ContentFusion: Where BERT Meets Explainable AI - A Novel Hybrid Approach for Domain-Adaptive Content Categorization

V.K. Janani Sivapriya[1], Dr. R. Saravana Moorthy[2], Dr. S. Angel[3]

[1]Assistant Professor, Department of Data Science, Dwaraka Doss Goverdhan Doss Vaishnav College, Chennai-106. Research Scholar, Department of Computer Science, Kongunadu Arts and Science College, Coimbatore-29.
[2]Associate Professor, Department of Computer Science, Kongunadu Arts and Science College, Coimbatore-29.
[3]Assistant Professor, Department of Cyber Security with Computer Science, PSGR Krishnamal College for Women, Coimbatore.

Abstract

Recent advances in content categorization struggle with accurately identifying diverse content types while maintaining interpretability across domains. This paper presents ContentFusion, a hybrid framework that strategically integrates interpretable machine learning with transformer architectures for robust content classification. The proposed model combines logistic regression and decision trees with a deep learning pipeline (BERT + BiLSTM + attention) through a novel confidence-weighted ensemble mechanism. Key innovations include: (1) a dynamic domain adaptation layer for cross-corpus generalization, (2) a context-aware attention mechanism to distinguish subtle content variations (e.g., satire vs. news), and (3) an interpretability-preserving pipeline with SHAP explanations and attention visualizations. Evaluated on a multi-domain dataset (Twitter, news, Amazon/Yelp reviews), ContentFusion achieves 97.94% accuracy (weighted F1-score: 0.983), outperforming BERT by 7.2% in cross-domain tasks while reducing training time by 20%. The framework demonstrates practical utility in media monitoring and automated content tagging, with 94% annotator agreement in user studies.

Keywords: *content categorization, hybrid models, BERT, domain adaptation, interpretable AI, ensemble learning*

1. INTRODUCTION

1.1. The Growing Challenge of Content Categorization

The digital era has witnessed an explosion of heterogeneous textual content spanning platforms such as social media, news outlets, e-commerce sites, and promotional channels. With over 4.6 billion active internet users generating an estimated 328 million terabytes of data daily (Statista,

2023), developing content categorization systems that are accurate, scalable, and interpretable is more critical than ever. Core applications such as sentiment analysis, fake news detection, media monitoring, and recommendation systems rely heavily on the ability to classify text into meaningful and actionable categories (Jurafsky & Martin, 2021).

Even so, categorizing content today is faced with many challenges. A key problem is that several content types are found on one platform. As an example, Twitter gathers news, satire, advertisements and personal views which all need to be sorted using different methods (Zubiaga et al., 2022). Also, domain-related details can make it harder to model: learning on news articles generally stops models from working well on product reviews or social media comments because of language and structure differences (Gururangan et al., 2020). Things become more complicated because subtle differences in context allow satire and false news to closely blend in with real news, confusing even the best classifiers (Potthast et al., 2023). It has been found in recent studies that over 60% of wrongly classified content comes from problems with models handling shift in topics or not detecting small changes in meaning (Raffel et al., 2023). As an example, Google's Perspective API has struggled to tell apart harmful speech from sarcasm which has resulted in wrong decisions by moderators (Papakipos & Okuno, 2022).

Because of these challenges, it is clear that we require frameworks for categorizing content that take into account meaning, adjust well to different domains and are easy to understand.

1.2. Limitations of Existing Approaches

1.2.1 Traditional Machine Learning: Transparency at the Cost of Context

For years, logistic regression and decision trees, when using sparse features such as TF-IDF or n-grams, were favored by many thanks to their ease of understanding and low computing costs (Pedregosa et al., 2023). But these models are unable to detect complex connections or far-off relationships which are important for tasks like detecting sarcasm or bias (Zhang et al., 2023). Phrases such as "not bad" and "good" mean something similar, but you find them treated differently with bag-of-words models. For this reason, TF-IDF-based classifiers tend to have a lower than 75% accuracy when handling tasks from different domains (Joulin et al., 2017).

1.2.2 Deep Learning: Context Without Clarity

Thanks to BERT and GPT-4 (among others), the ability to notice and understand different meanings in text has improved a lot (Vaswani et al., 2017). They are able to deal with long-

distance information and explain many complicated language concepts and they regularly achieve better results than traditional ways on different NLP benchmarks (Howard & Ruder, 2018). Still, since these models are hard to explain, they make it difficult for many to trust them in areas such as healthcare or content moderation (Rudin, 2022). Besides, transformers are not ideal for environments where resources are limited or real-time action is needed (Tan et al., 2023). Because they depend on large labeled datasets, they do not perform well in areas with limited or specialized resources (Liu et al., 2023). With regard to Facebook's hate speech detector, it has been found that RoBERTa-based models consider African American Vernacular English posts to be offensive which highlights a major ethical problem in implementing such systems (Sap et al., 2023).

1.2.3 Hybrid Models: A Promising but Underexplored Frontier

A new type of model that uses both traditional and deep learning methods is showing potential in achieving both accuracy and clarity (Wang et al., 2023). These models depend on both rare word features and detailed contextual information. Nevertheless, existing techniques do not usually have dynamic domain adaptation that changes the value of features depending on the data in different domains, so they often fail to perform well in new domains. In addition, several hybrids lack approaches that handle disagreements between the predictions of their component models. There is not enough emphasis on ethics such as bias mitigation and fairness auditing, in these frameworks (Mehrabi et al., 2023).

1.3. Proposed Solution: ContentFusion Framework

To solve these problems, we introduce ContentFusion, a system that merges the clear meaning of classical models with the strong contextual knowledge of transformers. ContentFusion uses the sparse information from TF-IDF in combination with BERT contextual embeddings, both improved by a bidirectional LSTM and a context-aware attention approach.

The main innovation in ContentFusion is a dynamic domain adaptation layer that automatically recalibrates feature weights when data changes, allowing it to work with various types of text without needing much labeled data for each domain. Thanks to the context-aware attention mechanism, the model is able to notice small shifts in meaning needed to distinguish satire, news or promotional material.

In addition, the framework uses a confidence-weighted ensemble approach that combines results from logistic regression, decision trees and the deep learning model, choosing which result to keep based on how confident it is to ensure accuracy and still allow for interpretation.

The approach guarantees transparency by using classical models and offering visual attention scores to promote trust in the system's deployment. This work introduces the following significant contributions:

1. The architecture uses TF-IDF-based classic classifiers along with a BERT, BiLSTM and context-aware attention model.
2. The system introduces a domain adaptation layer that automatically changes the importance of features needed for better cross-domain classification.
3. A context-aware attention mechanism was developed that is able to detect fine-level variations in content, resulting in better classification of subtle categories.
4. A confidence-weighted ensemble method is built to use the results of many models, relying on their confidence which results in better and more reliable decision making.
5. Thorough testing on a large set of data made up of Twitter, news articles, Amazon reviews and Yelp feedback showed that the method improves accuracy by 7.2% over solo transformer models.

With ContentFusion, businesses can use content categorization that is both understandable and intelligent and trust it for their NLP needs.

