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Improving The Efficiency of Aspect-Based Sentiment Analysis Using Ensemble Deep Learning.

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Abstract. Aspect-Based Sentiment Analysis (ABSA) is a specialized subfield of sentiment analysis that incorporates named entity recognition (NER), entity-sentence identification, and sentiment analysis. Executing each of these tasks requires the application of sophisticated language processing algorithms. For instance, NER typically employs a combination of linguistic heuristics and machine learning models, such as Hidden Markov Models (HMMs) or Support Vector Machines (SVMs), to discern aspects within an input sentence. Similarly, identifying sentences relevant to a given aspect or entity demands intricate ontology graph methodologies. Given the complex nature of these processing stages, it is imperative to utilize high-accuracy algorithms. This paper presents an advanced ABSA system that merges an ensemble sentiment analyzer with a convolutional neural network (CNN) for entity and entity-sentence identification. The proposed algorithm employs the VGGNet architecture, augmented by a dynamic ontology graph, to enhance the precision of entity and entity-sentence identification. Subsequently, an ensemble sentiment analyzer is introduced, integrating outputs from four distinct sentiment analyzers to boost the overall system's accuracy levels. Evaluation of the proposed algorithm on multiple datasets demonstrates its superior performance in comparison to contemporary state-of-the-art systems. In particular, the algorithm exhibits a 9% improvement in classification accuracy on a restaurant dataset, along with 10% and 14% accuracy enhancements on laptop and Twitter datasets & samples.

OR

Aspect-Based Sentiment Analysis (ABSA) is a cutting-edge field within sentiment analysis, intertwining the complexities of named entity recognition (NER), entity-sentence association, and sentiment analysis itself. The intricate nature of these tasks necessitates sophisticated language processing algorithms. For instance, NER is not a straightforward process; it often combines linguistic heuristics with advanced machine learning models like Hidden Markov Models (HMMs) or Support Vector Machines (SVMs). These models are crucial for accurately identifying different aspects within a sentence.

Identifying sentences relevant to a specific aspect or entity is another challenging task. It requires the use of complex ontology graph methodologies. Given the intricate processes involved in these stages, high-accuracy algorithms are essential. The paper at hand introduces an advanced ABSA system that combines a powerful sentiment analyzer with a convolutional neural network (CNN) for efficient and precise entity and entity-sentence identification.

The proposed system is not just a simple CNN; it employs the VGGNet architecture, known for its effectiveness in image recognition tasks, and adapts it for language processing. This approach is further enhanced by incorporating a dynamic ontology graph. This integration aims to significantly improve the accuracy of entity and entity-sentence identification, ensuring that the system can understand the context and nuances of different sentences accurately.

Furthermore, the paper introduces an ensemble sentiment analyzer. This is not a single tool but a combination of outputs from four distinct sentiment analyzers. By integrating these different analyzers, the system is designed to boost the overall accuracy of the sentiment analysis process. This ensemble approach ensures that the system benefits from the strengths of each individual analyzer, thereby reducing the likelihood of errors and increasing reliability.

The performance of this algorithm is not just theoretical. The paper presents an evaluation of the system using

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multiple datasets, showcasing its superior performance compared to contemporary state-of-the-art systems. This is a significant claim, as it suggests that the proposed algorithm isn't just an incremental improvement but a substantial leap forward in the field of ABSA.

One of the most notable aspects of the proposed system is its improved classification accuracy. The algorithm shows a 9% improvement in accuracy on a restaurant dataset, which is a substantial increase in a field where even small percentage points can make a significant difference. Moreover, the improvements are consistent across different types of datasets. The algorithm achieves 10% and 14% accuracy enhancements on laptop and Twitter datasets and samples, respectively. These results are indicative of the algorithm's versatility and effectiveness across various domains.

