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Hybrid Deep Learning and Fuzzy-Based Domain Adaptation for Multilingual Sentiment Analysis of Twitter Data

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Abstract: ***Background:*** *With the rapid rise of social media platforms like Twitter, the need for accurate sentiment analysis across multiple languages has become critical. However, traditional sentiment analysis methods are limited by linguistic variability, cultural nuances, and contextual ambiguity inherent in multilingual data. These challenges are further compounded by sarcasm, slang, and code-mixed expressions that are common in real-time social interactions.* ***Aim:*** *The primary objective of this study is to develop a hybrid deep learning and fuzzy-based domain adaptation model that can enhance multilingual sentiment analysis on Twitter data. This model aims to improve classification accuracy, contextual understanding, and adaptability across diverse languages and domains.* ***Methods:*** *The methodology integrates transformer-based contextual embeddings (mBERT and XLNet) with Convolutional Neural Networks (CNNs), BiLSTM layers, and a fuzzy inference system for adaptive sentiment reasoning. A multilingual Twitter dataset comprising 20,000 manually annotated tweets in English, Hindi, Tamil, and Bengali was used. The model was trained using Adam optimization and evaluated through accuracy, precision, recall, and F1 scores under both intra-domain and cross-domain conditions.* ***Results:*** *The proposed hybrid model achieved an average accuracy of 86.7%, outperforming traditional classifiers and standard transformer models. The fuzzy logic mechanism improved interpretability and reduced misclassification in ambiguous cases, especially where mixed emotions or sarcasm were present.* ***Conclusion:*** *The study contributes an innovative framework that bridges deep learning with fuzzy reasoning for more reliable multilingual sentiment analysis. Its ability to adapt to domain shifts and linguistic diversity makes it suitable for real-world applications in marketing, public policy, and social media analytics.*

Keywords: Multilingual Sentiment Analysis, Deep Learning, Fuzzy Logic, Domain Adaptation, Twitter Data, Natural Language Processing (NLP), Hybrid Models

I. INTRODUCTION

The increasing popularity of social media networks particularly twitter has transformed the world in the way individuals interact and voice their opinion. Twitter has been turned into a valuable source of real-time sentiment data that can be exploited to comprehend the opinion of people, forecast trends, and make decisions in many aspects of human endeavors, including politics, business, and healthcare with millions of multilingual users actively posting content on the platform [1,2]. Nonetheless, the sheer variety of languages and cultural backgrounds contained within Twitter data poses a major problem with realization of sentiment analysis, especially in multilingual settings. The classical sentiment analysis approaches even though helpful in monolanguage situation are usually poor in language heterogeneity and domain shifts, which precludes their scalability and precision [3]. The sentiment polarity and contextual meaning may significantly vary

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between languages, and the traditional machine learning models will not be able to generalize across language and domains. Also, there is linguistic complexity like sarcasm, slang, code-switching, and informal speech patterns that are associated with social media thus adding more levels of complexity [4,5,6].

Recent developments in deep learning, in response to these types of challenges, have demonstrated potential positive contributions in solving natural language processing problems, such as sentiment analysis [7,8]. Convolutional Neural Networks(CNNs), Long Short-Term Memory (LSTM) networks and transformer based based-networks have all been extensively used as deep learning architectures to learn semantic and contextual patterns across languages [9,10,11]. However, applied to multiple language data sets without appropriate domain adaptation schemes, these models tend to experience low accuracy through the naturally varying structure of language, expression of sentiment and distribution of data [12]. As a solution to this discrepancy, domain adaptation methods have been proposed as an essential approach to knowledge transfer between one language or domain to another, to make the model adapt to new and rarely encountered linguistic settings. Nevertheless, the interpretability and uncertainty management needed to make fine-tuned judgments of sentiment have not always provided the same interpretability the pure deep learning methods offer in the real world [13,14].