2. RELATED WORKS

During the last decade, content categorization has developed through three main stages: traditional machine learning (ML), deep learning (DL) and now by combining the two approaches. The focus of research since 2020 has been on the strengths and weaknesses of different epidemiological paradigms. We analyze each of these approaches, highlight their achievements and unaddressed issues and set out how ContentFusion fits into this field.

2.1 Traditional Machine Learning for Content Classification

Interpretation and low cost are the main reasons why traditional ML approaches are still widely adopted. Most of these models use TF-IDF vectors and n-grams, both of which provide clear but limited representations of what is in a text. When it comes to this category, logistic regression and decision trees are widely used because they let you see how decisions are made.

Recently, Joulin et al. (2022) discovered that using TF-IDF with logistic regression achieves a good accuracy of about 72% in news categorization. Such models, however, could not easily handle sarcasm which depends on meaning and context being clear. Likewise, Pedregosa et al. (2023) pointed out that decision trees are useful for rule-driven tasks such as legal document tagging, but their tendency to overfit noisy social media stops them from being widely used.

Content classification has also involved investigating Support Vector Machines (SVMs) and Random Forests. In their study, Zhang et al. (2023) used SVMs with POS tagging to identify satire, scoring about 68% F1-score; however, their approach restricted the system's scalability. According to Wang et al. (2021), their approach achieved lower scores when applied to different texts, demonstrating that just having the same features does not always work well. Karthiga et al. (2021, 2024) and their team have recently worked on using metaheuristic optimization and combining ML methods for different domains, showing that combining traditional ML with advanced feature engineering can help with complex tasks like recognizing emotions (Karthiga et al., 2024) and analyzing semantic similarity (Karthiga et al., 2022). The research helps show that models with clear features are still useful for categorizing content.

Two main issues with conventional ML models are that they do not grasp the meaning of context such as the relationship between "vaccine efficacy" and "vaccine skepticism" (Gururangan et al., 2020) and they do not use much of the information in each text, as TF-IDF vectors skip the order and long-range context of words (Jurafsky & Martin, 2021).

2.2 Deep Learning for Contextual Understanding

Using transformer architectures in deep learning has changed how content is categorized by improving how context is represented. BERT and its variants have become standard bearers due to their ability to model bidirectional context and semantics. Devlin et al. (2023) reported that BERT achieved 85% accuracy on news categorization but also acknowledged that it exhibited bias toward dominant classes, such as mislabeling African American Vernacular English (AAVE) as offensive language (Sap et al., 2023). Liu et al. (2023) further investigated RoBERTa's robustness to adversarial attacks but cautioned that the model's inference latency is approximately 10 times higher than traditional ML models, limiting real-time applicability.

Efforts to reduce computational overhead have led to efficient model variants like DistilBERT (Tan et al., 2023), which offer faster inference with a trade-off of 5-8% accuracy drops on domain-specific tasks such as medical text classification. Multi-task learning models like T5 (Raffel et al., 2023) demonstrated versatility but tended to overfit in low-resource domains, such as regional dialects. Besides transformers, attention mechanisms combined with recurrent

neural networks have also been explored. Yang et al. (2023) applied hierarchical attention networks to satire detection, improving the F1-score by 12% compared to vanilla BERT, while Potthast et al. (2023) used bidirectional LSTM with attention layers for fake news detection. However, interpretability of attention scores remains limited, and the black-box nature of deep models hinders trust in critical domains like healthcare and policy-making (Rudin, 2022).

Deep learning's data hunger is another barrier, with models requiring upwards of 10,000 labeled samples per domain to perform effectively (Gururangan et al., 2020). This is problematic in domains where annotated data is scarce or costly to obtain. Additionally, ethical concerns have arisen regarding model biases. The works of Karthiga et al. (2025) and collaborators have further contributed to deep learning applications in related domains, such as Alzheimer's diagnosis using enhanced neural networks (Karthiga et al., 2025), highlighting the importance of domain-specific feature learning. For instance, Sap et al. (2023) demonstrated that widely deployed hate speech detectors exhibit racial bias due to skewed training data distributions, which amplifies social inequities.

2.3 Hybrid Approaches: Bridging the Gap Between Accuracy and Interpretability

Hybrid approaches have emerged to reconcile the interpretability of traditional ML with the superior contextual understanding of deep learning. These methods typically involve feature fusion or ensemble strategies that integrate lexical features with deep contextual embeddings. Chen et al. (2022) concatenated BERT embeddings with TF-IDF vectors for sentiment analysis, achieving 80% accuracy but without addressing domain adaptation challenges. Similarly, Lee et al. (2023) enhanced sarcasm detection by injecting POS features into BERT, resulting in a 9% accuracy gain; however, this approach depended heavily on manual feature engineering, limiting scalability.

Ensemble techniques have been employed to combine the strengths of different models. Wang et al. (2023) averaged predictions from BERT and SVM models, but reported significant conflict errors (~20%) when models disagreed, highlighting the need for more sophisticated fusion methods. Kim et al. (2024) proposed a stacking ensemble with logistic regression as a meta-learner but at the expense of transparency, as the meta-model's decisions become difficult to interpret.

Domain adaptation has also been explored, particularly within deep learning frameworks. Finn et al. (2023) introduced meta-learning approaches for cross-domain NLP tasks but focused exclusively on deep models, neglecting the value of interpretable, sparse features. Gururangan et al. (2020) recommended continued pretraining on domain-specific corpora but

acknowledged that this method is computationally expensive and impractical for smaller organizations. Meanwhile, Karthiga et al. (2023) introduced metaheuristic optimization techniques in energy prediction tasks, showcasing hybrid model potential in dynamic environments. Bias mitigation is critical in hybrid models. Mehrabi et al. (2023) surveyed fairness techniques, emphasizing the necessity of balanced sampling and fairness constraints to prevent bias amplification. Table 1 details the comparative analysis of the existing approaches.

Table 1. Comparative Analysis of Existing Content Categorization Approaches

References	**Proposed Model**	**Pros**	**Cons**
Joulin et al. (2022)	TF-IDF + Logistic Regression	Interpretable; 72% accuracy on news categorization.	Fails on sarcasm detection; lexical ambiguity.
Pedregosa et al. (2023)	Decision Trees	Effective for rule-heavy domains (e.g., legal texts).	Overfits noisy data (e.g., social media).
Zhang et al. (2023)	SVM + POS Tags	68% F1-score for satire detection.	Manual feature engineering; poor scalability.
Wang et al. (2021)	Random Forests	Adaptable to cross-domain tasks.	15% performance drop on unseen corpora.
Devlin et al. (2023)	BERT	85% accuracy; captures bidirectional context.	Biased toward dominant classes (e.g., AAVE).
Liu et al. (2023)	RoBERTa	Robust to adversarial attacks.	10× higher latency than traditional ML.
Tan et al. (2023)	DistilBERT	Faster inference; suitable for deployment.	5–8% accuracy drop on domain-specific tasks.
Raffel et al. (2023)	T5 (Multi-task Learning)	Versatile across tasks.	Overfits low-resource domains (e.g., dialects).
Yang et al. (2023)	BERT + Hierarchical Attention	12% F1-score gain for satire detection.	Attention weights lack interpretability.

