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An Aspect based Multi-label Sentiment Analysis using Improved BERT System

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Abstract— Digital interaction has become more prevalent as a result of the increasing development of social Media and Web, making the customer active players. Customers' reviews uploaded on the Internet today provide crucial data towards other clients due to the vast quantity of reviews provided by consumers today. Since this type of information is extremely important for decision-making, it is extremely popular among internet users. Because of this, an automation system to analyses and retrieve insight from textual data is required. Sentiment classification is a well-known sub-area of Artificial Intelligence and Natural Language Processing that studies how people feel (NLP). The sentiments of participants in previous studies were calculated without taking into account the aspects indicated in a reviewing instances. In recent years, scholars have become interested in aspect-based sentiment analysis (ABSA). Numerous existing systems treat ABSA as if it were a single-label classification problem. This issue is addressed in this paper by presenting ways that make use of multilabeling classifiers for classification, which overcomes the problem. So rather than single label classifiers, the suggested approach employs the upgraded BERT system just for word embedding, with classification performed using multilabeling classifiers rather than single label classifiers. According to all methodologies, the label that is utilised for all learning classifiers identifies aspects by expressing their emotions. In this technique, the findings achieved via experimentation show that they are superior to the findings acquired through other existing researches when employing the system provided in this approach.

Keywords: *Aspect Based Sentiment Analysis (ABSA), Text classification, multilabel classifier, Dimensionality reduction, Bidirectional Encode Representation from Transformers (BERT), Artificial Intelligence*

1. Introduction

The recent growth of the Web has had an impact on every part of our lives, and as a result, the necessity for shows up analysis is growing at an exponential rate. Decision-making processes in businesses are being influenced by the flood of information that is being generated on a daily basis. Opinion mining is the study of people's attitudes, reactions, emotions, and other feelings about organizations including such services, products, topics, and events, as well as their attributes, based on input from Web pages. It is a type of data analysis. In addition to sentiment classification, opinion mining, and sentiment mining, other terms for this process include objectivity evaluation, providing services, emotional analysis, and opinion mining, and so on. In the field of Artificial Intelligence and Natural Language Processing, "Sentiment Analysis" will become the most wide anticipated and adopted area. The most widely used application of sentiment analysis is Understanding and identifying the implicit and explicit attributes in the social media interactions. It is beyond a doubt that the problem of doing sentiment classification on social media interactions is a difficult big data analytics problem to solve. When it comes to categorizing texts inside a certain linguistic unit, the classifications positive, negative, and neutral were utilised in early studies of sentiment analysis. This was done under the assumption that a sentence is a self-contained element in terms of expressing emotions.

Text analytics can be used for a variety of purposes, including the study of information, social networking sites material, and product, movie, and other reviews. The generic viewpoint provides just a partial picture of the product evaluations and reviews. As a result, ABSA is the primary focus of the investigation. Sentiment Analysis, Aspect extraction and sentiment prediction for something like the retrieved aspects are all tasks that are included in ABSA's capabilities. The focus of this research is on the prediction of sentiment based on aspects. There are a number of extant works that treat ABSA as an assigned assignment, such as aspect extraction or emotion forecasting only. Specific to this study would be to consider it as a problem that must be solved from beginning to end; that is, to estimate emotions for the elements that were discussed in the review.

Many of the current solutions to sentiment analysis problems do not take the context into consideration, and therefore rely upon classification models including such ternary or multi - class classification classifiers to complete the classification task. In some cases, a review occurrence may have several different features and opinions about either of those characteristics, culminating in a categorization of the review instance as a multi-class classification problem for the purposes of this classification. The following is an example of a mobile phone evaluation scenario: "The video quality is excellent, however I am dissatisfied with the audio quality." There are two parts to this sentence: the quality of the camera and the quality of the audio. In it, the opinion on camera quality is positive, however the view on audio quality is unfavorable.

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Consequently, single label classifiers are unable to generate accurate predictions in such situations.

