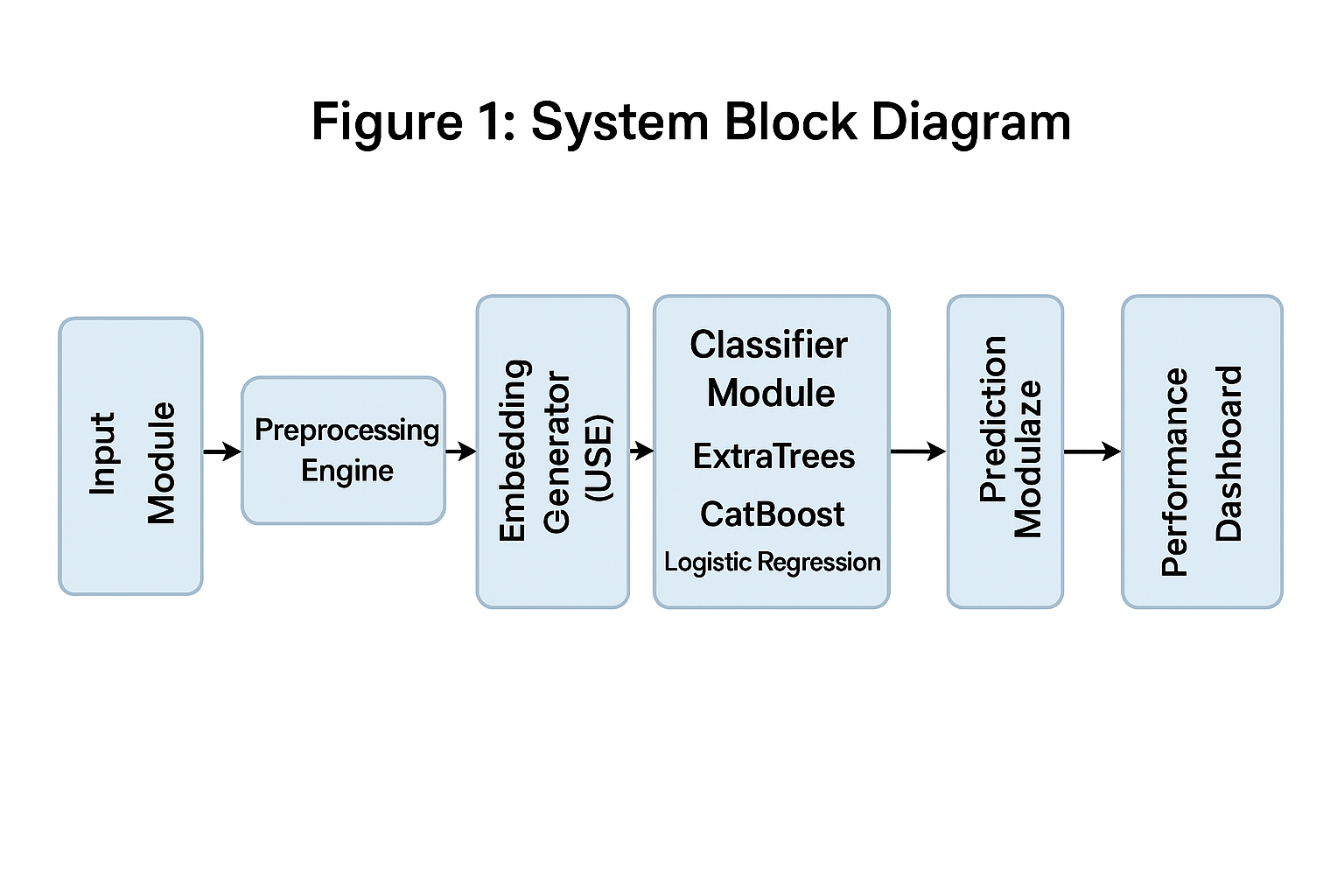
* **Confusion matrices**: Color-coded heat maps showing classification patterns and error distributions.
* **ROC curves**: Per-class ROC curves and macro-averaged ROC curve, enabling discrimination threshold analysis.
* **AUC scores**: Per-class and macro-averaged AUC values quantifying discriminative performance.