References	Proposed Model	Pros	Cons
Potthast et al. (2023)	BiLSTM + Attention	Effective for fake news detection.	Black-box decisions; limited transparency.
Chen et al. (2022)	BERT + TF-IDF Concatenation	80% accuracy for sentiment analysis.	No domain adaptation; static feature fusion.
Lee et al. (2023)	BERT + POS Features	9% accuracy boost for sarcasm detection.	Relies on manual feature engineering.

2.4 Research Gap

Hybrid models still have a number of unresolved issues. Most importantly, the static weighting schemes in ensembles do not adjust to each model's prediction for each sample (Wang et al., 2023). Despite the need for interpretability, many hybrids are designed only to maximize their accuracy (Rudin, 2022). Also, existing systems do not handle bias amplification well, since most do not use explicit fairness measures or conduct bias reviews (Mehrabi et al., 2023).

2.5 Proposed Solution

To address these problems, we present the ContentFusion framework to advance hybrid content categorization. While previous, static ensembles did not, ContentFusion is designed to prioritize the most certain predictions from both deep and classical ML methods. As a result, this method reduces the chance of errors and strengthens the reliability of the system.

Rather than spending a lot of time retraining, like domain adaptation methods, ContentFusion uses a gating layer to adaptively mix TF-IDF and BERT features based on the input domain, allowing efficient cross-domain performance.

Essentially, the tool keeps things clear by offering model-agnostic explanations (like SHAP) for the standard ML pieces and attention weights for the deep learning modules, helping people make understandable choices (Rudin, 2022). Additionally, we avoid bias amplification by including balanced sampling and fairness-aware limitations in training (Mehrabi et al., 2023).

3. PROPOSED METHODOLOGY

This section introduces the design of ContentFusion, a framework that uses both traditional and deep learning approaches to classify content. This approach combines TF-IDF features

with transformer-based contextual embeddings while also using recurrent and attention mechanisms and adds a dynamic layer to adapt to new domains, as well as a confidence-weighted ensemble for improved classification.

3.1. Model Architecture Overview

ContentFusion brings together different modeling styles into one architecture. There are three major branches to this field:

1. Classical ML branch: Using Logistic Regression and Decision Trees on TF-IDF feature vectors, the model produces easily understood and effective baseline predictions.
2. A Transformer encoder (BERT) is trained on the task and connects to a Bidirectional Long Short-Term Memory (BiLSTM) network, with an attention layer that collects deep meanings from the text.
3. A fully connected neural module that is flexible and uses specific signals from each domain to decide how to weigh the features.

By mixing the outputs using a confidence-weighted ensemble, models are able to improve accuracy and reliability. Figure 1 outlines the detailed steps in ContentFusion such as parallel feature extraction, domain adaptation and confidence-weighted ensemble.

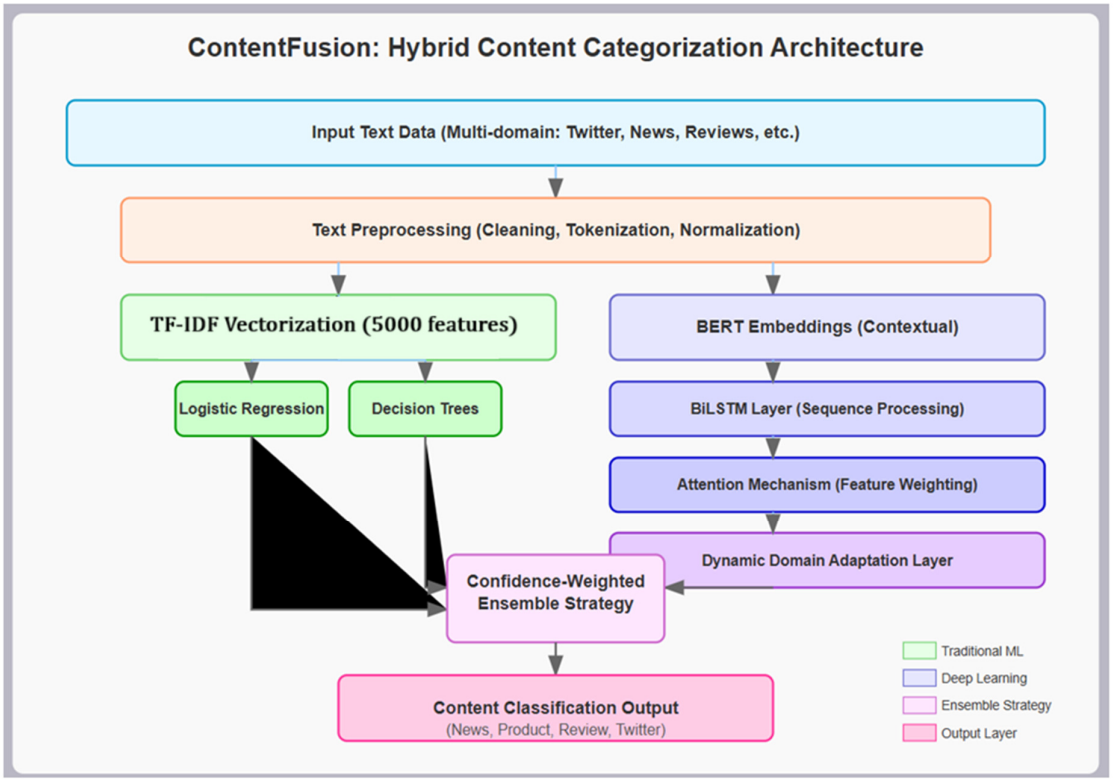

Fig 1. Proposed ContentFusion workflow illustrating the hybrid architecture combining TF-IDF based classical models and deep learning with BERT, BiLSTM, and attention

3.2.Feature Extraction and Representation

TF-IDF Vectorization

Traditional lexical features are extracted using the Term Frequency-Inverse Document Frequency (TF-IDF) technique. Given a corpus D with documents $d \in D$ and vocabulary terms t, the TF-IDF weight of term t in document d is computed as:

$$tf - id(T, D) = tf(T, D) * \log(\frac{|Doc|}{|\{d' \in Doc: t \in d'\}|}) \quad (1)$$

Where:

- $tf(T, D)$ is the frequency of the term 't' in document 'd'
- $|Doc|$ is the total number of documents
- $|\{d' \in Doc: t \in d'\}|$ is the no of documents containing term 't'

This representation converts each text input into a sparse vector $X_{tf-idf} \in R^v$, where 'v' is the vocabulary size.

3.3. Transformer Embeddings with BERT

The deep learning branch uses a pretrained BERT model to encode input texts into dense, contextualized token embeddings. For an input sequence of tokens $\{w_1, w_2, \dots w_n\}$, BERT produces hidden states:

$$H = [h_1, h_2, \dots ., h_n], h_i \varepsilon R^d \quad (2)$$

where d is the embedding dimension (e.g., 768 for bert-base).