The performance of the classifier is determined in part by the feature set used in the class prediction task, which is in turn determined by the classifiers. The application of Artificial Intelligence and natural language processing (NLP) towards the ABSA binary classification is critical. In a machine learning-based approach for ABSA, the performance of the classification method is determined by the extraction of features and selection techniques. Improved classification accuracy is achieved through the use of appropriate feature sets. In recent decades, state-of-the-art pre-trained natural language processing systems like as the OpenAI Algorithmic Which would have been previously known as the Transformer (OpenAI GPT), ELMo, and BERT are often used to automate activities. While there are a variety of models available, the OpenAI GPT is a left-to-right approach, while ELMo is a concatenated of both left-to-right and left to right models, and BERT takes into account token context from both the left and right sides, among others. Because these models have already been trained, they are not as reliant on the labelled data.

Because language models such as BERT do both word embedding and classification, there is no need for an additional feature selection phase in the process. It takes into account the relationships between the words in a phrase and calculates the word embedding, which is then used for classification in the following step. The next part provides a high-level overview of the multilabel classification system and the BERT system.

Our research has gathered restaurant reviews and rating information from a semeval Datasets. The classifier's performance is evaluated once it has been subjected to sentiment analysis. Despite the fact that this paper concentrates on restaurant reviews, the same approach may be extended to recommendations of any other sector, such as kitchen equipment, literature, electronic devices, movies, and so forth.

Following are important contributions of proposed work

1) Use of enhanced BERT algorithm or end-to-end ABSA that uses BERT for embedding and classification.
2) Use BERT multi-label classifiers and ML algorithms to examine the performance of a proposed BERT based ABSA model.

2. Review of Literature

This section discusses the work that has been done on ABSA in the past. This study is concerned with an end-to-end ABSA, and the purpose of this part is to assess the current state of research in this field. Specifically, this section discusses systems that solve the ABSA problem by employing machine learning techniques such as CNN and BERT.

According to the research presented in [1] various strategies for overcoming issues connected to domain heterogeneity were proposed, which took into account both the content domain and the language domain. With the help of domain data, the methodology of lexicon expansion was applied to improve sentiment categorization by evaluating the words used in the sentences. Two enormous unannotated emerging corpora, as well as five existing sentiment lexicons, were employed as seed and baseline data in conjunction with it. When compared to the seed lexicon, the results demonstrate that the extended lexicon significantly enhances the effectiveness of a emotion classification technique.

It is necessary to employ a deep neural network [2]. To be more specific, the investigations published in [2] and [3] combined supervised and unsupervised with machine learning can recognize sentiments, attributes, and keywords in the data. It was proposed in [2] that using a weakly supervised approach of learning that is based on a Artificial Intelligence, it would be able to categorize phrases that differentiate among positive and negative phrases (CNN). According to the model, every character is displayed as a continuous value vector, and that each sentence is expressed as a matrix whose columns correspond to the word vectors that were utilised in the sentence. The CNN model has been trained with the use of those phrase matrix as input and the emotions labels as outputs, respectively. As opposed to the prior CNN-based text classification model, the suggested class activation map (CAM2) classifications and localization system that relies upon that class activation map (CAM2) employs zero paddings to assist CNN in recognizing every word equally regardless of where it appears in the sentence.

An aspect-based sentiment evolution of customer reviews was described by the author in [3], who proposed an analytical pipeline that was semi-supervised and helped by deep learning]. This method investigates the use of deep learning techniques for the representation and categorization of textual data. They also handle both feature extracting and emotion identification simultaneously in this study, building on previous studies that tackled both aspects extractors and emotion identification separately. Because the data available is restricted to convey a particular harvesting and perception proof of identity from Twitter, this is not very interesting and informative to investigate whether there are any discrepancies between feature extraction and classification and sentiment identification. Given the limited data available, it is not very interesting and informative to investigate whether there are any discrepancies among both feature extraction and classification and sentiment identification. In their experimental studies, they concentrated on three available alternatives and could be used for both purposes at the same time.

In [4], the authors suggested a cascading feature selection strategy and classifier ensemble for ABSA that used particle swarm optimization (PSO) to optimize the selection of features. They made use of features that were characterized in terms of the properties of classification techniques and domains, among other things. The Support Vector Machine (SVM) classifier, the Conditional Random Field (CRF) classifier, and the Maximum Entropy (ME) classifier, were all employed.

