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ENSEMBLE LEARNING WITH XLNET, XLM, AND BERT HYBRIDIZED BY SVM CLASSIFIER FOR ASPECT-BASED SENTIMENT ANALYSIS ON ONLINE REVIEWS

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Abstract:
Aspect-Based Sentiment Analysis (ABSA) is a critical task in natural language processing (NLP) that aims to identify and analyse sentiments towards specific aspects in textual data. This paper proposes an ensemble learning model for ABSA that combines the strengths of three state-of-the-art transformer-based models, namely XLNet, XLM, and BERT, with a Support Vector Machine (SVM) classifier. The proposed hybrid ensemble model seeks to leverage the unique features of XLNet, XLM, and BERT to enhance ABSA performance by capturing fine-grained sentiment information and contextual dependencies. XLNet utilizes an autoregressive framework to capture bidirectional dependencies, XLM specializes in cross-lingual language modeling, and BERT employs a masked language modeling approach for contextualized representations. By combining these models, we aim to exploit diverse contextual information and improve the overall sentiment analysis accuracy at the aspect level. In our approach, the outputs of XLNet, XLM, and BERT are used as input to an SVM classifier separately. The SVM classifier is trained to classify the sentiment polarity of aspects based on the features extracted and the ensemble classifier used for final predictions. The proposed hybrid ensemble model (BX2_Ensemble) with XLNet, XLM, and BERT, along with the SVM classifier, offers a promising approach for ABSA applications, providing enhanced performance and robustness in capturing sentiment information at the aspect level with improved sentiment analysis accuracy of 98.01%, 97.87% and 97.74% on three different datasets which are based on Amazon reviews, Twitter and TripAdvisor datasets.

Keywords: Ensemble Learning, XLNet, XLM, BERT, ABSA, SVM, Hybrid Model, Transformer models.

1. INTRODUCTION

Aspect-Based Sentiment Analysis (ABSA) is a crucial task in natural language processing (NLP) that aims to identify sentiments expressed towards specific aspects or entities in textual data. The ability to accurately extract sentiment information at the aspect level has significant applications in various domains, including customer feedback analysis, product reviews, and social media monitoring. To tackle the challenges associated with ABSA, researchers have explored the use of advanced machine learning models, such as transformer-based models and ensemble learning techniques. Various processing steps in ABSA are shown in figure 1.

Transformer-based models, such as XLNet, XLM, and BERT, have demonstrated exceptional performance in a wide range of NLP tasks by capturing contextual information and learning representations at a fine-grained level [1][2][3]. These models excel at capturing the nuances of language, making them ideal candidates for ABSA. However, no single model can capture all aspects of sentiment analysis with absolute accuracy due to inherent biases and limitations in the training data.

To overcome the limitations of individual models, ensemble learning has emerged as a promising approach. Ensemble learning combines multiple models to improve prediction accuracy by leveraging their diverse perspectives and strengths [4][5]. By fusing the outputs of multiple models, ensemble methods can compensate for individual model weaknesses and provide more robust and accurate sentiment predictions.

In this paper, we propose an ensemble learning model that integrates XLNet, XLM, and BERT as a hybrid model for ABSA. XLNet utilizes an autoregressive framework to capture bidirectional dependencies, XLM specializes in cross-lingual language modeling, and BERT employs masked language modeling for contextualized representations [1][2][3]. By combining these transformer-based models, we aim to leverage their complementary features and enhance the sentiment analysis capability.

To achieve this, we employ a Support Vector Machine (SVM) classifier as the ensemble learning component. SVM is a widely-used supervised learning algorithm known for its effectiveness in handling high-dimensional data and achieving good generalization performance [6]. The SVM classifier learns to classify sentiment polarity at the aspect level based on the fused features extracted from the ensemble of transformer models.

1.1. Steps involved in ABSA:

Step 1. Pre-process the dataset while taking into account the input text corpus.

Step 2. Create Word Embeddings of the text input (Vectorize the text input and produce tokens).

Step 3. Contextualization : The embedded tokens are fed into multi-layer transformer network, which captures the contextual information by attending to the surrounding tokens.

Step 4. Aspect Terms Extraction -> Aspect Categories Model

Step 5. Aspect Classification -> Sentiment Model

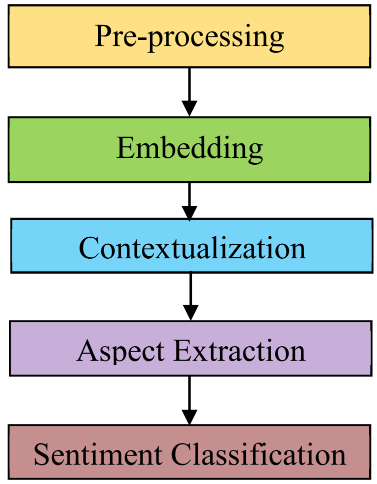

Figure 1: Steps involved in ABSA

1.2. Major challenges in the current literature:

- Looking at it from a linguistic standpoint, the identification of aspects and their associated sentiments through automated means presents numerous challenges. This is primarily due to the presence of intricate linguistic phenomena that are intricate to interpret and comprehend..
- Specifically, pinpointing the accurate aspect can be regarded as the most challenging subtask in this analysis. This difficulty arises from the fact that customers have the potential to express their opinions on a multitude of aspects..
- The results won't be effective if the data size is small.
- Establishing the connections between different aspect groups will help the model.
- Too much outside information can modify a sentence's meaning and have an impact on performance.
- One of the limits is that there are no boundaries on who can write product or service reviews and from where in the world. Customers are duped by opinion spammers who attempt to alter their thoughts by either enhancing or diminishing the reputation of the target company.