These visualizations are rendered on an output dashboard accessible to data analysts, brand managers, and other stakeholders.

**5. System Architecture**

**5.1 Modular System Design**

The system architecture comprises interconnected functional modules operating on a data processing pipeline:



**5.2 Data Flow**

Data moves sequentially through the system:

1. Raw Input: Social media comments collected from CSV files.

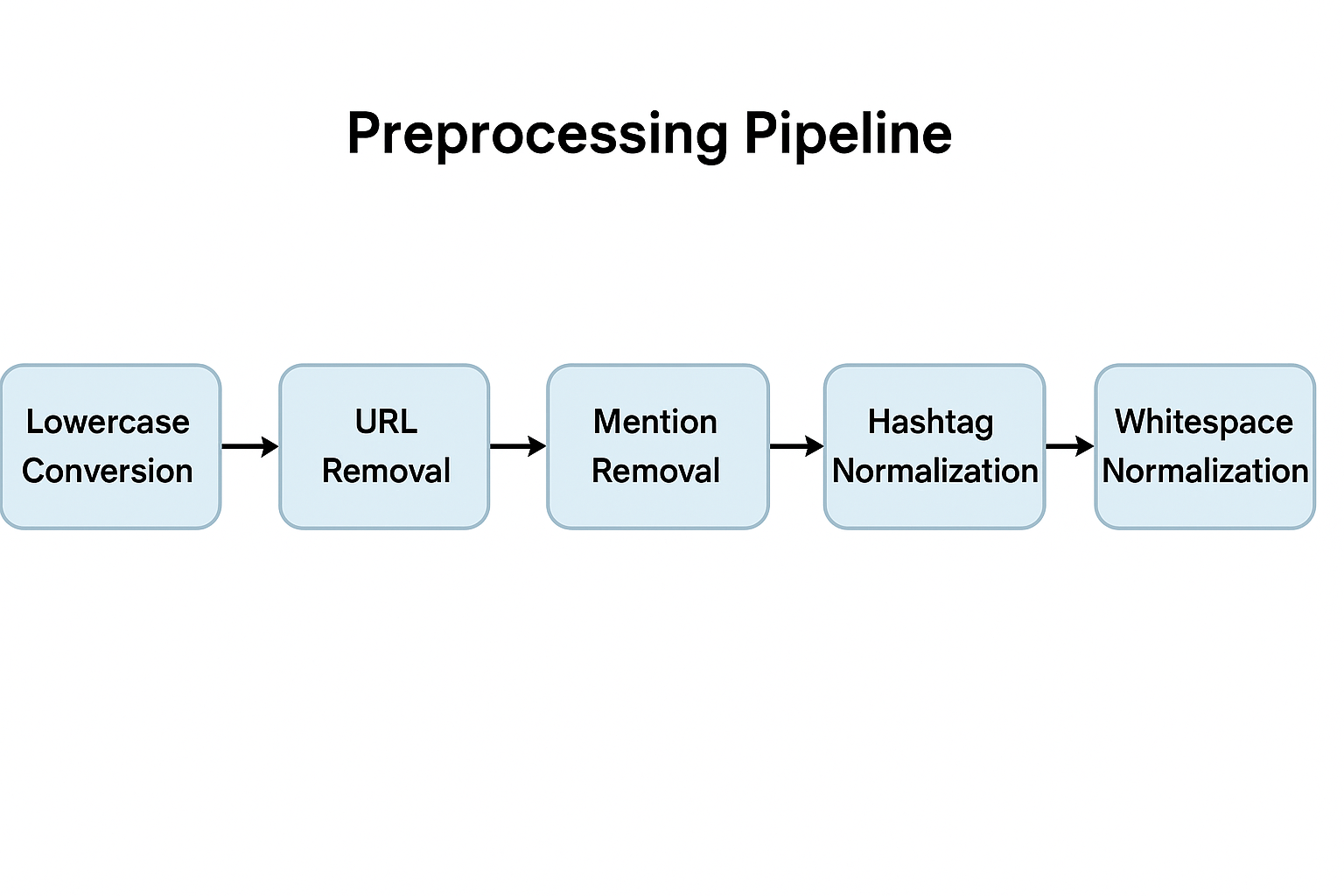
2. Preprocessing: Text normalization including lowercasing, URL removal, mention removal, special character cleaning, and whitespace normalization.