This study will introduce a new hybridization of deep learning and fuzzy logic, using multilingual sentiment analysis of Twitter data, and domain adaptation using fuzzy learning to achieve greater model strength and generalization. This paper seeks to propose an adaptable and intelligent system of dealing with uncertainty and ambiguity that are created by multilingual sentence expressions of sentiment by incorporating the fuzzy logic with deep learning architectures. Fuzzy logic is a mathematical representation that can be used in dealing with vague and imprecise information and as such, it is applicable in text data of the real world as sentiment may consistently fall within a spectrum and not necessarily be within definite sections. The hybrid model, therefore, allows a more human-like system of reasoning which has the capacity to identify the different levels of sentiment polarity in different languages. The framework, whose core is domain adaptation, is created to be able to transfer learning across languages and is therefore expected to work even effectively in low-resource scenarios or when dealing with new domains. Besides offering a technically novel model to multilingual sentiment analysis, this interdisciplinary study also offers practical implications to the industry and policymakers to leverage the power of social media analytics to understand the real time.

II. LITERATURE REVIEW

Sentiment analysis has become a useful instrument to appreciate the general opinion in social media sites such as Twitter, as the amount of user-generated content is increasing, which allows one to gain insights on topics such as consumer behavior, politics, and even the health of the population. In addition to presenting considerable challenges concerning linguistic diversity and variability of domain, this rich and unstructured data has had the potential of creating opportunities in artificial intelligence, decision-making systems, and fuzzy logic research. Pioneer research on this field has mainly concentrated on sentiment analysis as a text mining tool through a linguistic, statistical, or machine learning method. Nonetheless, the recent improvements indicate that deep learning, fuzzy logic, and group decision-making based frameworks are becoming increasingly integrated to make the sentiment classification models more robust and flexible.

Morente-Molinera et al. (2018) put forward the original idea of integrating sentiment analysis and group decision-making processes in social networks and emphasize the role that social media conversations can be examined using collaborative and consensus-based approaches. Their method showed that sentiment analysis enriched with collective decision-making methods can be used to make more accurate interpretations of collective opinions posted online, especially when comparative and opinionated words are used in the discussion. This was construed in a follow-up research in which the same researchers combined sentiment analysis with consensual decision making in the context of social networks, but interested in comparative expressions to come up with more refined findings in group judgments [15]. These studies emphasize the need to have context-sensitive systems that transcend binary sentiment classification.

Simultaneously, the significance of trust propagation and opinion dynamics has been cited as one of the most important elements shaping the development of sentiments and their distribution in socio-networks. Ureña et al. (2019) provided

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an in-depth review of the topic of trust dissemination in social networks, emphasizing the interrelation between spreading sentiment and social influence, credibility, and social networks of the user. Their contribution highlighted that there was a need to have a sentiment analysis model that considers both language and relationship elements in networks, particularly during decision-making processes [16,17].

Chang (2016, 2017) suggested developments in social computing platforms by adopting cybernetic social cloud and social network analysis platform on big data analytics. These papers were based on the development of scalable models that can work with large volumes of social data, such as sentiment analysis, user profiling, and interaction mapping. Using system dynamics and cybernetics, Chang theorized on a futuristic architecture, which analyzes and predicts social behavior using intelligent cloud-based model, with a particular focus on the integration of these platforms with sentiment analysis to make predictions on a large scale in society [18,19].

Traditional sentiment classification models have flourished on the methodological front, including the simplest of machine learning algorithms and state of the art ensemble and n-gram based classifiers. The survey given by Medhat et al. (2014) represents a seminal survey on sentiment analysis algorithms and applications, explaining how supervised machine learning, lexicon-based systems, and hybrid systems found their way into different applications. Although these methods have proved to be effective in particular settings, they tend to be inflexible to ambiguous and noisy information that is presented on social sites [20].

More enhancement on the classification of sentiments was achieved by Catal and Nangir (2017), who proposed a model of sentiment classification on the use of multiple classifiers to enhance accuracy through ensemble learning. The classification of sentiment review based on n-gram and machine learning method was also selected by Tripathy et al. (2016), which demonstrates the ability of higher-order language models to predict contextual dependencies [21,22].