1.3. Solutions to the Challenges:

- By combining the short sentences to form a big statement, which makes it easier to understand the sentiment, the data sparsity problem can be resolved.
- Pre-processing techniques are used to remove grammatical problems before modelling the data.
- Long sentences are excellent for understanding the sentiment and identifying correlation patterns.
- Aspects can be accurately extracted by defining the relationships between the aspect categories.
- By incorporating sentiment knowledge into BERT and identifying aspect sentiment correlations, performance can be enhanced.
- In order to prevent malicious user reviews, opinion spam filtering is handled by the cross-platform compatibility.

2. RELATED WORK

Aspect-Based Sentiment Analysis (ABSA) has garnered considerable interest within the realm of natural language processing (NLP). Researchers have dedicated their efforts to exploring diverse approaches aimed at enhancing sentiment analysis specifically at the aspect level. This section provides an overview of the related work that has investigated ensemble learning techniques, transformer-based models, and SVM classifiers in the context of ABSA.

2.1. Ensemble Learning for ABSA:

Ensemble learning has been widely used to improve the performance of sentiment analysis models. Li et al. [7] proposed an ensemble model that combined aspect-specific graph convolutional networks to capture aspect-level sentiment information. Their approach demonstrated improved sentiment analysis accuracy by leveraging multiple models and their respective strengths. Similarly, Zhang et al. [8] explained ensemble learning to combine multiple neural network models for aspect-based sentiment classification, achieving better overall performance compared to individual models.

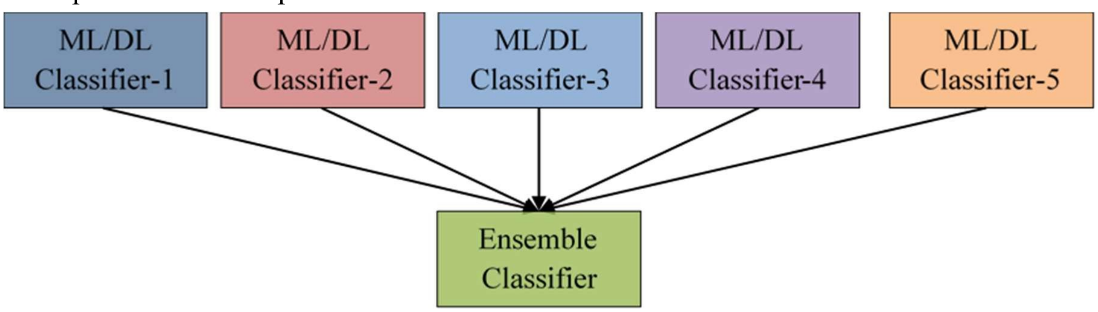

Figure 2: Ensemble classification model

2.2. Transformer-Based Models in ABSA:

Transformer-based models, such as XLNet, XLM, and BERT, have shown remarkable success in various NLP tasks. Sun et al. [9] utilized BERT for aspect-based sentiment analysis by constructing auxiliary sentences to enhance aspect understanding. Their work demonstrated the effectiveness of BERT in capturing context and achieved state-of-the-art results on several benchmark datasets. Mewada et al. [10] proposed a hybrid model that combined BERT and a Graph Convolutional Network (GCN) for ABSA. Their approach effectively integrated global contextual information and local syntactic dependencies to improve sentiment analysis accuracy.

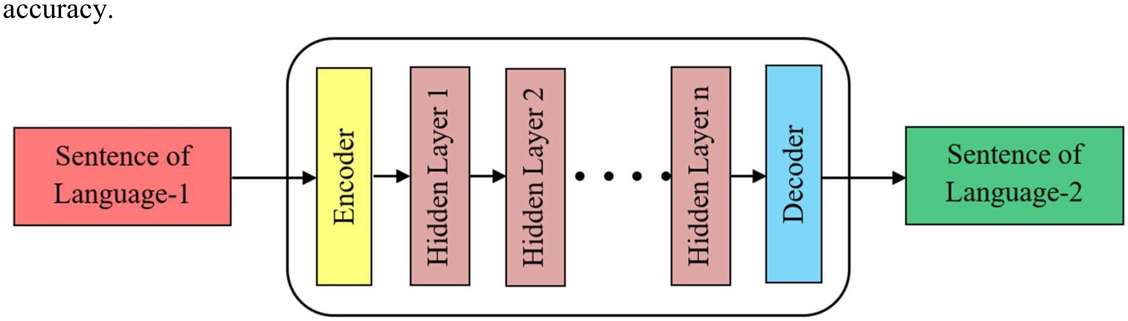

Figure 3: General Transformer Architecture

2.3. SVM Classifiers for ABSA:

Support Vector Machines (SVM) classifiers have been widely used in sentiment analysis tasks, including ABSA. Zhang et al. [11] employed an SVM classifier with word embeddings and aspect embeddings to predict sentiment polarity at the aspect level. Their work showed that

SVM classifiers can effectively handle high-dimensional feature representations and achieve competitive results in ABSA tasks. Huang et al. [12] proposed a hybrid model that combined SVM classifiers with aspect-aware attention mechanisms, enhancing aspect-level sentiment analysis performance.