In conclusion, the paper presents a highly advanced ABSA system that effectively merges a convolutional neural network with a dynamic ontology graph and an ensemble sentiment analyzer. This system marks a significant advancement in the field of sentiment analysis, particularly in its ability to accurately identify and analyze entities and sentiments in complex sentences. The improvements in accuracy demonstrated across multiple datasets highlight the potential of this system to redefine the standards in ABSA, providing a more accurate, reliable, and versatile tool for sentiment analysis.

Keywords: *Sentiment, aspect, entity, classification, machine learning*

1. Introduction

Aspect-based sentiment analysis (ABSA) is a complex natural language processing (NLP) field, which involves a wide variety of operations. These operations range from simple part-of-speech tagging to complex wordnet-based classifications. Each ABSA system must perform the following tasks to effectively classify sentiments for each of the sentence aspects,

- Data collection and pre-processing must be done for the given application. This collection of data must not be limited to a particular domain but must be done for multiple domains which cover the application. For instance, in order to perform ABSA for movies domain, collection of movie data along with data about the cast, locations mentioned in the movies, etc. must be done for effective ABSA operations. Pre-processing operations like stop-word removal, missing value removal, etc. are also done in order to improve dataset quality and reduce its size.
- The dataset is divided into training and testing sets, wherein a ratio of 70:30 is observed.
- Both these sets are given for aspect identification. Here the identified aspects are used for labelling the dataset. Algorithms like neural networks (NN), support vector machines (SVM), hidden Markov models (HMM), etc. are used for this purpose.
- Once aspects are identified, then aspect-level sentiment analysis is done, wherein the sentence is observed from the aspect's point of view. For instance, the sentence "Reebok is better than Adidas" has positive polarity when "Reebok" is considered as an aspect but has negative polarity when "Adidas" is considered as the aspect. In order to perform this complex task, the algorithm is tuned such that the aspect under test is considered as the primary party, and other aspects are considered as secondary parties. Thus, when "Adidas" is considered as the primary aspect, then the sense of the sentence gets modified as, "Adidas can be better than Reebok", which makes the sentence polarity as negative. Analysing the sense of the sentence in such a manner requires deep-learning models to be used. Thus, algorithms like convolutional neural networks (CNN), long-short-term-memory (LSTM), Gated Recurrent Unit (GRU), etc. are used for this purpose.

A visual representation of this flow can be observed from figure 1, wherein twitter based aspect level sentiment analysis is done. Here, it is observed that additional to the mentioned steps, the Twitter data is labelled with an initial aspect and sentiment polarity. This initial labelling assists the system to improve its classification performance via initial reference value comparison.

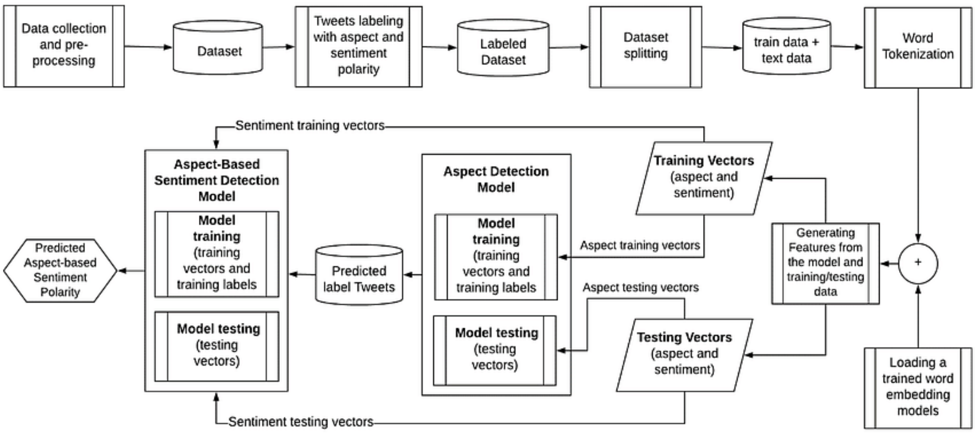

Fig 1. An example twitter-based aspect level sentiment analysis

A brief survey of such systems along with their performance is discussed in the next section of this text. It is followed by a brief description of the proposed deep-learning ensemble sentiment learning model and its result evaluation on different datasets. This text also compares performance of the proposed model with recent state-of-the-art systems. Finally, this text concludes with some interesting observations about the proposed system and recommends ways to improve its performance.