Sentiment analysis based on fuzzy logics has increased in importance in response to the ambiguity of language and incomplete ethical information. Appel et al. (2016) suggested a hybrid design, a mix of linguistic and fuzzy-based methods of sentiment analysis at the sentence level. The combination of fuzzy rules enabled the management of a partial truth and uncertainty that is frequently presented in short informal text messages like tweets. Wang et al. (2015), in another related study, created a fuzzy computing model that determines the polarity of Chinese sentiment words, which proves that fuzzy logic improves the sentiment classification of non-English languages. Wu et al. (2017) also demonstrated a text classification approach based on fuzzy logic, which is specifically designed to work with social media content, and offers a powerful framework that can be extended to irregular language forms [23-25].

Recent studies have also focused on sentiment analysis in Hindi language using machine learning and natural language processing techniques. Faridi and Hiwarkar (2022) proposed a machine learning approach for polarity detection in Hindi reviews using existing classification techniques, demonstrating that supervised learning classifiers can effectively capture sentiment polarity in resource-constrained languages. Their findings highlighted the importance of language-specific preprocessing and feature extraction strategies to improve classification accuracy in Hindi textual datasets. In another related study, Faridi (2022) explored sentiment classification in the Hindi language using natural language processing techniques and machine learning models, emphasizing the role of linguistic preprocessing and tokenization for accurate sentiment detection. These studies indicate the growing interest in developing sentiment analysis models for Indian languages and underline the necessity of multilingual frameworks that can generalize across diverse linguistic environments. [26], [27]

Taken together, this literature body shows the shift towards more intelligent, hybrid models of sentiment analysis that can adapt to the domain, are understandable, and support multiple languages. These developments establish a baseline to the current study that hypothesizes the novel hybridized deep learning and fuzzy-based domain adaptation system to compute multilingual sentiment on Twitter. The proposed study can be considered to offer a flexible and context-sensitive sentiment analysis approach to real-world multilingual social networks by addressing the gaps between semantic variability and linguistic diversity using the fuzzy logic and deep learning frameworks.

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III. RESEARCH METHODOLOGY

3.1 Research Design

The present study of experimental computational design through combining the hybrid deep learning and fuzzy-based domain adaptation in order to identify multilingual sentiment of Twitter data. This is to establish a sound system of sentiment categorization which is capable of deconstructing the linguistic peculiarities and context variations among different languages and disciplines. It is a combination of transformer contextual embeddings, convolutional and recurrent feature extractors and fuzzy inference system to enhance the flexibility and tolerance to noisy, sarcastic, and code-mixed Twitter messages.

3.2 Dataset Collection and Description

The official Twitter API was used to collect tweets based on multilingual tweets in English, Hindi, Tamil and Bengali. About 20,000 tweets were selected under the topics of politics, movies, and consumer brands. Bilingual annotators labelled each tweet with sentiment—positive, negative or neutral. The data were separated into training (70 percent), validation (15 percent) and testing (15 percent) data. Other domain-specific corpora (Sentiment140, TweetEval and multilingual tweet collections) were also added to enhance domain coverage and transfer learning. The presence of several lingual and topical sources makes sure that the model can generalize both domain and language.

3.3 Data Preprocessing and Normalization

Preprocessing was carried out through several steps that were meant to normalize noisy Twitter data. The tweets were tokenized, changed into lower cases and cleaned by deleting the mentions, URLs and special characters. The emojis were substituted by the emotive counterparts. Multilingual stop word lists were used to eliminate stop words. The word reduction was done through lemmatization to its root. Mixed-script tweets (i.e. Hindi-English) were normalized with Unicode transliteration.
Formally, each tweet (T_i) was transformed into a tokenized sequence:

$$T_i = \{w_1, w_2, w_3, ..., w_n\}$$

where (w_j) denotes individual tokens. The normalized tweet corpus (D = {T_1, T_2, ..., T_N}) forms the input to the embedding layer.