2.4. Other Approaches for ABSA:

Dong et al. [13] proposed a sentiment analysis method that combines a BiLSTM (Bidirectional Long Short-Term Memory) with a Capsule Network. The experimental results demonstrated that the proposed method achieved improved performance compared to traditional methods, indicating the effectiveness of incorporating capsule networks into sentiment analysis tasks.

Ali et al. [14] presented an aspect-level sentiment analysis method using a bidirectional-GRU (Gated Recurrent Unit) in the context of Smart Internet of Things (SIoT). The experimental results demonstrated that the proposed method achieved improved performance in aspect-level sentiment analysis tasks, indicating its potential for effectively analyzing sentiments in SIoT scenarios.

Chen et al. [15] introduced a transfer capsule network for aspect-level sentiment classification. The experimental results showcased that the proposed method outperformed existing approaches, demonstrating the effectiveness of utilizing capsule networks for aspect-level sentiment analysis tasks.

Bie et al. [16] presented a multitask multi view neural network for end-to-end aspect-based sentiment analysis. The experimental results demonstrated the effectiveness of the proposed approach in jointly predicting aspect terms and sentiment polarities, achieving improved performance compared to baseline methods and showcasing the benefits of utilizing multiple views in sentiment analysis tasks.

Wu et al. [17] introduced S_I_LSTM, a stock price prediction model that incorporates multiple data sources and sentiment analysis. The experimental results demonstrated the effectiveness of the proposed approach in predicting stock prices, highlighting the potential benefits of leveraging multiple data sources and sentiment analysis in financial prediction tasks.

Yue et al. [18] conducted a comprehensive survey of sentiment analysis in the realm of social media. It provided a comprehensive overview of different techniques, methodologies, and applications, thereby serving as a valuable resource for researchers and practitioners interested in sentiment analysis in social media.

Yang et al. [19] proposed a sentiment analysis approach for Chinese e-commerce product reviews using a combination of sentiment lexicon and deep learning techniques. The experimental results showed that the proposed method achieved improved performance in sentiment analysis tasks, highlighting the effectiveness of leveraging both lexical resources and deep learning models for sentiment analysis in the context of Chinese e-commerce reviews.

Kumar et al. [20] presented an aspect-based sentiment analysis approach using deep networks and stochastic optimization. The experimental results demonstrated the effectiveness of the proposed method in accurately identifying sentiment polarity towards different aspects, highlighting the potential of deep learning and stochastic optimization techniques in aspect-based sentiment analysis tasks.

Tubishat et al. [21] proposed a method for explicit aspects extraction in sentiment analysis using optimal rules combination. The experimental results showed that the proposed approach achieved improved performance in aspect extraction, indicating the effectiveness of utilizing optimal rules combination for explicit aspects identification in sentiment analysis tasks.

Harish et al. [22] presented a hybrid feature extraction method for sentiment analysis on IMDb movie reviews. The experimental results demonstrated that the proposed approach achieved promising performance in classifying movie reviews, indicating the effectiveness of the hybrid feature extraction technique for sentiment analysis tasks in the context of IMDB reviews.

Rezaeinia et al. [23] introduced an improved approach for sentiment analysis based on pre-trained word embeddings. The experimental results demonstrated that the proposed method achieved better performance in sentiment classification tasks, highlighting the benefits of utilizing enhanced pre-trained word embeddings for sentiment analysis.

Ling et al. [24] proposed a vision-language pre-training approach for multimodal aspect-based sentiment analysis. The research aimed to leverage the synergy between visual and textual information, and while there is no specific outcome mentioned, it contributes to the ongoing exploration of multimodal techniques in sentiment analysis.

Bensoltane et al. [25] presented a transfer learning-based approach for Arabic aspect-based sentiment analysis. The experimental results demonstrated the effectiveness of the proposed method in accurately identifying aspect-level sentiment in Arabic text, indicating the potential for transfer learning techniques in sentiment analysis tasks specific to the Arabic language.

Tian et al. [26] conducted research on aspect-level sentiment analysis based on text comments. The study explored various techniques and methodologies, contributing to the advancement of aspect-level sentiment analysis and providing valuable insights for analyzing sentiment in textual comments.

Yang et al. [27] proposed a novel approach for aspect-based sentiment analysis, incorporating a new target representation and dependency attention mechanism. The experimental results demonstrated the effectiveness of the proposed method in accurately capturing sentiment information towards specific aspects, highlighting the potential of target representation and dependency attention in improving aspect-based sentiment analysis tasks.

Chang et al. [28] investigated the use of deep learning and information visualization techniques for predicting aspect-based sentiment in the context of the airline industry during the COVID-19 pandemic. The study revealed insights into the impact of COVID-19 on different aspects of the airline industry, highlighting the potential of combining deep learning and information visualization for sentiment analysis in industry-specific contexts.

Ma et al. [29] introduced Sentic LSTM, a hybrid network designed for targeted aspect-based sentiment analysis. The experimental results demonstrated that the proposed approach achieved improved performance in capturing sentiment towards specific aspects, highlighting the effectiveness of combining sentiment analysis with LSTM models for targeted aspect-based sentiment analysis tasks.