The authors of [5] reported on a study wherein they adopted and refined the prevailing context-based word representations, that also ultimately results in phrases with exactly equal word vectors but a significantly improved refinement model when compared to the previous model. They concluded that the present context-based word embedding was superior to the previous model. Each word vector should be developed in such a manner that it can be increasingly equivalent to terms in the lexicon that are technically and sentimentally similar. This model keeps words that are comparable as neighbors with a higher rank, whereas words that are different have been given a lower rank in the model. The advantage of this approach is that it can be used to any word embedding system that was before word embedding system.

Research Presented in [6], compared sentimental sentence classification. The used LSTM. The Target independent LSTM has been shown to be more efficient than a number of other approaches in many studies. ABC was presented by the authors of [7] as combining additional subtasks: aspect recognition and sentiment prediction, according to the authors. As a result, a new model, FEA-NN, employs CNN-BiLSTM to investigate the relationship among aspect and sensation. The "Improved Word Vector" technique uses word embedding (IWV). This is the first strategy to use bi-directional LSTM to classify sentiment. It has three layers: encoder, decoder, and attention.

According to [8], text categorization challenges include excessive dimensionality and sparseness of text data, among other things. BiLSTM is utilised to get the context representations of the preceding and succeeding contexts.

In [9] authors presents a useful way for analysing feelings. Three independent procedures are combined in it: semantic mining, word2vec feature transformation, and CNN implementation for mining opinions. CNN was used to gather opinions. A genetic algorithm was used to tune the CNN and the parameters.

The authors of [10] offer a cascaded feature selection and classifier ensemble utilising PSO for ABSA. An ensemble of PSOs was built after the feature selection module. It decreases the dataset's dimensionality. The retrieved features are then utilised to forecast each sample's class label.

The study [11] suggested a multilayer design for customer reviews. Word embedding and compositional vectors were employed in representation learning. BackPropagation was used to train a model for aspect rating prediction as well as producing aspect weights. The proposed model outperforms other common techniques in tests. Using a non - linear and non-categorization methodology for sentiment analysis, the authors of [12] presented their findings. A text segmentation algorithm, feature extraction algorithms, and multi-label classification algorithms are the three primary components of the proposed prototype. We used raw segmented words, opinion characteristics based on three different sentiment dictionaries: “the National Taiwan University Sentiment Dictionary (NTUSD), the HowNet Dictionary (HD), and the Dalian University of Technology Sentiment Dictionary (DUTSD)” and an unstructured collection of words. The DUTSD dictionary outperforms the other two sentiment dictionaries in terms of overall performance. ABSA is represented using the BERT representation technique [13, 14]. Many earlier techniques regarded labels as symbols devoid of meaning and neglected the relationships between labels, resulting in information being lost as a result. The investigators in [13] deal with this issue in more detail.

In this methodology [13], the hybrid BERT model adds label semantics through the use of adjective attention, which looks for and discovers semantic relationships between label space and text space at the same time in both label and text space. In ABSA, BERT is utilised, and it must be entered in a word sequence format, which does not provide any more context information about the word. Through the use of this technique, the author integrates recurrent attention over the character-level hidden state with the BERT front-end encoder, allowing the model to accurately represent the sequential nature of sentences.

The study in [14] proposed a GBCN process that makes use of the gated elements with situational aspect integrating to control and enhance BERT presentation for ABSA by utilising gated elements with situational aspect embedding.

Using unstructured rule-based techniques (RubE), the authors in [15] established a method for extracting objective and subjective attributes from reviews that was not supervised. In this study, the authors discovered objective aspects by incorporating patterns and relationships specific to the review. They went on to extract subjective characteristics by combining double propagation with indirect dependency and comparative building, among other techniques. The findings reveal that RubE is significantly more advanced than the competition in terms of product characteristic extraction technology.

In [16] the authors presented the AS-Reasoner methodology to address challenges connected to the expression of precise sentiments in text. When different phrases in a sentence are assigned different relevance levels, the AS-Reasoner is able to capture the most important sentiment expressions connected with that particular aspect.