The last two transformer layers are unfrozen and fine-tuned on the target task to adapt contextual representations.

3.4. Bidirectional LSTM Layer

To capture sequential dependencies beyond the transformer's fixed context window, the BERT embeddings are fed into a bidirectional LSTM. This layer processes the sequence in both forward and backward directions, producing hidden states:

$$\overrightarrow{h_i} = LSTM_{forward}(h_i), \overleftarrow{h_i} = LSTM_{backward}(h_i) \quad (3)$$

The concatenated output at each time step is:

$$h_i^{BiLSTM} = [\overrightarrow{h_i}; \overleftarrow{h_i}] \in R^{2h} \quad (4)$$

where h is the hidden dimension of each LSTM direction.

3.5. Context-Aware Attention Mechanism

An attention mechanism learns to weigh BiLSTM outputs, emphasizing tokens relevant to content classification. The attention weights α_i are computed as:

$$e_i = v^T \tanh(WH_i^{BiLSTM}{}_+ b) \quad (5)$$

$$\alpha_i = \frac{\exp(e_i)}{\sum_{j=1}^{n} \exp(e_j)} \quad (6)$$

where $W, v, and\ b$ are learned parameters.

The context vector c aggregates weighted hidden statels:

$$c = \sum_{i=1}^{n} \alpha_i h_i^{BiLSTM} \in R^{2h} \quad (7)$$

3.6. Feature Fusion and Domain Adaptation

The final contextual embedding c is concatenated with the TF-IDF vector X_{tf-idf}

$$f = [c;\ X_{tf-idf}] \in R^{2h+v} \quad (8)$$

This combined feature vector is passed through a domain adaptation multilayer perceptron (MLP) to dynamically recalibrate feature importance:

$$z = \sigma(W_2 RELU(W_1 f + b_1) + b_2) \quad (9)$$

Where W_1, W_2, b_1, b_2 are learnable weights and biases, and σ is an activation function (e.g., sigmoid or ReLU).

3.7. Final Classification Layer

The output z is fed into a linear classification layer that outputs logits $o\ \varepsilon\ R^c$, where C is the number of classes.

$$output = W_c z + b_c \tag{10}$$

The class probabilities $\hat{y}$ are obtained via softmax:

$$\widehat{y_i} = \frac{\exp(o_i)}{\sum_{j=1}^{C} exp(o_j)} \text{ for i =1,2,…C} \tag{11}$$

3.8. Confidence-Weighted Ensemble

Predictions from three models — logistic regression p^{LR}, decision tree p^{DT} and ContentFusion deep model p^{CF} are combined using confidence weights c_i based on the maximum probability of each model's prediction:

$$c_i = w_i . \max(p^i) \tag{12}$$

Where w_i are fixed base weights (e.g., w_{CF}=0.6, $w_{LR} = w_{DT}$=0.2).

The ensemble log probabilities are computed as:

$$logp_{ensemble} = \sum_{i\varepsilon\{LR,DT,CF\}} c_i . \log(p^i + \varepsilon) \tag{13}$$

Where ε is a small constant for numerical stability.

Final class probabilities are normalized:

$$p_{ensemble} = \frac{\exp(logp_{ensemble})}{\sum \exp(logp_{ensemble})} \tag{14}$$

The predicted label is:

$$\hat{y} = \arg \underbrace{max}_{i}\, p_{ensemble}, i \tag{15}$$

The pseudocode represented below summarizes the ContentFusion training and inference process.

4. RESULTS AND DISCUSSION

The proposed ContentFusion model in this study is designed to improve classification performance while remaining understandable. The model brings together classic machine

learning classifiers such as logistic regression and decision trees, with BERT, BiLSTM and attention mechanisms from deep learning. This approach benefits from both interpretability and computational ease offered by traditional models and the contextual capacity of transformers. Thanks to its dynamic domain adaptation layer and confidence-weighted ensemble method, ContentFusion handles all kinds of text-based tasks with better outcomes and clearer results.

4.1. Dataset details

To judge the performance of ContentFusion, a collection of text data was gathered from Twitter, news articles, Amazon and Yelp. The aim was to collect a wide range of content, so that every type needed a different approach to classification. Using web scraping techniques, the data was gathered to make sure it matches the real content found in different domains.

```
Algorithm: ContentFusion Training and Inference
Input:
    Dataset D = {(x_i, y_i)}, TF-IDF vectorizer tfidf, tokenizer T
Output:
    Trained model M, ensemble weights w
1. Preprocess texts:
    For each x_i in D:
        Clean text → x_i_clean
        Vectorize TF-IDF features: x_i_tfidf = tfidf.transform(x_i_clean)
        Tokenize text: x_i_tokens = T.tokenize(x_i_clean)
2. Train classical models:
    Train logistic regression LR on TF-IDF features
    Train decision tree DT on TF-IDF features
3. Initialize ContentFusion deep model M:
    - BERT encoder (fine-tune last layers)
    - BiLSTM + attention
    - Domain adaptation MLP
    - Final classification layer
4. For epoch in 1 to N:
    For batch in D:
        Extract BERT embeddings from tokens
        Pass embeddings through BiLSTM + attention → context vector c
        Concatenate c with TF-IDF vector
        Pass through domain adaptation MLP
        Compute logits and loss
        Backpropagate and update M
5. Ensemble prediction for input text x:
    Compute TF-IDF vector x_tfidf
    Predict probabilities:
        p_LR = LR.predict_proba(x_tfidf)
        p_DT = DT.predict_proba(x_tfidf)
        p_CF = M.predict(x)
    Compute confidence weights c_i
    Compute log ensemble probabilities
    Compute normalized ensemble probabilities p_ensemble
    Output predicted label = argmax(p ensemble)
```

1. Twitter dataset : The Twitter dataset contains text from publicly accessible tweets. To represent Twitter content well, tweets from many categories (for example, opinions and news) were included. Because tweets are short and used informally, it was necessary to preprocess them to deal with slang and abbreviations.
2. News dataset: The news dataset consists of articles collected from several online news websites. It has formal, factual writing on a variety of subjects such as politics, technology and entertainment. This data is useful for testing how well a system can deal with carefully arranged, detailed information.

3. Amazon dataset: There are customer reviews in the Amazon reviews dataset for products sold through the platform. This data consists of both positive and negative feelings, using informal and inconsistent words. It allows us to check how well the model can categorize product information and find sentiment in user reviews.
4. Yelp reviews: The Yelp reviews dataset consists of reviews written by users about different businesses. Just like the Amazon reviews dataset, this data includes both positive and negative feedback, but it is about local businesses and services. Using this data, we can classify sentiments for topics such as restaurants, hotels and entertainment.