Kumar et al. [30] presented a semi-supervised hybrid approach for aspect and sentiment classification, leveraging the power of BERT (Bidirectional Encoder Representations from Transformers) models. The experimental results demonstrated that the proposed approach achieved improved performance in aspect and sentiment classification tasks, highlighting the effectiveness of combining BERT with semi-supervised learning for sentiment analysis.

Liu et al. [31] provided a comprehensive survey of deep learning methods for aspect-based sentiment analysis. The survey covered various techniques and methodologies, highlighting the state-of-the-art approaches and trends in the field, thereby serving as a valuable resource for researchers and practitioners interested in aspect-based sentiment analysis using DL.

Do et al. [32] conducted a comparative review of deep learning approaches for aspect-based sentiment analysis. The study examined various techniques and evaluated their performance, providing insights into the strengths and limitations of different deep learning models for aspect-based sentiment analysis tasks.

3. PROPOSED HYBRID ENSEMBLE MODEL

The proposed Model aims to build upon the existing literature by integrating ensemble learning techniques with a hybrid model consisting of XLNet, XLM, and BERT for ABSA as shown in figure 3.1. By leveraging the diverse strengths of these transformer-based models and employing an SVM classifier, our approach aims to enhance aspect-level sentiment analysis accuracy and robustness.

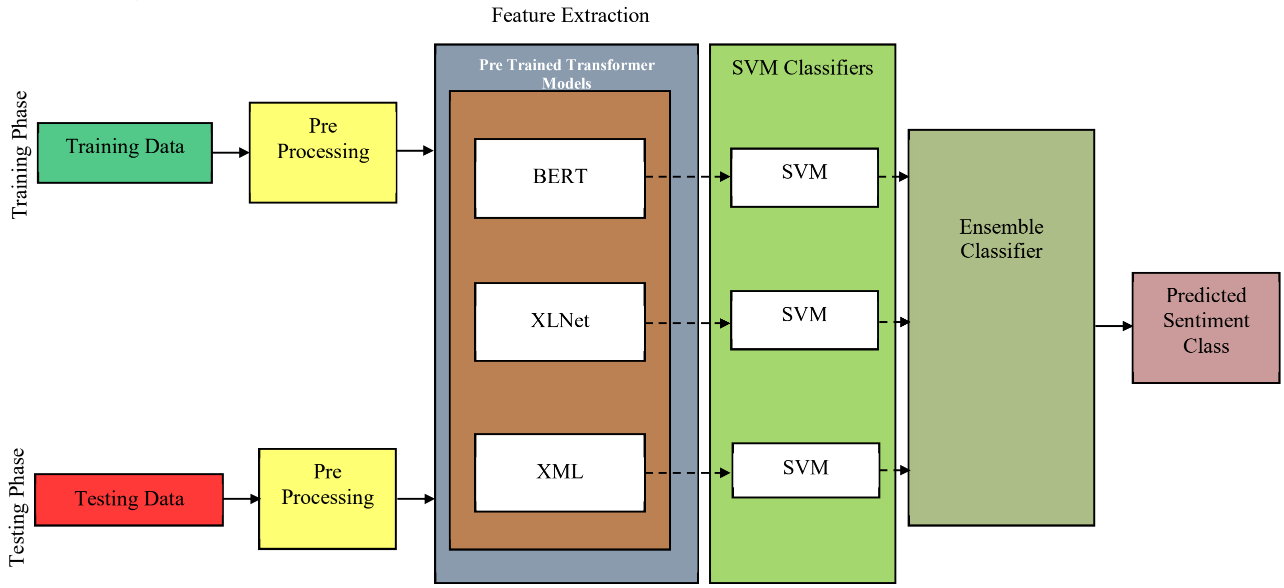

Figure 4: Hybrid Ensemble Model

We conducted experiments to evaluate the performance of our proposed model against individual transformer models and baseline methods, providing insights into the effectiveness of the ensemble learning approach in ABSA tasks.

3.1. Datasets:

In this work three different online datasets with diverse domains are used. Following are the datasets used for the sentiment classification

A. Amazon Reviews: Unlocked Mobile Phones:

The "Amazon Reviews: Unlocked Mobile Phones" dataset contains customer reviews specifically related to unlocked mobile phones available on Amazon. This dataset provides valuable insights into customer opinions, sentiments, and experiences with various unlocked mobile phone models. It includes review texts, ratings, helpfulness votes, product metadata, and other relevant information.

B. Twitter Dataset

The dataset provides a large and diverse collection of tweets, making it valuable for training machine learning algorithms to classify sentiments in short texts.

C. TripAdvisor hotel reviews

The TripAdvisor hotel reviews dataset is a commonly used dataset for sentiment analysis and opinion mining tasks related to hotel reviews. It contains a collection of user-generated hotel reviews and associated metadata from the TripAdvisor website. The dataset typically includes information such as review text, ratings, review date, traveler type, and other relevant attributes.

3.2. Data Pre-processing:

Data pre-processing is the process of transforming raw data into something that can be used by a machine learning model. In this work Case folding, Removing punctuation marks, Tokenization, Removing Stop Words, Stemming and Lemmatization are used as aspect based pre-processing techniques.

***A.* Case Folding**

Case-folding refers to a process wherein a sequence of characters is modified by replacing any characters that are not in lowercase with their corresponding lowercase equivalents.