They presented a study [17] wherein the researchers examined the polarity-bearing elements of the JST model, which was well received. Utilizing the review data as well as the non-linear and non-sentiment data sets, they discovered that unsupervised classification techniques developed using an individual feature vector enriched using polarity-bearing subjects surpassed unsupervised classification models on both of the data sets. Their prototype outperforms the Structural Correspondence Learning (SCL) algorithm for cross-domain opinion classification and has made significant progress that is comparable to that of the Spectral Feature Alignment (SFA) method. This was accomplished by continuing to expand the extracted features and approaches suggested based on information gain criteria, which allowed them to outperform the Structural Correspondence Learning (SCL) algorithm for cross-domain opinion classification.

On the basis of data machine learning and natural language processing technologies, the authors' work [18] presented a collection of mining algorithms for summarising product reviews, which they had built themselves. The objective is to offer an overview of a bigger wide range of customer evaluations of an online shopping company that are based on a variety of different factors. According to the authors, organizations are actively acquiring things on the internet and expressing their views about such commodities on the Web in the form of reviews, which they predict will become increasingly significant in the future. When product manufacturers and merchants summaries client feedback, they not only benefit from the information, but they also benefit from the information.

According to the authors of a publication [19], they have designed and are currently testing a movie rating and review-summarization system for use in a mobile context. In their study, the findings of integrating classification technique to movie reviews were used to determine how well a film was rated. For feature-based summarising, the authors present a technique based on Latent Semantic Analysis (LSA) to identify related product features. This technique is important since it is necessary to identify product features in order to do feature-based summarization. Product features were combined with opinion terms that were selected using a statistical approach in order to provide a feature-based summary of the data.

3. Implementation Details

This research proposed the approaches for completing an end-to-end ABSA work from start to finish. The purpose of this study is to examine the performance of ABSA employing simple BERT for language model and multilabel classifications to determine how well it performs for classification.

a. *Multi-label classification*

There are two types of classification problems: single label and multilabel. The binary or multiclass classifier for a single label can be used. Single-label classifiers cannot classify textual material that contains multiple class labels. Ex: “Picture quality is good but the sound is muddy”. This statement has two class descriptors, visual quality and audio. The multilabel classifier is used to categorise textual input having several labels. It has recently gained popularity. Classification approaches include problem transformation, algorithm adaptation, and ensemble classification. Problem transformation strategies include BR, CC, and LP [21].

b. *Improved BERT*

It is an NLP model with BERTBASE and BERTLARGE versions. BERTBASE: 110 million parameters, 12 transformer blocks 24 transformer blocks, 340 million variables, 16 attention heads BERT is a transformer encoder stack. Pre-trained BERT models can help with NLP. Because they are pre-trained models, they can be utilised for numerous text categorization tasks without changing the architecture. It analyses both left and right token context. BERT models can be used for a variety of tasks, including sentiment classification and sentence predictions. Following that, the model takes the [CLS] symbol, followed by the paragraph tokens, and finally the [SEP] symbol as a paragraph separator. The BERT obtains a summation of token, segment, and positional embedding information, among other things. Position embedding captures a token's position in a sentence, segment embedding helps answer questions, and token embedding employs Word vocabulary. An informative summative embedding. This embedding feeds the fully connected network, which classifies it.

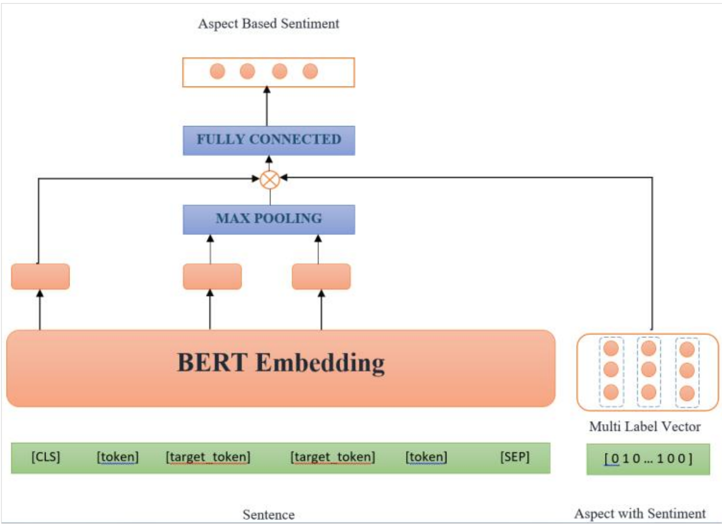

Fig. 1. Proposed Architecture for Improved BERT Mechanism

Proposed enhance BERT system architecture is shown in Figure 1. BERT is now widely used in NLP. The suggested approach uses multilabel classifiers to choose features. This model doesn't pick features. The BERT model has two extensions. The CLS tag output is usually fed into the fully connected layer. Throughout this research, the maximum pooling of the target terms is taken and contributed to the final result at CLS. In this case, the result is received as input by the entirely connected layer. The BERT model is also augmented using multibit label input that captures aspects and sentiments.