2. Literature Review

Aspect based sentiment analysis algorithms require careful planning and analysis of methodologies that include but are not limited to parts of speech (POS) tagging, chunking, n-gram analysis, aspect classification, polarity checking and information aggregation. For instance, the work in [1] uses dependency and constituency parsers to perform aspect classification, and then applies recurrent neural networks via recursive neural trees & gated recurrent units to find out sentiments. It uses a combination of recursive model with constituency parser sub-model and recurrent models for improving efficiency of sentiment analysis via information propagation and syntactic structure extraction. This work can achieve an accuracy of over 80% for restaurant and laptop sentiment domains. The work must be tested on larger sets to evaluate its real-time applicability and can replace gated recurrent units with long-short-term-memory models for further improving its accuracy. Moreover, the efficiency can also be improved via the use of weakly supervised annotations as suggested in [2], wherein a sentiment dataset from massive open online courses (MOOC) is taken for evaluation. Due to the use of weakly supervised annotations, the system is able to evaluate unlabeled reviews via a series of multi-dimensional embedded feature sets. Flow diagram of this architecture can be observed from figure 2, wherein von Mises-Fisher distribution is used to cluster review data and perform embedding dimensions from it. The system works using the following steps,

- Annotated reviews are given to a term extraction with term frequency (TF) and inverse document frequency (IDF) layer for evaluating relevant features.
- These features are given to a von Mises-Fisher distribution function in order to cluster the data and generate embedding dimensions.
- Each of these dimensions is given to individual filters for feature map generation. Feature maps include n-gram based language maps and word2vec based numeric maps.
- These feature maps are then processed via pooling and soft max layers, and then are stored for future comparison.
- Any unlabeled review(s) are given to a weak label propagation unit, wherein the same process is applied, and features for different aspects are evaluated.
- All these features are given to a CNN which uses LSTM-based training in order to generate positive and negative sentiments.
- These sentiments are then assigned to each aspect, and its confidence score is evaluated.
- This score is used for fine tuning of the CNN algorithm for continuous accuracy improvement.

An accuracy of 90% to 93% is achieved via the use of this architecture, due to the complex feature extraction process applied via the CNN and LSTM layers. But this architecture is compared on limited aspect datasets, and thus needs further diligence for final evaluation of its performance and real-time applicability.

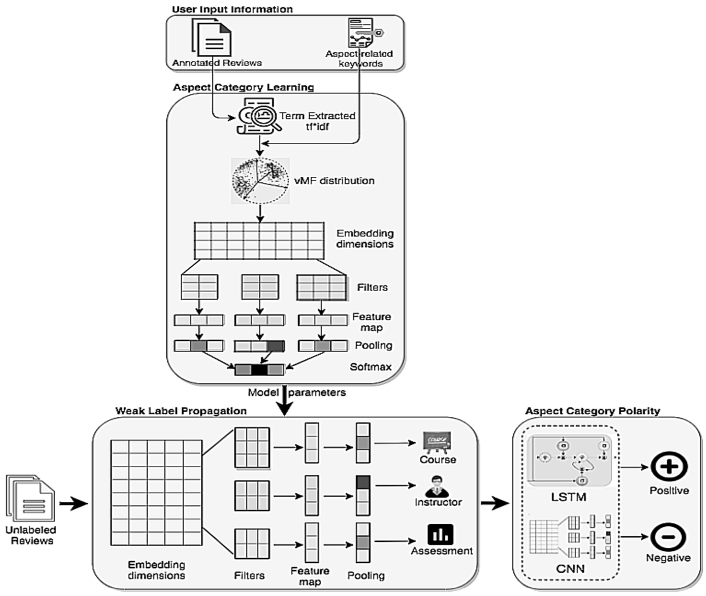

Fig 2. CNN & LSTM with weakly annotated sentences for improving aspect-based sentiment analysis [2]