***B.* Removing punctuation marks**

By removing punctuation, texts are treated equally, as the technique eliminates differences caused by punctuation. For example, the words "data" and "data!" are considered the same after punctuation removal.

***C.* Tokenization**

Tokenization is a fundamental technique in natural language processing that involves breaking down phrases and paragraphs into smaller, language-assignable units or tokens.

***D.* Removing Stop Words**

Stop words play a crucial role in numerous applications as they enable us to focus on the essential words by eliminating commonly used words in a language.

***E.* Stemming**

Stemming is a technique that reduces the size of word-forms by converting them to their respective stems. Stemming involves stripping a word down to its root or removing suffixes and prefixes, resulting in a word stem.

***F.* Lemmatization**

Lemmatization is a linguistic process that involves correctly performing tasks by utilizing vocabulary and morphological analysis of words. The objective is to remove only inflectional endings while returning the base or dictionary form of a word, which is known as the lemma.

3.3. Pre-trained Transformer models:

After pre-processing, the datasets are fed to the pre trained transformer model for feature extraction. BERT, XLNet, XML are the transformer models used in this work. The description of transformers as follows

***A.* BERT:**

The labelled data is fed to BERT pre trained model to extract aspects which is a subtask of proposed model aims to identify and analyze opinions and sentiments expressed towards specific aspects in a text. It has the ability to capture contextual information and understand the relationships between words make it well and then fine-tuning BERT using this labeled data. The fine-tuning process adjusts the pre-trained BERT model to better suit the specific ABSA task at hand. This process allows BERT to learn the patterns and relationships between aspects and sentiments, enabling it to make accurate predictions on test data.

In this work instead of using softmax classifier, SVM is used for sentiment classification. Finally the predicted output are fed to the ensemble classifier.

***B.* XLNet:**

XLNet leverages the idea of autoregressive modelling uses a permutation-based approach that allows it to consider all possible permutations of the input tokens. This approach enables XLNet to capture bidirectional dependencies between all words in a sentence, unlike traditional left-to-right or right-to-left models. The fine-tuning process involves preparing the dataset with annotated aspects and associated sentiments, and then adapted the XLNet model to the specific ABSA task by training it on this training data. In this work instead of using softmax classifier, SVM is used for sentiment classification. Finally the predicted output is fed to the ensemble classifier.

***C.* XLM:**

The pre-processed embedded tokens are passed through XLM's transformer layers, which captures the contextual information by attending to the surrounding tokens. XLM is trained to identify aspects or entities in the text by utilizing labeled data specific to the ABSA task. The extracted features from each transformer are fed the well proved machine learning classifier SVM for predicting the aspect polarity of the reviews.

Finally an ensemble classifier combines predictions by majority polarity. This is done through majority polarity prediction from SVM classifiers and final prediction will be done.

4. RESULTS

The predicted sentiment classes have to be validated with some metrics for performance analysis. In this work, following metrics are adapted to validate the classifier predictions.

Validation Metrics:

$$\text{Accuracy} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N}$$

$$\text{Sensitivity} = \frac{T_P}{T_P + F_N}$$

$$\text{Precision} = \frac{T_P}{T_P + F_P}$$

$$\text{F1-Score} = 2\,\frac{PPV * TPR}{PPV + TPR}$$

4.1. Results of Amazon Reviews dataset

Figure 5 shows, training accuracy, validation and training loss graph for Amazon Reviews dataset. At the end of the training, the overall accuracy reached 98.01%.