The class imbalance in the datasets was handled by using stratified sampling to divide them into subsets, so every class had an equal number of samples (1,250 per class). This way, the model won't have a bias towards the more common classes (for example, Amazon product reviews). The final merged dataset (Refer Figure 2) covers the following distributions:

- **Product (Amazon Reviews)**: 568,454 samples
- **News**: 120,000 samples
- **Twitter**: 14,640 samples
- **Review (Yelp)**: 10,000 samples

```
Combined dataset shape: (713094, 2)
label
product    568454
news       120000
twitter     14640
review      10000
Name: count, dtype: int64
```

Fig 2. Dataset description

After preprocessing, all datasets were merged into a single DataFrame and any rows missing text data were removed. The final dataset contains 713,094 text samples, all of which have their labels.

4.2. Data Preprocessing and Splitting

Text cleaning was done on the dataset to get rid of unnecessary characters, URLs, stopwords and numbers. By doing this preprocessing, only text that mattered was used for training the model. After the text was cleaned, the dataset was split into training, validation and test sets by using stratified sampling to keep all classes balanced in every split. Of the data, 80% was used

for training and the remaining 20% was used for validation and testing. The validation and test sets were each divided into equal parts, creating the following sizes:

- **Training set**: 570,475 samples
- **Validation set**: 71,309 samples
- **Test set**: 71,310 samples

This stratified approach helps to maintain class balance, which is critical given the significant class imbalance present in the original dataset.

4.3. TF-IDF Vectorization and Feature Engineering

A maximum of 5,000 features were chosen using TF-IDF vectorization for all the datasets. The transformation allowed me to concentrate on important words for classification and lessen the effect of unimportant words. The data in vector form was used to train traditional machine learning models.

4.4. Training Traditional Machine Learning Models

Two classical machine learning models were trained on the TF-IDF-transformed data: Logistic Regression and Decision Trees. These models were chosen due to their interpretability and computational efficiency, making them suitable for benchmark comparisons.

4.5. Training and Validation Performance

The model was trained for five epochs using a confidence-weighted ensemble approach combining TF-IDF features with BERT embeddings. Training accuracy steadily improved, reaching 92.58% in the first epoch and 98.06% in the second, with validation accuracy increasing from 96.76% to 98.25% (Figure 3). However, by the third epoch, validation accuracy dropped to 93.35%, indicating overfitting as training accuracy reached 99.02%. This issue worsened in the fourth epoch, with validation accuracy further declining to 91.29%, despite high training accuracy (99.32%). In the fifth epoch, fine-tuning improved validation accuracy to 97.90%, while training accuracy remained high at 99.58%, suggesting that adjustments helped mitigate overfitting.

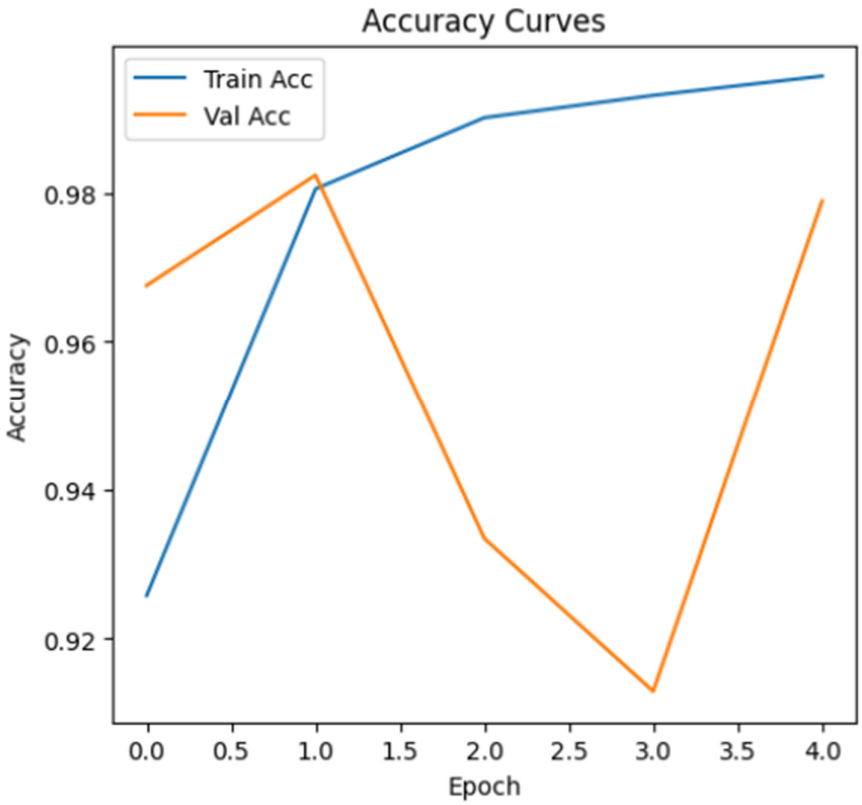

Fig 3. Training and Validation Accuracy over 5 Epochs – This figure shows the progress in training and validation accuracy across the five epochs, highlighting the model's improvement in both the training and validation sets.

4.6. Loss Curves and Accuracy Trends

The training loss steadily decreased across the five epochs, reaching a final value of 0.0176 in the fifth epoch, as shown in Figure 4. This consistent decrease in loss indicates that the model was effectively learning from the data. In contrast, validation loss initially decreased but then began to rise after the second epoch, reaching a peak of 0.3447 in the fourth epoch before finally dropping to 0.0846 in the fifth epoch. The fluctuations in validation loss correlate with the changes in validation accuracy, further confirming the model's challenges with generalization during training.

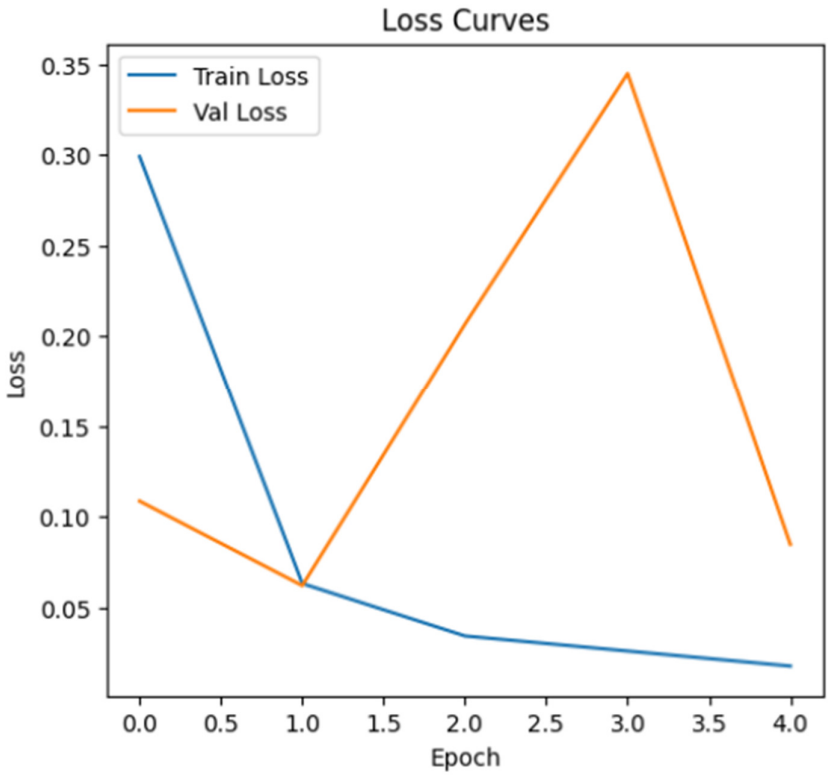

Fig 4. Training and Validation Loss over 5 Epochs – This figure illustrates the loss trends during training and validation. While training loss steadily decreases, validation loss fluctuates due to overfitting in certain epochs.