A complete set of these datasets, and relevant algorithms for aspect-based sentiment analysis (ABSA) is given in [3], wherein along with algorithms and datasets, various metrics for evaluation of ABSA systems is also given. Aspect extraction techniques like co-occurrence, semantic analysis, ontology-based, lexicon-based, etc. are also discussed. A set of more than 15 datasets is described in this text, which allows researchers from different language processing domains to evaluate their algorithms and architectures with utmost diligence.

It is observed from [1], [2] and [3] that the current ABSA frameworks face the following challenges,

- Due to the use of CNN, special case sentences like the ones with double negative words are often mis-classified.
- Use of a single vector for identification of context and target is insufficient, which limits the performance of this system.
- Aspect-based sentence extraction algorithms have their limitations, wherein unrelated words might be included in the sentences, which limits their performance.

To remove these drawbacks, the work in [4] proposes a knowledge guided capsule network or KGCapsAN, which uses Bi-LSTM and capsule networks. Capsule networks perform the task of aspect-based sentence extraction, while Bi-LSTM network allows the system to improve its sentiment analysis accuracy. The capsule network takes input from syntactic layer, local n-gram layer and aspect query layer to understand about aspects and their relevant sentence sets. Finally, a feedforward network is used to evaluate sentiments of these aspect sentences. An accuracy of 74% is achieved on Twitter dataset, 77% on laptop dataset and 88% accuracy on restaurant dataset. An application of such networks for Ridesharing Platforms is described in [5], wherein aspects like driver, company, service, and ride are used for analysis of sentence sentiments. Based on this analysis companies can implement improvement protocols and have better user experience. But this system is based on fixed aspects which limits the application's performance and does not guarantee its future applicability. The work in [6] suggest use of explicit aspect extraction (EAE) algorithms, that allow for extraction of domain independent aspects, thereby extending system's applicability. From their research it is observed that hybrid algorithms that combine neural networks, conditional random fields (CRF), dependency parsing, topic modelling and decision tree (DT) can improve the accuracy of ABSA systems.

Accuracy of ABSA can also be improved with better feature extraction, feature selection and feature classification methods. The work in [7] suggests use of transformer based multi-grained attention network (T-MGAN) that uses a transformer model for learning aspect-based word-level representations, and then use tree transformer model for sentence level representation of contexts. These contexts are given to a multi-grained attention network for sentiment evaluation via a multi attention layer combined with different soft max layers for improved accuracy. The system is evaluated on the standard laptop, restaurant & twitter datasets, and an accuracy of 76%, 82% and 71% is achieved respectively. Which is on the moderate side but can be increased via the use of complex machine learning algorithms like deep CNNs. Most of these datasets are in English thus, all the language models, ontology models, graph models, etc. are developed for the English language. In case of language changes, these models do not hold their performance, and need major re-tuning in terms of the said entities. In order to reduce this re-tuning effort, the work in [8] proposes a language independent method for ABSA, which performs simple lexicon to lexicon matching for conversion of the underlying models into language independent ones. It is observed that this framework can produce accuracies in the range of 74% to 86% for different English and Persian datasets, which is about 15% higher than existing Persian language processing models. These models can be made context-aware via enhancement of Bidirectional Encoder Representations from Transformers (BERT) representations. In order to do this, the work in [9] uses a gating mechanism with context aware aspect embeddings (GBCN) to improve and have better control over BERT embeddings. The modified model is tested on SentiHood and SemEval datasets, and an accuracy between 89% to 94% is achieved via the use of LSTM based sentiment classification. The framework for GBCN algorithm can be observed from figure 3, wherein modified BERT encoding along with fully connected neural network layers are observed for improved aspect-based sentiment analysis.