4. Result And Discussion

a. *Dataset Description*

The datasets utilised in this study are the SemEval 2014 customer review dataset. [20]. Following figure shows the restaurant review dataset.


```
<sentence id="425">
    <text>The price is reasonable although the service is poor.</text>
  - <aspectTerms>
        <aspectTerm to="9" from="4" polarity="positive" term="price"/>
        <aspectTerm to="44" from="37" polarity="negative" term="service"/>
    </aspectTerms>
  - <aspectCategories>
        <aspectCategory polarity="negative" category="service"/>
        <aspectCategory polarity="positive" category="price"/>
    </aspectCategories>
</sentence>
```


Fig. 2. Restaurant review instance snippet

b. *Performance Parameters*

The accuracy for multiclass classifiers is defined below. TP stands for true positive, TN for true negative, and FP for false positive, and FN is for false negative. Humming Loss is another parameter. The Hamming loss illustrates how an instance's relevance to a class label is overestimated.

$$Hamming\_Loss = \frac{1}{|X|}\sum_{i=1}^{X}\frac{XOR(p_i, a_i)}{|L|}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

c. Results

Table 1 shows the hyper parameters setup used for improved BERT model.

Table 1. Hyper Parameters Setup for Enhance BERT algorithm

Parameters	**Value**
Dropout Rate	0.1
Batch Size	8
Max Epoch	6
Max Sequence Length	256
Optimizer	Adam
Learning Rate	2e-5
Layer norm eps	1e-12
Max length	20
Max position embeddings	512
Number of attention heads	12
Number of hidden layers	12
Vocab size	30522

Table 2 shows the Accuracy and hamming loss, one error, ranking loss, micro and macro F1 gained using ML and enhance BERT classifier for restaurant review dataset and graphical result comparison is shown in figure 3.

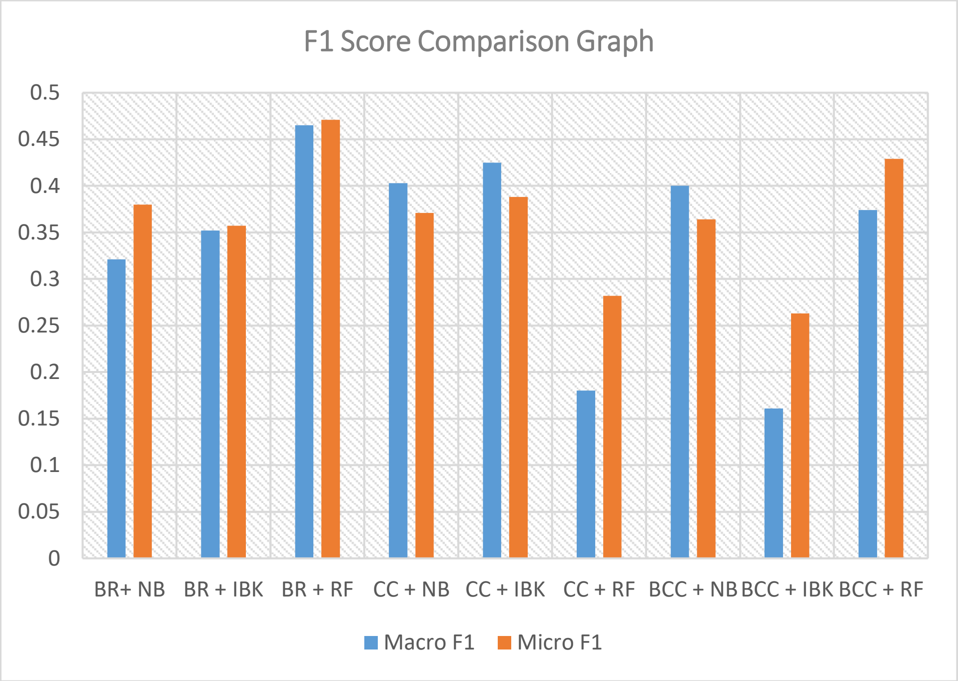

Fig. 3. F1 score comparison of ML Algorithms.