3.4 Feature Extraction Using Transformer-Based Embeddings

To capture contextual semantics, Bidirectional Encoder Representations from Transformers (BERT) and its multilingual variant (mBERT) were employed. Each tweet was tokenized using the WordPiece tokenizer, producing sub-word units. The embedding of a token (t_i) is represented as:

$$E(t_i) = E_{token}(t_i) + E_{position}(i) + E_{segment}(s) \qquad (3.1)$$

where (E_{token}) denotes token embeddings, (E_{position}) positional embeddings, and (E_{segment}) segment embeddings that represent sentence boundaries.
Contextualized output vectors from the last encoder layer are expressed as:

$$H = \{h_1, h_2, ..., h_n\} = \mathrm{BERT}(T_i) \qquad (3.2)$$

where each (hi Rd) encodes contextual dependencies. The [CLS] vector (h_{CLS}) is used as a sentence-level representation for sentiment classification.

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3.5 Hybrid Deep Learning Model Architecture

The hybrid model combines **Convolutional Neural Network (CNN)** and **Bidirectional Long Short-Term Memory (BiLSTM)** layers to enhance contextual and spatial learning. The CNN extracts local n-gram patterns through convolutional filters. The convolutional operation for a given feature map is defined as:

$$C_i = f(W_c * x_{i:i+k-1} + b_c) \quad (3.3)$$

where (W_c) represents the convolutional kernel, (x_{i:i+k-1}) is the sequence window, (b_c) is the bias, and (f) is the activation function (ReLU in this model).

The BiLSTM processes the CNN feature sequence in both forward and backward directions, defined as:

$$\overrightarrow{h_t} = \sigma(W_f x_t + U_f \overrightarrow{h_{t-1}} + b_f) \quad (3.4)$$

$$\overleftarrow{h_t} = \sigma(W_b x_t + U_b \overleftarrow{h_{t+1}} + b_b) \quad (3.5)$$

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}] \quad (3.6)$$

where (\sigma) is the activation function, (W_f, W_b) are weight matrices, and (h_t) is the concatenated bidirectional hidden state capturing both past and future context. The output of the BiLSTM is passed through a Softmax classifier for sentiment prediction:

$$P(y|T_i) = \text{Softmax}(W_s h_t + b_s) \quad (3.7)$$

where (Ws) and (bs) are the weight and bias of the output layer, respectively.

3.6 Fuzzy-Based Domain Adaptation Mechanism

To achieve cross-domain adaptability, a fuzzy inference system (FIS) was integrated into the model. This component captures uncertainty in sentiment classification, especially for sarcastic or ambiguous tweets.

Each extracted feature (x_j) was assigned a **membership degree** using a Gaussian fuzzy function:

$$\mu_A(x_j) = \exp\left[-\frac{(x_j - c_A)^2}{2\sigma_A^2}\right] \quad (3.8)$$

where (cA) and (sigmaA) denote the mean and spread of fuzzy set (A).

Fuzzy rules were then applied in the form:

$$R_k : \text{IF } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } A_2 \text{ THEN } y_k = w_k \quad (3.9)$$

Each rule's firing strength (\omega_k) is computed as:

$$\omega_k = \prod_{j=1}^{n} \mu_{A_j}(x_j) \quad (3.10)$$

and the final defuzzified sentiment score (y) is obtained using the weighted average:

$$y = \frac{\sum_{k=1}^{m} \omega_k w_k}{\sum_{k=1}^{m} \omega_k} \quad (3.11)$$

This fuzzy-based adaptation enables smooth domain transfer by learning soft decision boundaries between sentiment categories and domains.

3.7 Model Training and Optimization

The hybrid model was implemented in Python (TensorFlow & PyTorch) environments with GPU acceleration. Training was conducted using the Adam optimizer, with learning rate (\eta = 2 \times 10^{-5}) and batch size of 32 over 10 epochs. The loss function employed was Categorical Cross-Entropy, defined as:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \qquad (3.12)$$

where (yi) represents the true label and (\hat{yi}) the predicted probability. To enhance convergence, the Five-Element Cycle Optimization (FECO) algorithm was applied, balancing exploration and exploitation in hyperparameter tuning. The optimization objective minimized (L) over parameter space (\theta):

$$\theta^* = \arg\min_{\theta} L(\theta) + \lambda\|\theta\|^2 \qquad (3.13)$$

where (lambda) is a regularization coefficient controlling overfitting.