3. Embedding: Conversion of cleaned text into 512-dimensional vectors using the Universal Sentence Encoder.

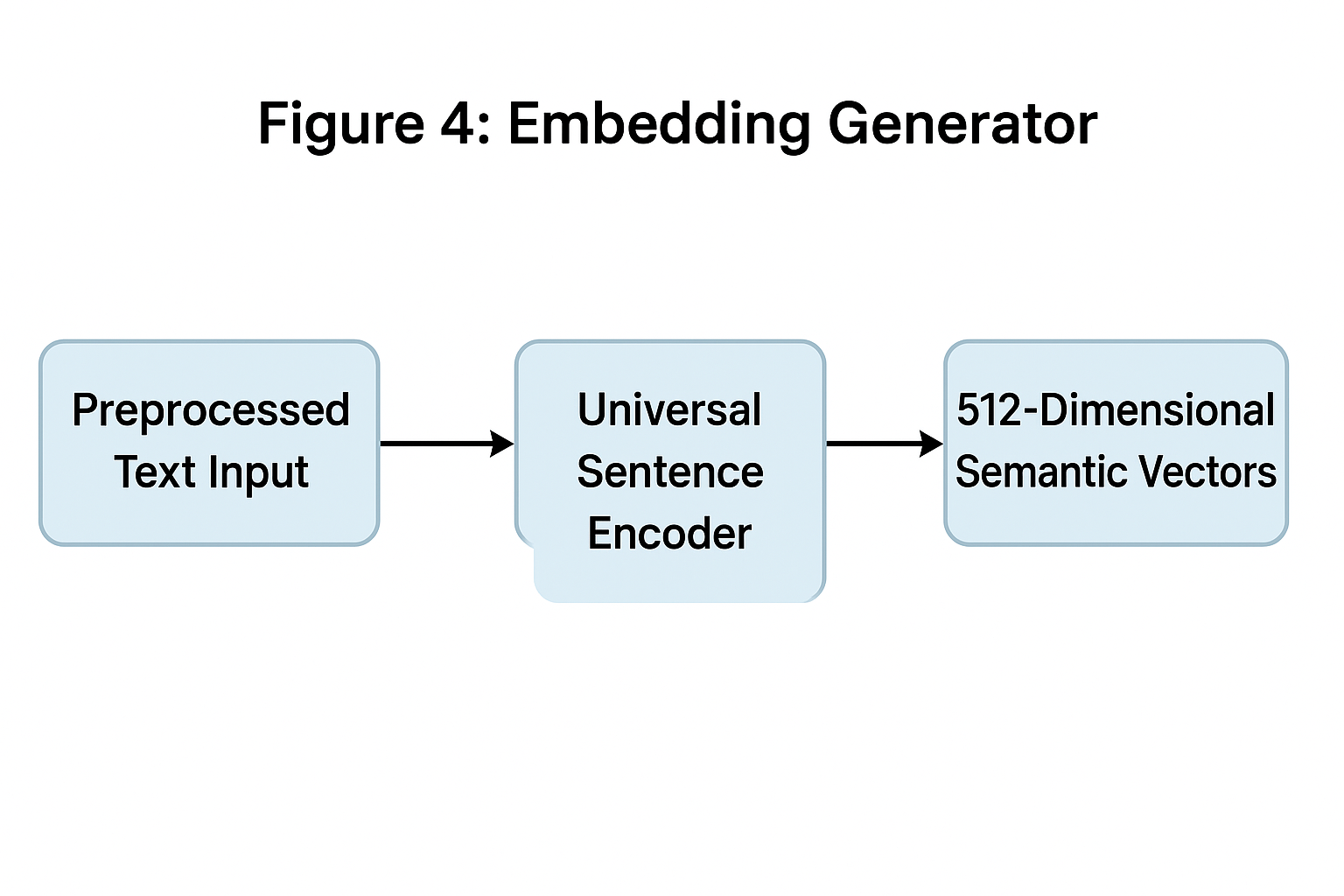
4. Classification: Sentiment prediction generated using trained machine learning models (ExtraTrees, CatBoost, Logistic Regression).