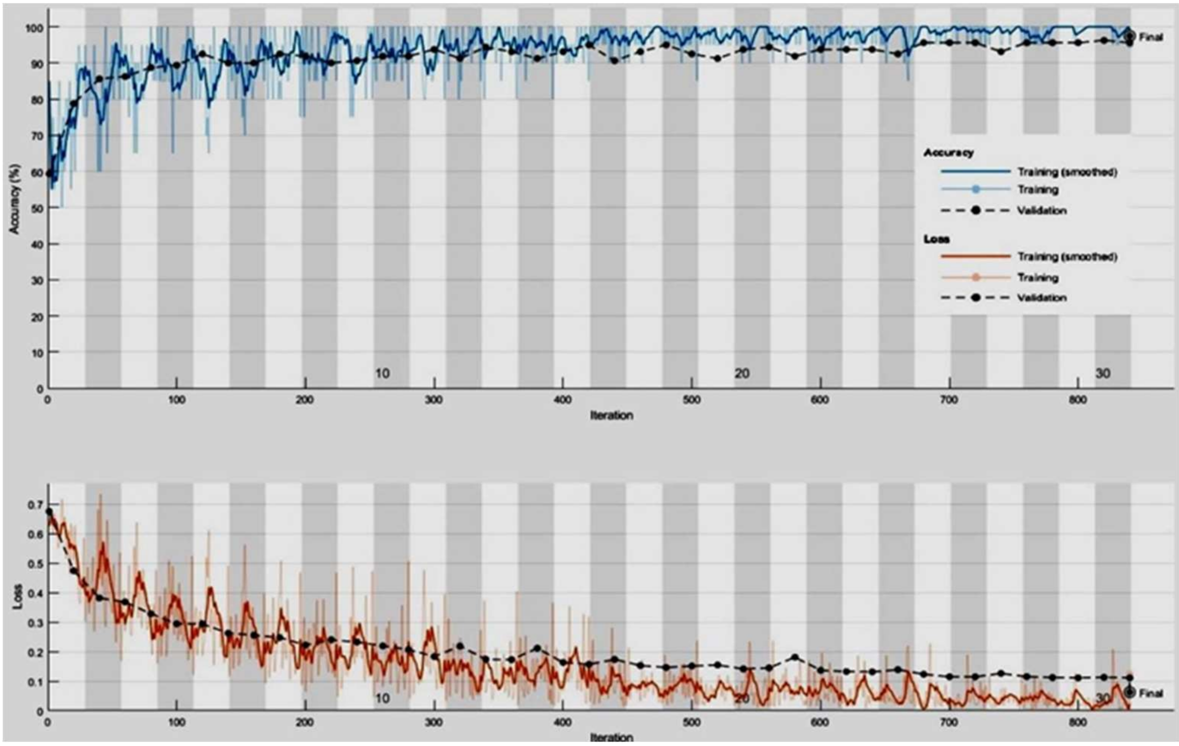

Figure 5: Training Accuracy, validation and loss graph for Amazon Reviews

Table 1 shows the performance metrics of BX2_Ensemble model on Amazon reviews

Table 1: Validation metrics of BX2_Ensemble model on Amazon reviews

Model	Accuracy	precision	Recall	F1-score
BERT_SVM	96.91	97.08	97.88	97.47
XLNET_SVM	97.32	98.24	98.92	98.57
XLM_SVM	97.66	98.53	98.97	98.74
BX2_Ensemble	98.01	98.34	99.17	98.75

Figure 6 shows Accuracy comparison with state of art transformer models plot on Amazon reviews

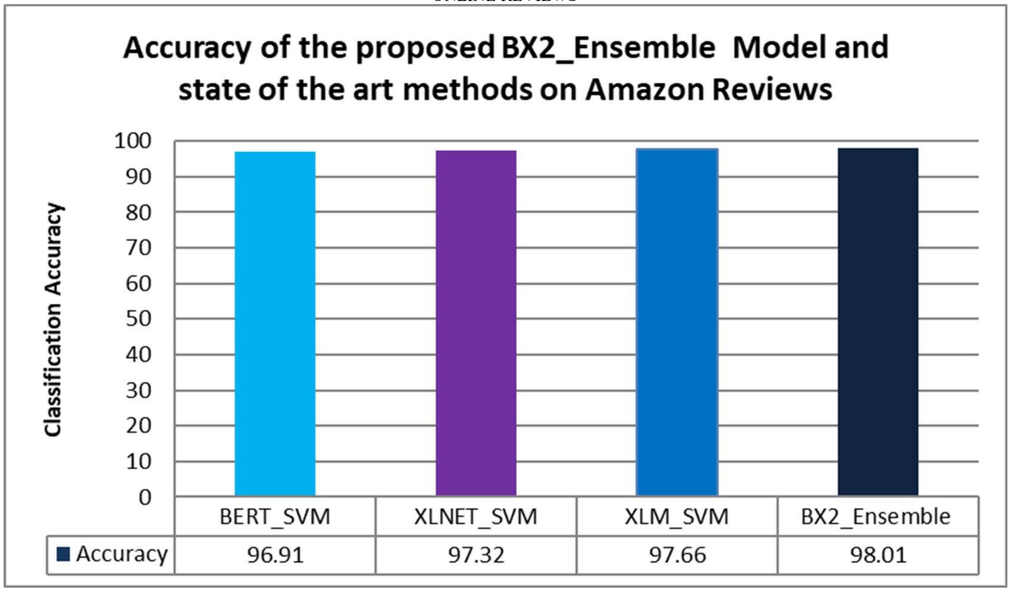

Figure 6: Accuracy comparison with state of art transformer models plot on Amazon reviews

4.2. Results of Twitter dataset

Figure 7 shows, training accuracy, validation and training loss graph for twitter dataset. At the end of the training, the overall accuracy reached 97.87%.