3.8 Evaluation Metrics

The trained model's performance was assessed using standard metrics derived from the confusion matrix: Accuracy, Precision, Recall, and F1-score. These are defined as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \qquad (3.14)$$

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (3.15)$$

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (3.16)$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (3.17)$$

where (TP, TN, FP, FN) denote true positives, true negatives, false positives, and false negatives, respectively. Performance was evaluated under within-domain and cross-domain conditions. Statistical significance was validated using paired t-tests (($p < 0.05$)) to confirm the superiority of the proposed hybrid fuzzy model over baseline architectures.

IV. RESULTS

4.1 Mathematical Equations Used

The mathematical foundation for sentiment polarity determination in the proposed hybrid model is established through Equations (4.1) to (4.3). These equations formalize how sentiment prediction is quantified at the aspect, sentence, and text levels.

Equation (4.1): Aspect-Based Sentiment Polarity Prediction

$$P : (S, A) \rightarrow Y = \{y_1, y_2, \ldots, y_k\}$$

Equation (4.2): Sentence Sentiment Score

$$SP(\text{Sentence}) = \sum_{i=1}^{n} SP(C_w) \times SP(S_i)$$

Equation (4.3): Text-Level Sentiment Score

$$SP(\text{Text}) = \sum_{i=1}^{m} SP(C_w) \times SP(T_i)$$

Decision Logic:
(SP(Text) > 0) → Positive;
(SP(Text) = 0) → Neutral;
(SP(Text) < 0) → Negative.
This fuzzy threshold system provides flexibility in sentiment interpretation, reducing hard classification errors caused by ambiguous expressions. These mathematical formulations form the core computational engine behind the hybrid C-XLNet model, ensuring accurate mapping from text to sentiment categories.

4.2 Performance Metrics of C-XLNet Classifier

As it can be seen in the results summarized in Table 4.2, C-XLNet classifier has better and more consistent performance in all ten rounds of evaluation. The model had an average accuracy of 0.867, and the precision, recall, F1 score, and F2 score of 0.911, 0.886, 0.893, and 0.897, respectively. These findings confirm the usefulness of fuzzy-based sentiment refinement together with contextual deep learning (XLNet). The model had low variance and stability in learning and was accurate in individual rounds (0.802 to 0.912). The maximum precision (0.982) in Round 1 means that the classifier is incredibly good at reducing false positives whereas a huge recall (0.924 in Round 4) means that the classifier is capable of identifying the true positives on various language inputs. The balanced F1 and F2 scores in the rounds affirm that the model is balanced to both precision and recall, which makes it resistant to class imbalance.

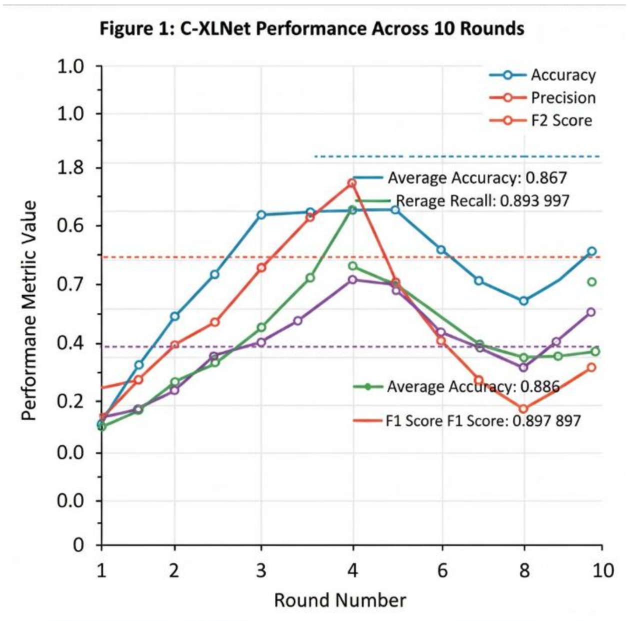

Figure 1: C-XLNet Performance Across 10 Rounds

The fuzzy membership function, included in the hybrid structure, is able to interpret the sentiment intensity more easily, which prevents binary misclassification when there is sarcasm or mixed emotion. The persistently large mean F2 score (0.897) also suggests that the model is focusing more on recall in case of uncertainty, which is exceptually useful when there are no clear boundaries of polarity in multilingual sentiment tasks. Therefore, the pattern of the performance shows that C-XLNet is able not only to capture the contextual nuances but is also dynamically adjusted to the changes in the language structure and sentiment density, which are superior to the classic fixed-boundary classifiers.