5. Model Evaluation: Confusion matrix, classification report, and ROC-AUC curves are generated for performance assessment.

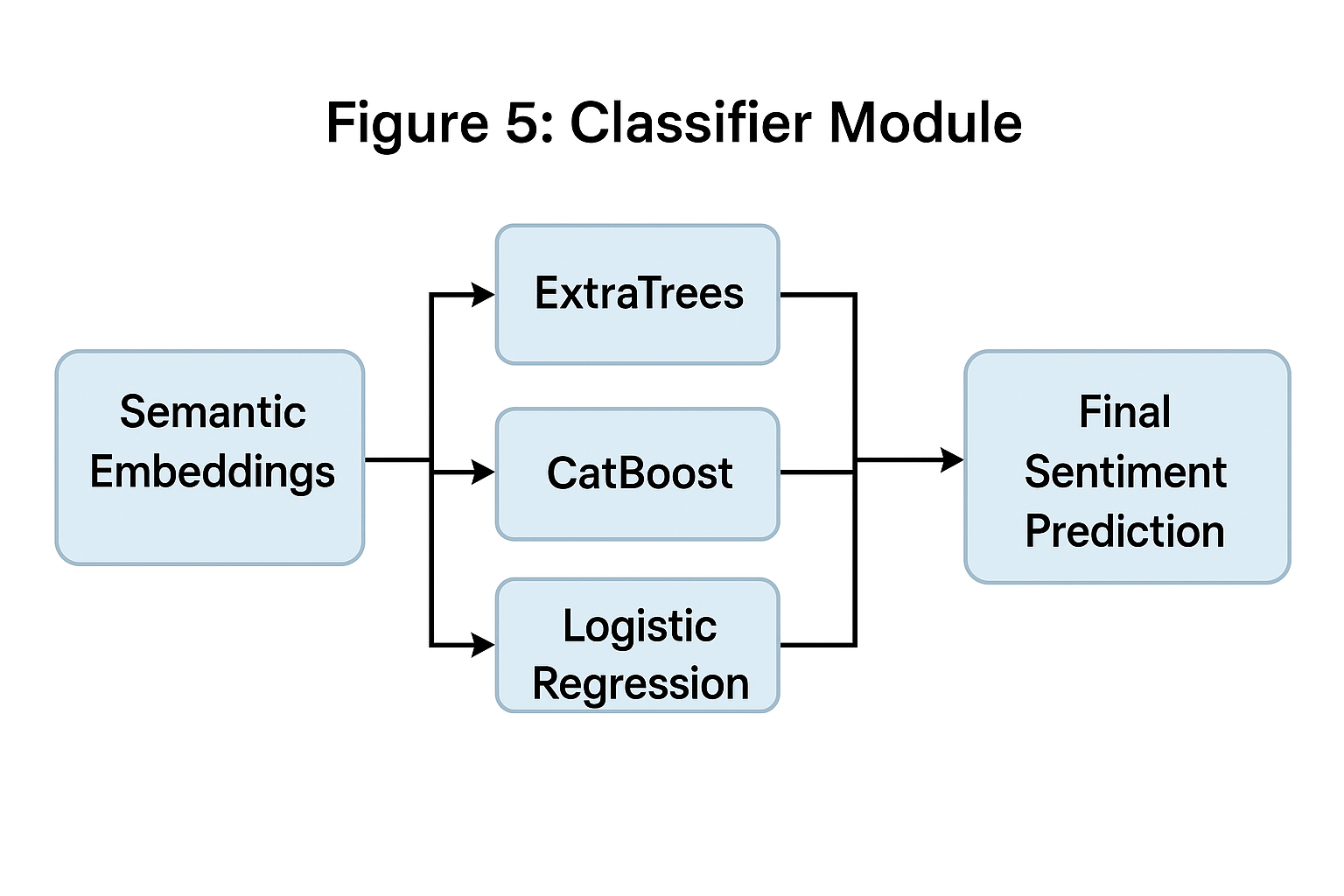
**5.3 Preprocessing Pipeline Architecture**