Table 2: Accuracy and hamming loss, one error, ranking loss, micro and macro F1 gained using ML and enhance BERT classifier for restaurant review dataset

ML Algorithm	**Baseline Algorithms**	**Accuracy (per label)**	**Hamming Loss**	**One Error**	**Ranking Loss**	**Macro F1**	**Micro F1**
SEMEVAL REUSTRANT REVIEW DATASET							
(4-WAY)							

BR	NB	0.92495	0.075	0.566	0.136	0.321	0.38
BR	IBK	0.9171999	0.083	0.623	0.383	0.352	0.357
BR	RF	0.9336499	0.066	0.508	0.14	0.465	0.471
CC	NB	0.92465	0.075	0.59	0.372	0.403	0.371
CC	IBK	0.93894994	0.061	0.533	0.395	0.425	0.388
CC	RF	0.94805	0.052	0.598	0.54	0.18	0.282
BCC	NB	0.92255	0.077	0.598	0.363	0.4	0.364
BCC	IBK	0.94715005	0.059	0.525	0.391	0.161	0.263
BCC	RF	0.941	0.053	0.631	0.551	0.374	0.429

Table 3 shows the Algorithms and their accuracy (per label). Enhance BERT outperforms all the ML algorithms. Figure 4 shows the graphical representation of accuracy comparison of ML and BERT algorithms.

Table 3. Accuracy (per label) of ML and enhance BERT Algorithms

Algorithms	Accuracy
BR + NB	92.49
BR + IBK	91.79
BR + RF	93.36
CC + NB	92.46
CC + IBK	93.89
CC + RF	94.80
BCC + NB	92.25
BCC + IBK	94.71
BCC + RF	94.10
BERT	96.25

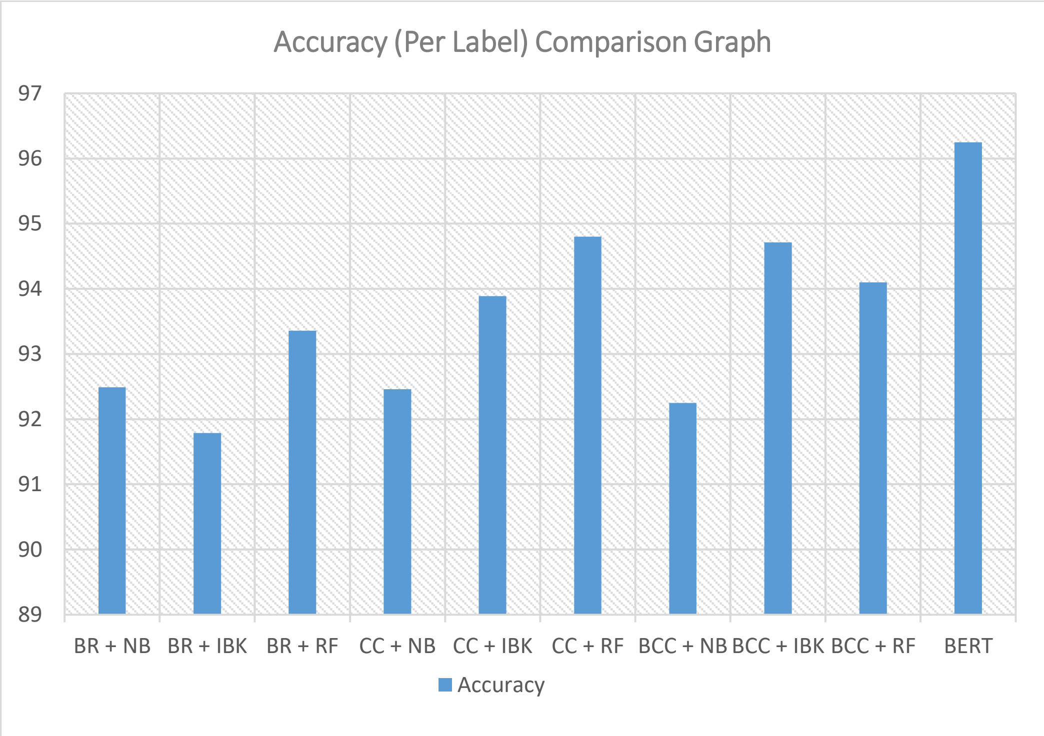

Fig. 4. Accuracy (per label) comparison graph of ML and enhance BERT Algorithms.