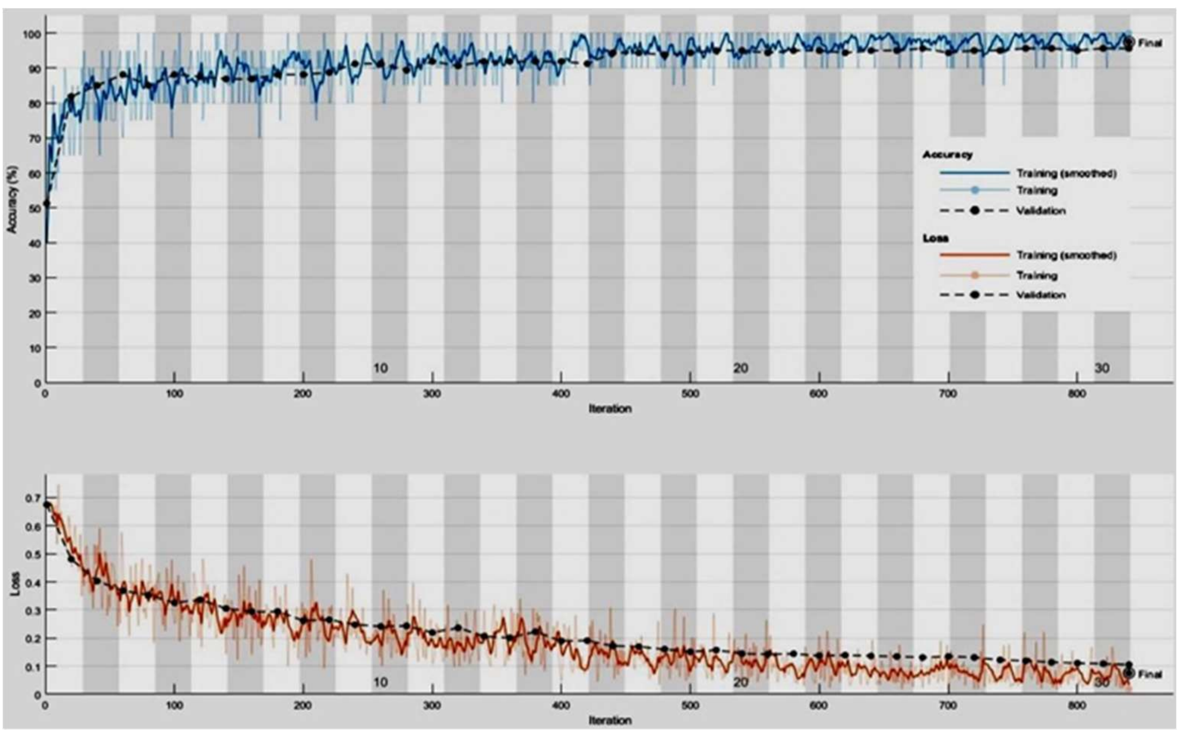

Figure 7: Training Accuracy, validation and loss graph for Twitter dataset

Table 2 shows the performance metrics of BX2_Ensemble model on Twitter dataset

Table 2: Validation metrics of BX2_Ensemble model on Twitter dataset

Model	Accuracy	precision	Recall	F1-score
BERT_SVM	95.63	96.73	98.12	97.42
XLNET_SVM	96.18	97.03	97.86	97.44
XLM_SVM	96.93	97.65	98.04	97.84
B X2_Ensemble	97.87	98.07	99.04	98.55

Figure 8 shows Accuracy comparison with state of art transformer models plot on twitter dataset.

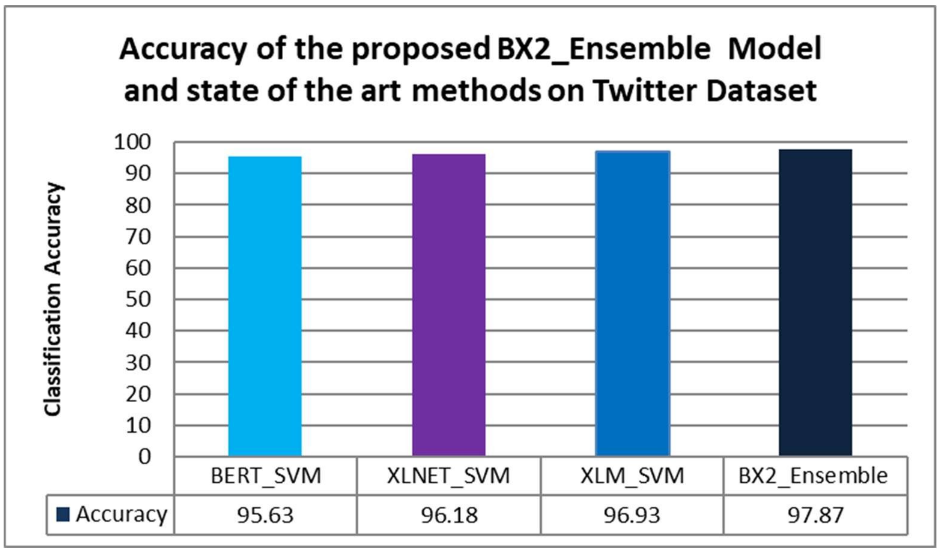

Figure 8: Accuracy comparison with state of art transformer models plot on Twitter dataset

4.3. Results of Trip dataset

Figure 9 shows, training accuracy, validation and training loss graph for trip dataset. At the end of the training, the overall accuracy reached 97.74%.

Table 3 shows the performance metrics of BX2_Ensemble model on Twitter dataset

Table 3: Validation metrics of BX2_Ensemble model on Twitter dataset

Model	Accuracy	precision	Recall	F1-score
BERT_SVM	95.66	96.46	97.08	96.76
XLNET_SVM	96.15	97.08	97.89	97.48
XLM_SVM	97.05	98.06	98.93	98.49
BX2_Ensemble	97.74	98.74	99.07	98.90