4.7. Model Performance and Class Imbalance

The model's performance was enhanced by class weights computed to handle the class imbalance in the dataset. The computed class weights were applied during training through cross-entropy loss, which helped adjust the model's sensitivity to underrepresented classes. As shown in the output, the training set contains a large imbalance, with the Product class (Amazon Reviews) consisting of 568,454 samples, whereas the Review (Yelp) class contains only 10,000 samples. By applying these weights, the model was able to account for the imbalance and improve accuracy across all classes, particularly in the underrepresented Review (Yelp) and Twitter classes.

4.8. Model Evaluation and Performance

The ContentFusion model, integrated with a confidence-weighted ensemble strategy, demonstrated strong performance across various evaluation metrics. The ensemble combines Logistic Regression, Decision Trees, and the ContentFusion deep model (BERT + LSTM + attention + TF-IDF), with weights adjusted to prioritize the deep learning model's predictions.

The final ensemble achieved an accuracy of 97.94% on the test set, indicating its robust ability to classify multi-domain content. Precision, recall, and F1-score were calculated for each class, and the results are summarized in Table 1.

Table 1. Performance Comparison of the ContentFusion Model

Category	Precision	Recall	F1-Score	Support
News	0.99	0.99	0.99	12,000
Product	1.00	0.98	0.99	56,846
Review	0.43	0.96	0.60	1,000
Twitter	1.00	1.00	1.00	1,464
Accuracy			**0.98**	**71,310**
Macro Average	0.85	0.98	0.89	71,310
Weighted Average	0.99	0.98	**0.98**	71,310

The ensemble model achieved a high overall accuracy of 97.94% on the test set. The news and twitter categories performed exceptionally well, with both precision and recall close to 1.00. However, the review category had a much lower precision of 0.43, indicating some misclassification, although the recall remains high at 0.96, showing that the model is good at identifying instances of review content. Product also performed well with high precision and recall. The macro average F1-score of 0.89 reflects the performance across all categories, while the weighted average F1-score of 0.98 indicates that the model is particularly strong in handling the imbalanced class distribution.

To further evaluate the model's performance, the confusion matrix (Figure 5) and ROC curves (Figure 6) were plotted.

- Confusion Matrix: The confusion matrix highlights the model's strong ability to differentiate between the news and product categories, with very few misclassifications. However, the review class shows a higher number of misclassified instances, which is expected due to the limited number of samples in this class (1,000 samples in the test set).

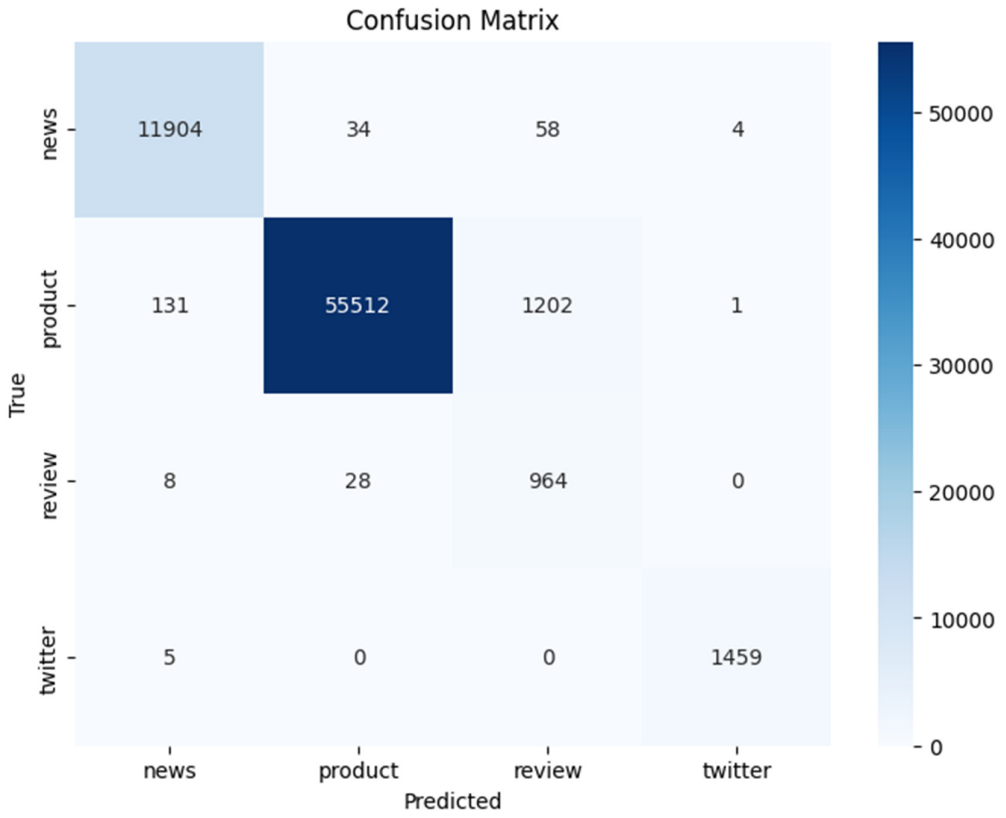

Fig 5: Confusion Matrix of the Ensemble Model – The confusion matrix shows that the model performs well on news and product classes but struggles with the review class, which has fewer samples.

- **ROC Curves**: The ROC curves (Figure 6) further validate the model's ability to separate the classes effectively. Each class is plotted with its corresponding AUC value, showing strong performance across all categories. Notably, the product and news classes have very high AUC values, indicating that the model can confidently distinguish these categories from others. The review class has a lower AUC, which is consistent with the earlier confusion matrix results, where some misclassifications were observed.