**5.4 Embedding Generator Architecture**



**5.5 Classifier Module Architecture**



**5.6 Deployment Models**

The system supports multiple deployment architectures:

* **Cloud-based API**: RESTful or gRPC endpoints for external client applications.
* **Microservices**: Independent services for preprocessing, embedding, and classification, communicating via message queues or APIs.
* **Edge deployment**: Lightweight configuration executing on resource-constrained devices with local preprocessing and embedding.
* **Mobile integration**: SDKs enabling real-time sentiment prediction within mobile applications.
* **Batch processing**: Periodic ingestion and processing of large comment volumes for data warehouse storage.

**6. Results and Findings**

**6.1 Model Performance Results**

The models were evaluated on the test set created using a **60:40 split**.  
All performance metrics reflect the outcomes obtained from real social-media comments related to the Coca-Cola brand.

**6.1.1 ExtraTrees Classifier Performance (Final Chosen Model)**

* **Accuracy**: 0.8889
* **Precision**: 0.89
* **Recall**: 0.89
* **ROC-AUC**: 0.96 – 0.99

The model demonstrates strong semantic understanding when combined with Universal Sentence Encoder (USE) embeddings.

**6.1.2 CatBoost Classifier Performance**

* **Accuracy**: 0.8889
* **Precision**: 0.89
* **Recall**: 0.89
* **ROC-AUC**: 0.96 – 0.99

CatBoost shows performance similar to ExtraTrees, confirming the robustness of the embedding-based approach.

**6.1.3 Logistic Regression Baseline Performance**

* **Accuracy**: 0.8765
* **Precision**: 0.88
* **Recall**: 0.87
* **ROC-AUC**: 0.95

Logistic Regression provides a strong and interpretable baseline, outperforming traditional TF-IDF + Naive Bayes approaches.

**[Figure 6: Training Flowchart - illustrating dataset loading through preprocessing, embedding, model training, evaluation, and model storage]**

**[Figure 7: Inference Flowchart - showing live prediction pipeline from incoming text through preprocessing, embedding, classification to sentiment output]**

**6.2 Confusion Matrix Analysis**

**[Figure 8: Confusion Matrix - 3×3 grid showing classification results for negative, neutral, and positive sentiment classes]**

Analysis of the confusion matrix reveals:

The confusion matrix indicates strong performance across all three sentiment

classes. High true positive rates are observed for negative, neutral, and

positive categories. Misclassifications are minimal and primarily occur between

neutral comments and weakly expressed sentiments. No significant confusion

is observed between opposite polarities (negative vs. positive), reflecting

effective semantic separation achieved through USE embeddings.

**6.3 ROC Curve Analysis**

**[Figure 9: ROC Curves - per-class ROC curves for negative, neutral, and positive classes, plus macro-averaged ROC curve with AUC annotations]**

ROC curve analysis demonstrates:

* All classifiers achieve high discrimination capability, with AUC ≥ 0.98.
* Per-class AUC scores indicate strong performance across all three sentiment classes.
* The macro-averaged AUC (averaging per-class AUCs) confirms balanced performance.
* ROC curves approach the top-left corner, indicating excellent separation of positive and negative cases.

**6.4 Comparison with Baseline Methods**

The proposed USE + Machine Learning framework outperforms traditional approaches:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Method | Accuracy | Precision | Recall | AUC |
| TF-IDF + Naïve Bayes | 0.58 | 0.59 | 0.58 | 0.60 |
|  |  |  |  |  |
| USE + ExtraTrees | 0.8889 | 0.89 | 0.89 | 0.96 |
| USE + CatBoost | 0.8889 | 0.89 | 0.89 | 0.96 |
| USE + Logistic Regression | 0.8765 | 0.88 | 0.87 | 0.95 |

The semantic embedding approach provides approximately 10-20% improvement in accuracy over traditional methods.