Table 4 shows the training and validation loss comparison of enhance BERT algorithm for 6 epochs. With increase in number of epoch the loss gets reduce. Figure 5 shows the training and validation loss comparison of enhance BERT algorithm.

Table 4. Training and Validation Loss comparison of enhance BERT Algorithms

Epoch	Training Loss	Validation Loss
1	0.3157	0.1859
2	0.1690	0.1526
3	0.1379	0.1348
4	0.1205	0.1287
5	0.0860	0.1219
6	0.0764	0.1102

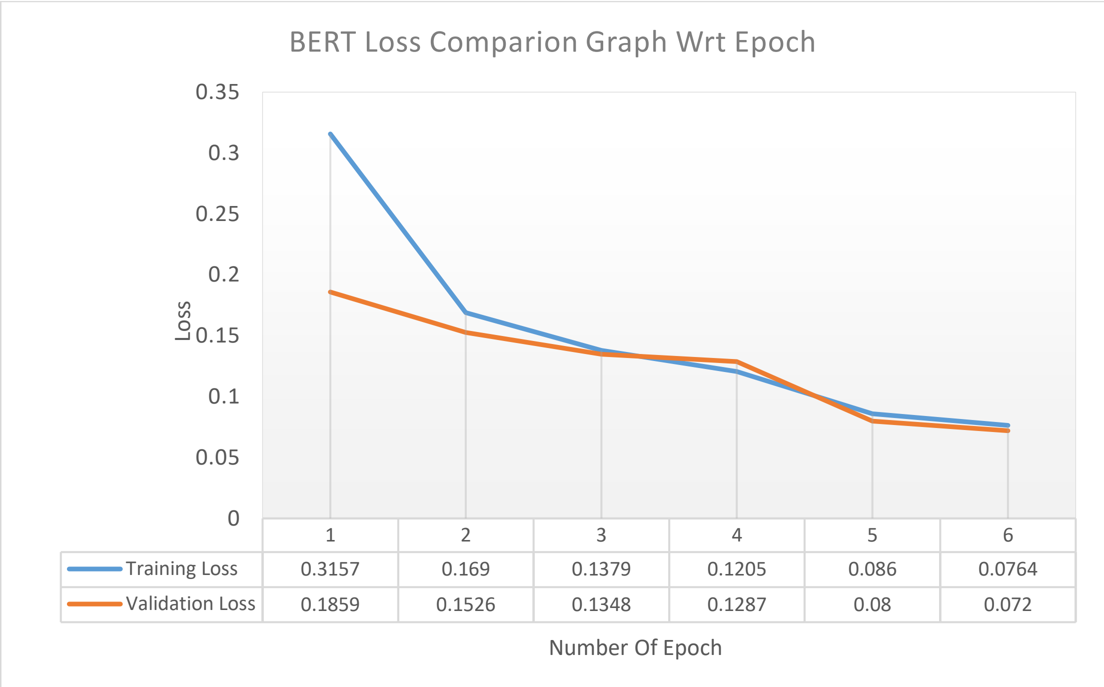

Fig. 4. Training and Validation Loss comparison of enhance BERT Algorithms

5. Conclusion

An end-to-end strategy for ABSA was proposed in this paper, rather than addressing classification technique and appearance categorization prediction as two separate tasks. Earlier methods employed single label ABSA classifiers. Here, multilabel classifiers were used. ABSA is offered in three ways. The upgraded BERT system is utilised for both word embedding and categorization. This system outperforms other systems. This research indicates that the BERT system works well when tokens in a sentence are considered in both directions. The per-label accuracy (4-way) of the enhanced BERT classifier is 96.25 percent. These are the restaurant review results. The experimental datasets are imbalanced. This research shows that machine learning solutions to text categorization issues require features linked by meaningful grammatical relations.

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