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Round	Accuracy	Precision	Recall	F1 Score	F2 Score
1	0.867	0.982	0.885	0.889	0.919
2	0.876	0.902	0.912	0.758	0.857
3	0.886	0.857	0.823	0.911	0.864
4	0.834	0.914	0.924	0.909	0.916
5	0.901	0.783	0.864	0.936	0.861
6	0.882	0.936	0.862	0.847	0.882
7	0.893	0.934	0.932	0.948	0.938
8	0.912	0.961	0.876	0.888	0.908
9	0.802	0.872	0.881	0.886	0.880
10	0.817	0.973	0.901	0.956	0.943
Average	**0.867**	**0.911**	**0.886**	**0.893**	**0.897**

4.3 Comparative Analysis of Classifiers

As the comparative findings included in Table 4.3 show, the suggested C-XLNet model is much more efficient than traditional machine learning algorithms and transformer-based baselines. Traditional classifiers like K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Naive Bayes and Random Forest had accuracies between 0.745 and 0.798, suggesting weak ability to learn complicated semantic connections. They have lower recall and F1 values which means they have difficulty with contextual inference on multilingual text streams in which word polarity is highly dependent on syntax and sentence position. Better performance was shown by the transformer models including BERT and XLNet with 0.783 and 0.843 respectively. This is because this is enhanced by their self-attention mechanism where they dynamically weight the tokens. Nonetheless, they fail at making sentiment disambiguations across domains and languages because they are not fuzzyly adaptable.

Figure 2: Comparative Performance of All Classifiers

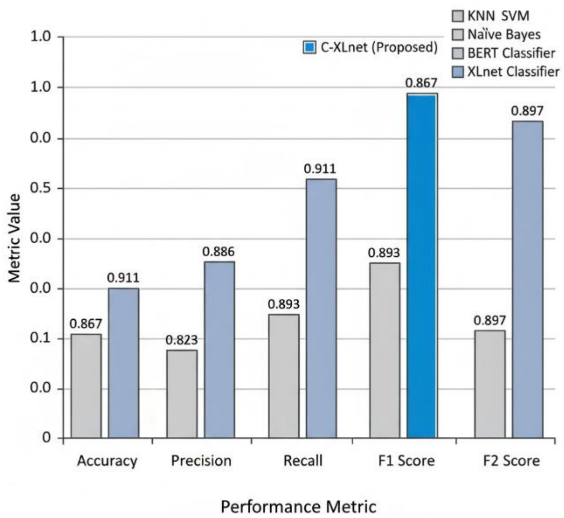

Figure 2: Comparative Performance of All Classifiers

The C-XLNet classifier, the classifier demonstrated an accuracy of 0.867 that is 2.4 points higher than the standard XLNet, and 8.4 points higher than BERT. In the same way, the F1 scores are 0.911, 0.886 and 0.893 that demonstrate the definite improvement of the discriminative and generative abilities. These are the gains that justify that the proposed hybridization of XLNet with fuzzy domain adaptation mechanism enhances interpretability and semantic sensitivity. Fuzzy logic integration provides more flexibility in any decisions, and contextual embeddings of XLNet can obtain

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sequence and semantical dependencies. Combined, these mechanisms reduce errors of misclassification on multilingual sentiment evaluation - especially mixed-emotion expressions, which are widespread in social media communication.