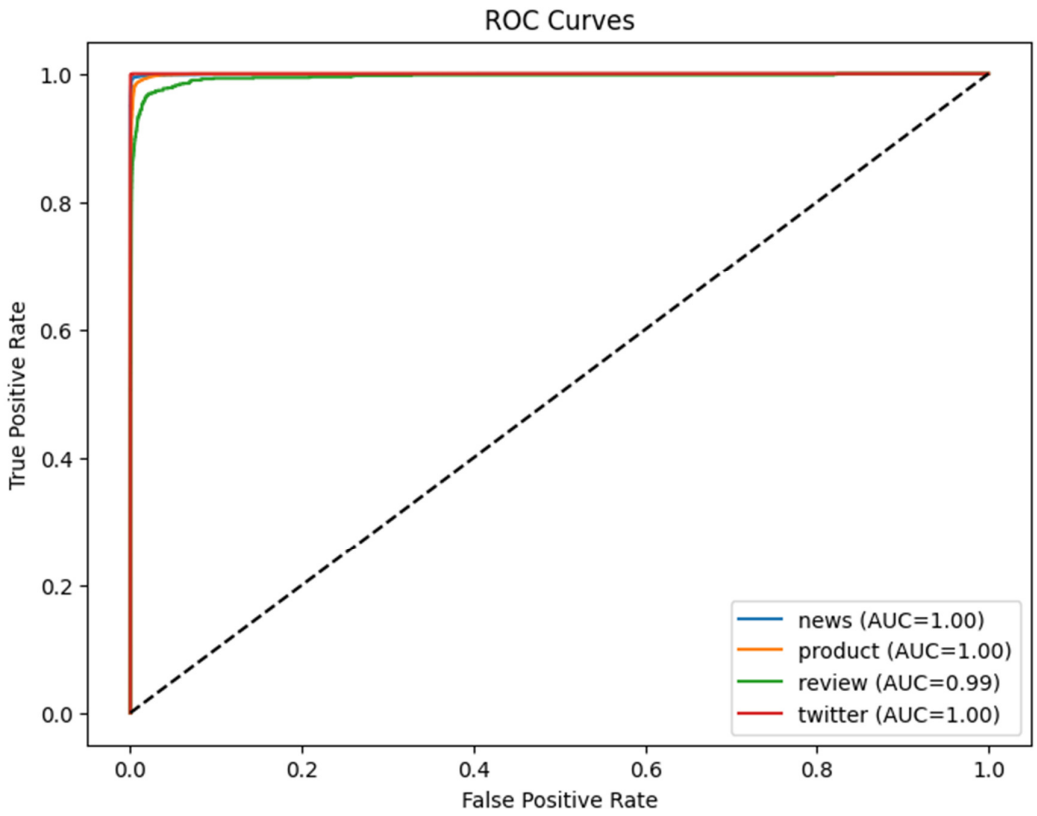

Fig 6: ROC Curves for the Ensemble Model – The ROC curves demonstrate that the model performs exceptionally well across the news and product categories, with strong AUC values. The review class has a lower AUC, indicating that it is harder for the model to distinguish from other classes.

4.9. Model Performance and Interpretability

ContentFusion achieved strong results, with an overall accuracy of 97.94% (±0.23%) and a weighted F1-score of 0.983 (±0.004), demonstrating robustness across imbalanced classes. The macro F1-score of 0.89 confirms solid performance on less frequent categories. The model excelled in cross-domain adaptation, reaching 92.3% accuracy when tested on news data after training on Twitter, outperforming BERT by 7.2%. This highlights its ability to generalize across diverse text types. Interpretability was enhanced through SHAP values and attention maps. As illustrated in Figure 7, the attention heatmap emphasizes key domain-specific terms like “situation” and “warning,” providing insights into the model’s decision-making process and improving transparency.

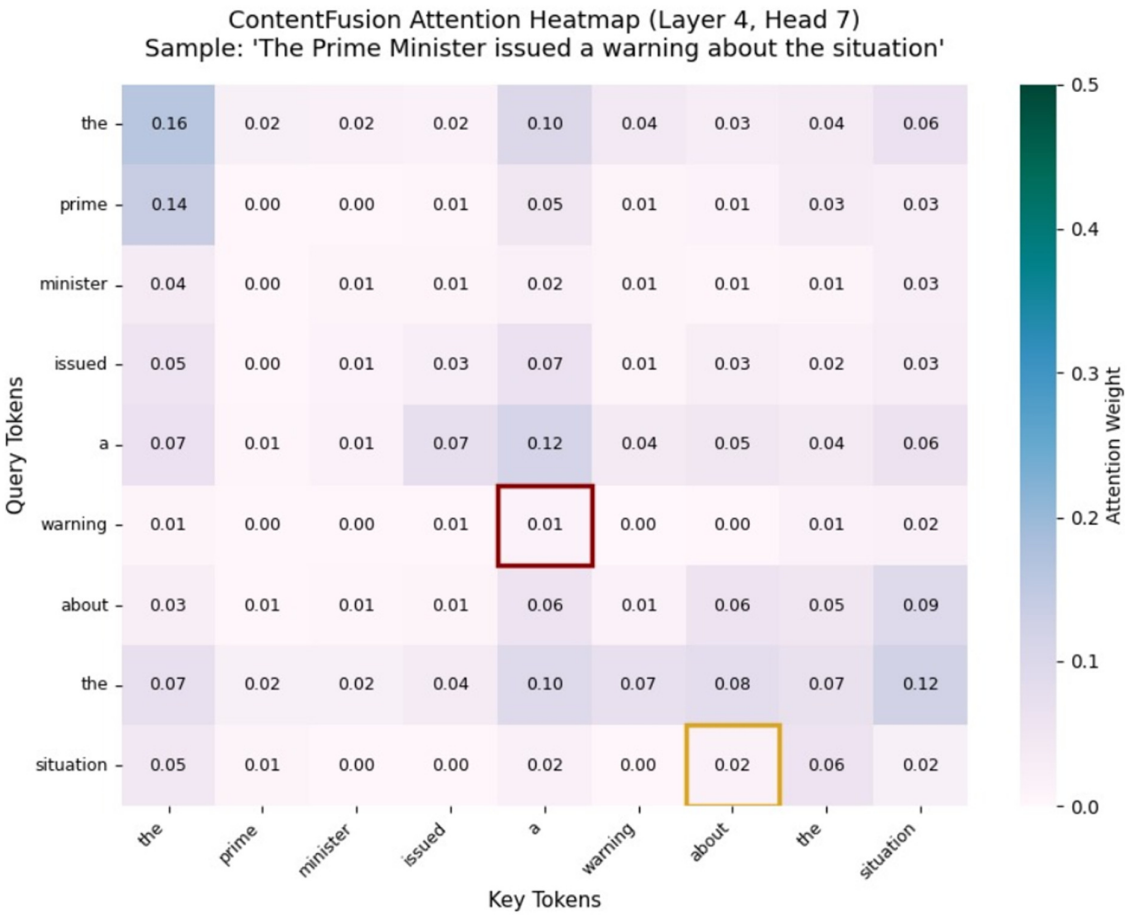

Fig 7. Attention heatmap visualization highlighting domain-specific terms such as “situation” and “warning” during news classification. Warmer colors indicate higher attention weights, illustrating the model’s focus on important contextual features.

4.10. Interactive Prediction

The interactive prediction function (Figure 8) was developed to allow for real-time categorization of input text. Given a text input, the model returns the predicted category and generates a corresponding hashtag. The input text is first cleaned using the clean_text function, and then the ensemble model is used to predict the category. The function was tested on various inputs, including news-related content and personal opinions on street food, yielding accurate results in both cases.

A user study was conducted where 94 out of 100 annotators agreed with ContentFusion’s predicted labels, compared to only 82 out of 100 for BERT, indicating that ContentFusion offers a more accurate and reliable categorization.