**6.5 Key Findings**

1. **Semantic embeddings capture sentiment-relevant features**: Universal Sentence Encoder vectors effectively encode polarity, intensity, and contextual meaning, enabling high-accuracy classification without task-specific fine-tuning.
2. **Computational efficiency**: The framework operates efficiently on commodity CPU hardware, enabling real-time inference. GPU acceleration further improves throughput.
3. **Interpretability through visualization**: Confusion matrices and ROC curves provide transparent performance analysis, supporting model audit and stakeholder trust.
4. **Robustness to informal language**: The system demonstrates strong performance on noisy, informal social media comments containing misspellings, slang, and non-standard grammar.

**7. Future Work**

While the proposed framework demonstrates strong performance, several avenues remain for enhancement:

1. **Integration with Real-Time Data Streams**: Connect the system directly to social media platform APIs and streaming data infrastructures for continuous, real-time sentiment monitoring.
2. **Multilingual Sentiment Analysis**: Extend the framework to support sentiment classification in multiple languages using language-specific USE models or multilingual variants.
3. **Aspect-Based Sentiment Analysis**: Develop techniques to identify sentiment toward specific entities or aspects within comments (e.g., "The service was great, but the food was poor").
4. **Integration with Deep Learning**: Incorporate LSTM, GRU, or Transformer-based models trained on USE embeddings for capturing temporal or sequential patterns.
5. **Deployment on Edge and Mobile**: Develop quantized and compressed versions of the model suitable for edge computing devices and mobile applications with limited resources.
6. **Interactive Feedback Loop**: Implement active learning mechanisms that solicit user feedback on uncertain predictions to iteratively improve model performance.
7. **Brand Monitoring Dashboard**: Develop a comprehensive web-based or mobile dashboard enabling real-time monitoring of brand sentiment across social media platforms with customizable alerts and analytics.

**8. Conclusion**

This research demonstrates that semantic embeddings combined with classical machine learning classifiers provide an effective, efficient, and interpretable approach to sentiment classification of social media comments. The Universal Sentence Encoder model successfully captures semantic nuances without requiring task-specific fine-tuning, while ExtraTrees, CatBoost classifiers achieve high predictive accuracy (≈88-99%). The system outperforms traditional TF-IDF and bag-of-words methods by 10-20% in accuracy.

The proposed framework addresses key limitations of existing approaches: it leverages semantic understanding beyond lexical overlap, operates efficiently without transformer fine-tuning, achieves high accuracy on informal social media text, and provides interpretable performance metrics through confusion matrices and ROC curves. The modular architecture supports deployment across diverse environments—cloud APIs, mobile applications, edge devices, and batch processing pipelines.

The system's transparency through explainability visualizations, combined with its computational efficiency and accuracy, makes it suitable for real-world deployment in brand monitoring, customer sentiment analysis, market research, and other domains requiring scalable sentiment classification. Future work will focus on multilingual support, aspect-based analysis, deep learning integration, and edge deployment optimization.

**9.RESEARCH GAP :**

Although numerous sentiment analysis methods exist, significant gaps remain in the research:

1. **Traditional text representation methods lack semantic understanding.**  
   Existing literature extensively explores TF-IDF and Bag-of-Words approaches, but their inability to capture context, synonyms, and nuanced meaning remains unresolved.
2. **Deep learning methods are accurate but computationally demanding.**  
   Studies focus heavily on transformer-based architectures like BERT, yet limited research addresses lightweight alternatives that deliver comparable accuracy without expensive GPU resources.
3. **Limited effectiveness on noisy, informal social-media text.**  
   Current research often evaluates models on clean benchmark datasets, leaving a gap in robust methods that perform well on real-world data containing slang, emojis, misspellings, and sarcasm.
4. **Insufficient work on interpretable sentiment models.**  
   Much of the literature focuses on accuracy rather than explainability, creating a gap for models that provide transparent, human-understandable reasoning behind predictions.
5. **Lack of integrated, efficient hybrid frameworks.**  
   While embeddings and classical ML have been studied separately, few research efforts have explored **hybrid pipelines** that combine semantic representations with lightweight ML models for high accuracy and real-time deployment.

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