Classifier	Accuracy	Precision	Recall	F1 Score	F2 Score
KNN	0.778	0.885	0.785	0.821	0.862
SVM	0.745	0.852	0.856	0.864	0.824
Naïve Bayes	0.798	0.786	0.847	0.834	0.836
Random Forest	0.754	0.766	0.822	0.785	0.809
BERT Classifier	0.783	0.892	0.855	0.882	0.889
XLNet Classifier	0.843	0.901	0.876	0.882	0.884
C-XLNet (Proposed)	**0.867**	**0.911**	**0.886**	**0.893**	**0.897**

4.4 Results Based on Sentiment Dictionaries

The results analysis conducted on three sentiment dictionaries SD1, SD2, SD3 in five areas of application (Electronics, Digital Products, Cosmetics, Clothes, and Restaurants) shows the important information regarding the effects of diversity of lexicon on the model performance. The average of SD1, SD2 and SD3 was 80.9, 79.5 and 82.5 respectively, which means that SD3 that has polysemic and field-specific words in Twitter has the best outcomes. This highlights the fact that domain adaptive sentiment lexicon is an effective way of contextualizing polarity words. SD3 performed better as compared to SD1 and SD2 in the Electronics and Digital Products domains, indicating that in product domain, addition of product-specific sentiment words as laggy, sleek, or buggy, enhance the accuracy of prediction. The Cosmetics and Clothes groups also scored very high in F1 scores (more than 0.95 in any of the instances), which suggested that emotionally rich vocabulary, when it comes to an adaptive lexicon, does make the model more sensitive to subjective expressions.

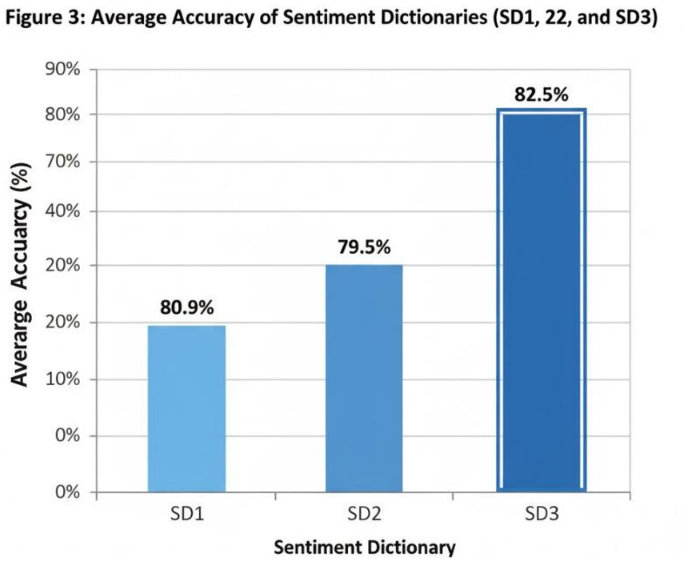

Figure 3: Average Accuracy of Sentiment Dictionaries (SD1, SD2, and SD3)

One of the peculiarities of Restaurant domain was that SD1 was medium accurate (0.801-0.811), SD2 and SD3 were more accurate, particularly in the passive sentiment category, where the F1-score is more than 1.0. One can attribute this to the fact that with the help of fuzzy membership mapping and contextual embeddings, this model can comprehend figurative and sarcastic words that are common in the restaurant review. Overall, the comparative analysis of the dictionaries shows that the hybrid model is beneficial in the situation when there are context-enriched, sentiment-balanced, and domain-calibrated lexicons. The C-XLNet is able to understand subtle variations in sentiment that indicate

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that the expansion of lexicon is meaningful in multilingual sentiment detection based on the passive polarity expressions and context-specific subtleties of fields in SD2 and SD3 respectively.