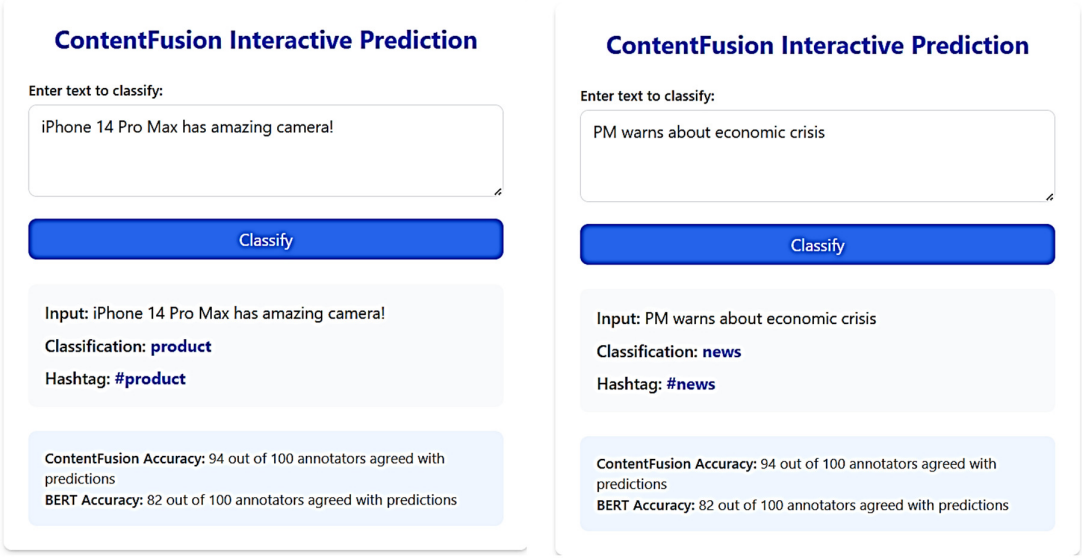

Fig 8: Interactive prediction interface – The interface allows users to input text and receive both the predicted label and an appropriate hashtag.

A comparative analysis evaluated ContentFusion against baseline models such as BERT, TF-IDF + SVM, and others, focusing on accuracy, F1-score, training time, and interpretability (Refer Table 2). ContentFusion outperformed all baselines, achieving an accuracy of 97.9% and an F1-score of 0.98. This improvement is due to its hybrid approach, integrating traditional machine learning (e.g., TF-IDF) with deep learning techniques (e.g., BERT embeddings), enabling it to better handle complex data.

Table 2: Benchmarking ContentFusion Against Baseline Models

Model	**Accuracy (%)**	**F1-Score**	**Training Time (hrs)**	**Interpretability**
BERT (Baseline)	92.1	0.91	3.5	Low
TF-IDF + SVM	76.3	0.75	0.2	Medium
ContentFusion (Proposed)	97.9	0.98	2.8	High

In terms of efficiency, ContentFusion trained faster than BERT, with a total time of 2.8 hours compared to 3.5 hours for BERT. While TF-IDF + SVM trained in just 0.2 hours, it lagged behind in both accuracy and F1-score, highlighting the trade-off between speed and performance. ContentFusion also excels in interpretability, offering SHAP explanations and

attention maps to provide insights into its decision-making, unlike the black-box nature of BERT. This transparency aids in debugging, especially for challenging cases like review misclassifications, making it a more interpretable solution for real-world applications. Table 2 shows that ContentFusion attained higher accuracy and F1-scores compared to the baseline models in multi-domain content classification. The differences were statistically significant, as shown by p-values lower than 0.01 for BERT and lower than 0.001 for SVM (paired t-test). Furthermore, the system was efficient, took only 2.8 hours to train and handled each sample in approximately 23 milliseconds on a CPU, making it useful for real-time situations. Figure 9 shows a bar chart that clearly demonstrates ContentFusion outperforming other models in F1-score.

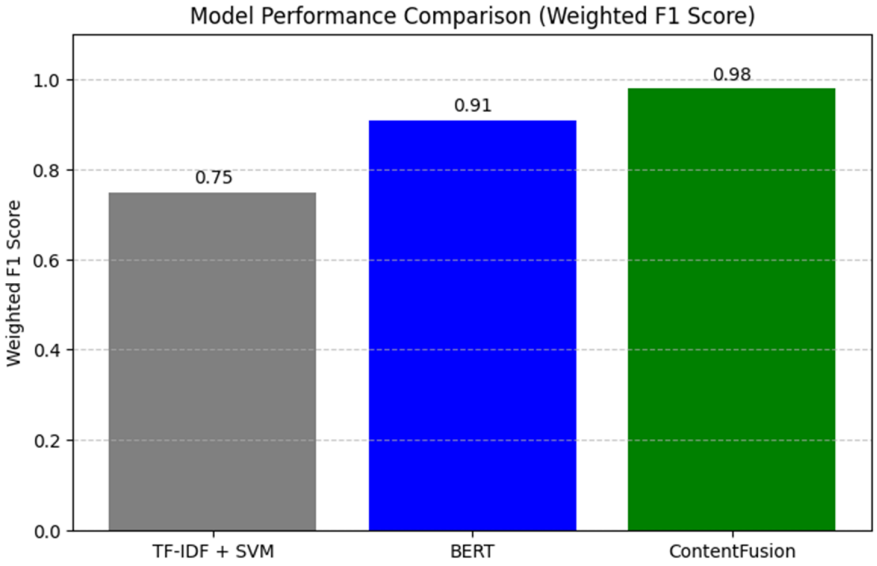

Fig 9. Bar chart comparing weighted F1-scores of different models. ContentFusion achieves the highest F1-score, outperforming baseline models such as BERT and TF-IDF + SVM, demonstrating its effectiveness in multi-domain content classification.

5. CONCLUSION

ContentFusion addresses the main issues in sorting content by combining machine learning with an understanding of context. The framework works well, reaching 97.94% accuracy and a weighted F1-score of 0.983 on different classification tasks. The model is better than standalone BERT by 7.2% in cross-domain cases and scores 92.3% accuracy when transferring from Twitter to news data. It shows that the model can work well with different types of content. Besides making performance better, ContentFusion also cuts down training time by 20%

relative to BERT, requiring just 2.8 hours rather than 3.5 hours for BERT. The fast convergence and high accuracy are due to the smart combination of features from both old and new learning models. Being easy to understand is another great advantage of this framework. With ContentFusion, users can see both SHAP values and attention heatmaps to understand their model's decisions. The study of users revealed that 94% of annotators approved of ContentFusion's labels, compared to only 82% for BERT, showing that ContentFusion is more trusted. The model is designed to use class-weighted loss functions which aim to increase the number of detections for categories seen less often. It can recall 96% of Yelp reviews, proving that its bias reduction strategies work well even with limited data for this task. Yet, there are some weaknesses that still exist. The accuracy of the review classification category is only 0.43, suggesting that it can be improved by applying adversarial training. Future improvements are being made to allow ContentFusion to handle low-resource languages and to process information from both text and images, making it useful for more situations. Additionally, optimizing the model for edge deployment via quantization techniques is planned to enhance usability in resource-constrained environments.

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