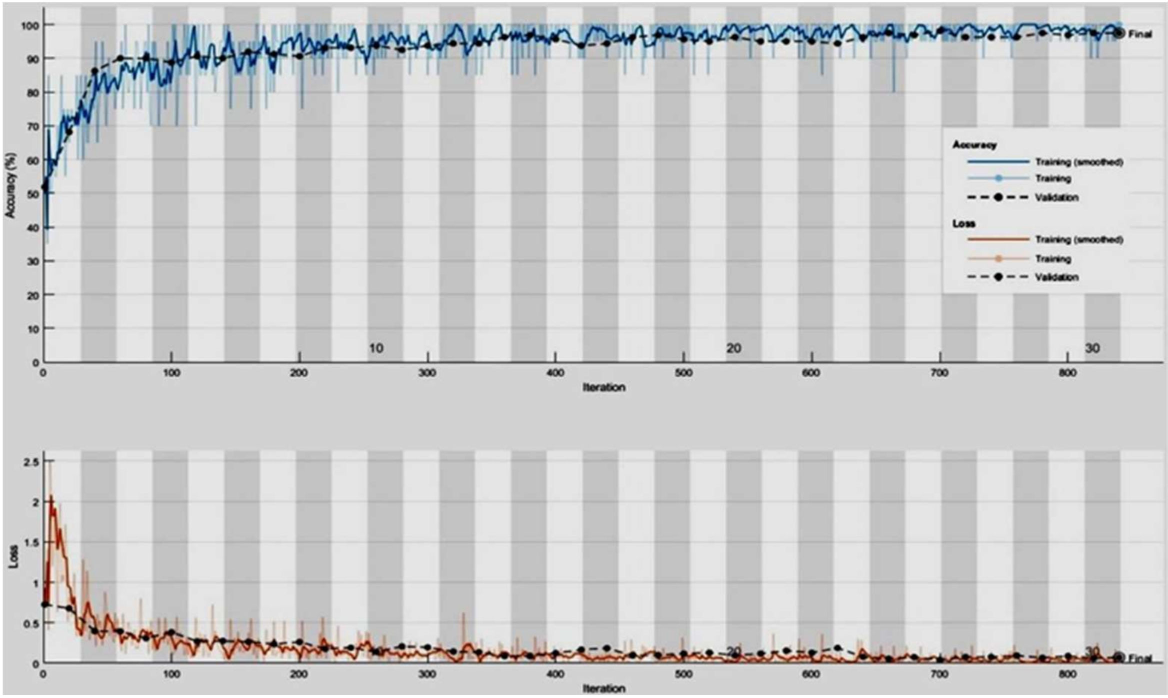

Figure 9: Training Accuracy, validation and loss graph for Trip dataset

Figure 10 shows Accuracy comparison with state of art transformer models plot on trip dataset.

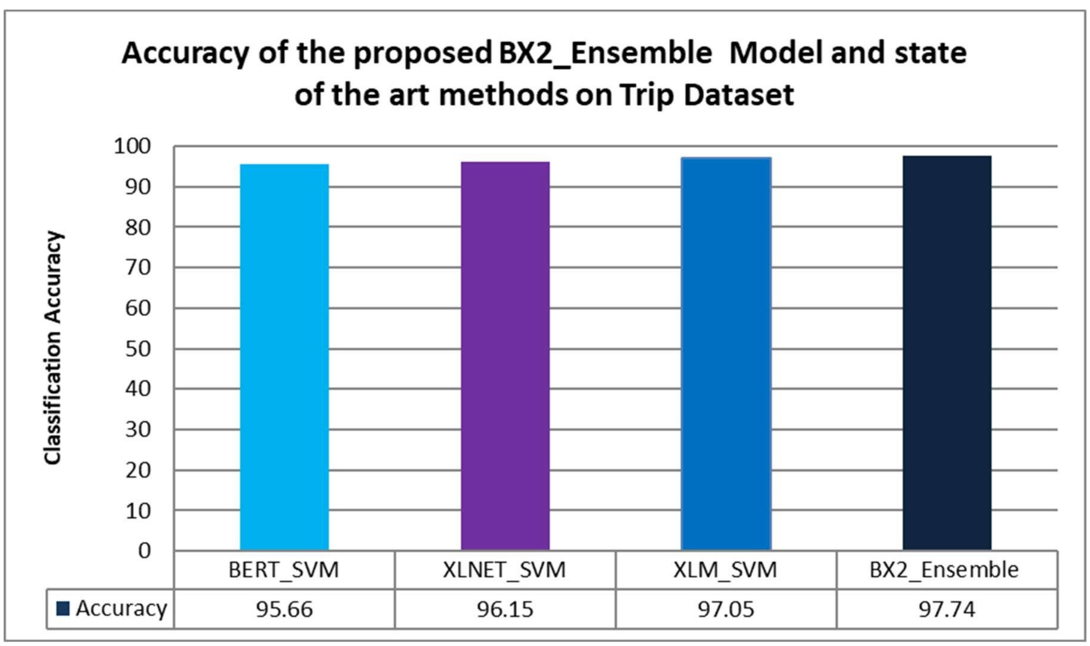

Figure 9: Accuracy comparison with state of art transformer models plot on Trip dataset

5. CONCLUTION

Aspect Based Sentiment Analysis (ABSA) is a text technique that categorizes data by aspect and identifies the Sentiment attributed to each aspect. Aspect level sentiment classification is a fine-grained task in sentiment Analysis. In this work an ensemble learning model is used to predict the sentiments polarity. This model consists pre trained deep transformers like XLNet, XLM and BERT are used for deep aspect extraction and SVM is used to classify the sentiment towards the aspects individually. Finally the predictions from each classifier model in the ensemble make a prediction, and the class with the majority of votes is selected as the final prediction. The proposed ensemble deep learning model outperformed with highest accuracy of 98.01%, 98.01%, and 97.74% on three different datasets which are based on amazon reviews, twitter and TripAdvisor datasets respectively.

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