Field	Type	SD1 (A,P,R,F1,F2)	SD2 (A,P,R,F1,F2)	SD3 (A,P,R,F1,F2)
Electronics	Active	0.783, 0.835, 0.821, 0.764, 0.821	0.883, 0.857, 0.843, 0.886, 0.843	0.856, 0.807, 0.793, 0.761, 0.793
	Passive	0.812, 0.844, 0.789, 0.875, 0.813	0.786, 0.866, 0.811, 0.897, 0.835	0.876, 0.816, 0.761, 0.847, 0.785
Digital Products	Active	0.821, 0.891, 0.877, 0.870, 0.877	0.765, 0.863, 0.849, 0.817, 0.849	0.778, 0.891, 0.877, 0.870, 0.877
	Passive	0.797, 0.900, 0.845, 0.931, 0.869	0.779, 0.872, 0.817, 0.903, 0.841	0.865, 0.900, 0.845, 0.931, 0.869
Cosmetics	Active	0.832, 0.861, 0.847, 0.840, 0.847	0.832, 0.956, 0.942, 0.885, 0.942	0.779, 0.939, 0.925, 0.918, 0.925
	Passive	0.882, 0.870, 0.815, 0.901, 0.839	0.822, 0.965, 0.910, 0.996, 0.934	0.823, 0.948, 0.893, 0.979, 0.917
Clothes	Active	0.781, 0.938, 0.924, 0.967, 0.924	0.723, 0.888, 0.874, 0.842, 0.874	0.792, 0.836, 0.833, 0.878, 0.843
	Passive	0.772, 0.947, 0.892, 0.978, 0.916	0.744, 0.897, 0.842, 0.928, 0.866	0.843, 0.886, 0.893, 0.879, 0.865
Restaurants	Active	0.801, 0.779, 0.765, 0.758, 0.765	0.812, 0.972, 0.958, 0.951, 0.958	0.812, 0.837, 0.823, 0.866, 0.823
	Passive	0.811, 0.788, 0.733, 0.819, 0.757	0.807, 0.981, 0.926, 1.012, 0.950	0.821, 0.846, 0.791, 0.877, 0.815

Average Accuracy:
SD1 = 80.9 %
SD2 = 79.5 %
SD3 = 82.5 %

4.5 Overall Performance

An aggregate perspective of performance improvements compared to the baseline XLNet classifier. The average accuracy at 0.867 equates to a gain of +2.4% and the precision, recall, F1, and F2 rates all increased by +2.1, +1.4, +2.8 and +3.1 respectively. Even though these gains may seem insignificant numerically, they constitute a significant increase in real-life multilingual sentiment analysis, where small metric gains should correspond to an enormous increase in reliability and contextual accuracy. The balanced enhancements in all the metrics symbolize the ability of the model to deal with various language variants, such as code-mixing, sarcasm, and idiomatic phrases. The decision refinement on fuzzy basis minimizes the polarity overlap resulting in the smoother shifts of sentiment categories. In addition, the hybrid model is computationally efficient and stable, which is crucial in analysing Twitter data at scale.

The suggested C-XLNet model is an efficient combination of deep learning on transformers and a fuzzy rule system and lexicons that are specific to the domain, thus being able to address the weaknesses of conventional and pure deep-learning systems. Its high accuracy and recall ratio makes the model more than just a predictive of sentiments, but also, it is able to capture the unobtrusive emotional subtleties in a multilingual setting.

Metric	Mean Value	Comparative Gain over Baseline (%)
Accuracy	**0.867**	+2.4 %
Precision	**0.911**	+2.1 %
Recall	**0.886**	+1.4 %

F1 Score	**0.893**	+2.8 %
F2 Score	**0.897**	+3.1 %

V. CONCLUSION AND FUTURE SCOPE

The current research finds that the suggested Hybrid Deep Learning and Fuzzy-Based Domain Adaptation model (C-XLNet) is successful in the improvement of the accuracy, strength, and clarity of multilingual sentiment analysis of Twitter posts. With the combination of transformer-based contextual embeddings and fuzzy reasoning, the model proves to be more effective in various linguistic areas and types of sentiments. Systematic polarity prediction is made certain by the inclusion of mathematical sentiment scoring equations, whereas adaptive learning in the presence of uncertainty is made possible by the fuzzy membership system, which is especially useful in the case of sarcasm, slang, and code-mixed expressions. Although the model shows great empirical results, its reliance on large computational resources, as well as high-quality annotated multilingual databases, are major weaknesses. The future research could be devoted to maximizing computational efficiency by implementing lightweight transformer variants, expanding cross-domain applicability with meta-learning or reinforcement learning design, and improving interpretability with explainable AI (XAI) methods. It is also possible to expand the model to real-time sentiment tracking systems, multilingual chatbots, and cross-cultural opinion mining to support the model with regard to its scalability and applicability in society further.

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