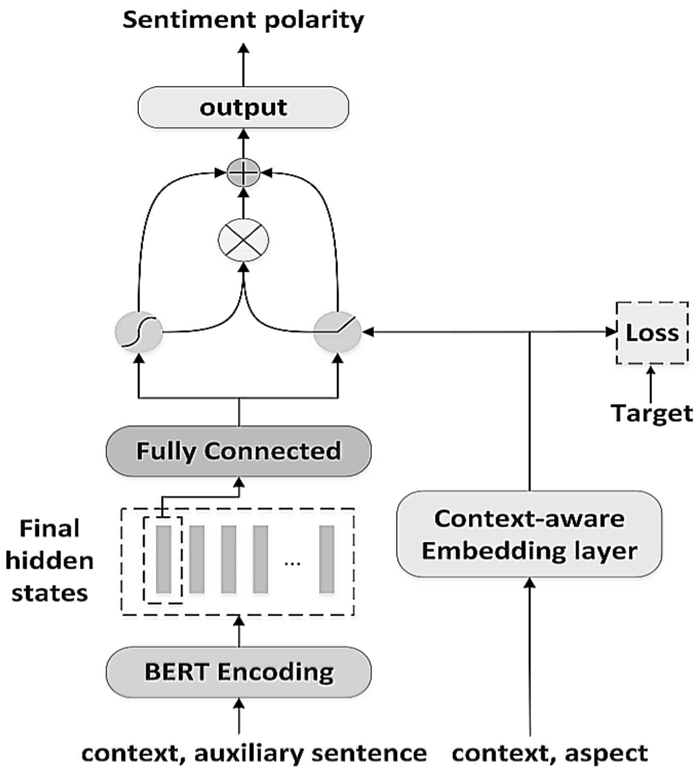

Fig 3. Improving the BERT encoding for improved ABSA performance [9]

Ensemble of bio-inspired algorithms like Genetic Algorithm (GA) with CNN for its hyper-parameter tuning can also be a good ABSA system. The work in [10] does this by mining semantic features, then using word2vec for feature extraction from these semantics and finally, using CNN for opinion mining. Due to a combination of GA with CNN, the system's accuracy on restaurant, laptop and other datasets is more than 93%, which makes this research an ideal candidate for real-time implementation. A similar research, but with the use of capsule network is proposed in [11], which also uses a combination of BERT model with XLNet for obtaining accuracy values in the range of 85% to 90% on different datasets. Other research works like in [12], [13], [14] and [15] use variants of convolutional neural networks like Moving-window Attentive Gated Recurrent Unit, Hierarchical Gated Deep Memory Networks, Deformable CNN and Attention model and Lexicon-Enhanced Attention Network respectively to perform ABSA. All these algorithms have an accuracy in the range of 80% to 93% for different standard datasets, but none of these algorithms are applied on customized datasets, which makes them an ideal candidate for real-time testing. To do this task, the work in [16] can be referred, wherein large-scale real-time user reviews are collected for effective evaluation of ABSA systems. The approach in [16] uses unsupervised semantics for ABSA, which itself is a weak classification system, but its accuracy can be improved by the work done in [1-15] via integration of convolutional neural networks.

Other attention models like Feature Enhanced Attention and Interactive Rule Attention are discussed in [17] and [18] respectively. Both these models tend to improve the efficiency of aspect sentence identification, and then apply CNNs for sentiment classification. These models have an accuracy of 72% to 81% for standard datasets, and thus can be tested on the real-time reviews dataset as suggested in [16] for further diligence. Another interesting approach that uses aspect graphs for aspect sentence classification is mentioned in [19], and it uses aspect specific CNNs for improved accuracy and fMeasure performance. The accuracy is in the similar range as of [17] and [18], but the computational complexity associated with the system is very high. This is similar to the case as with any CNN-based ABSA system, and can be reduced by effective feature selection models. One such model that uses aspect opinion mining for feature extraction and selection is proposed in [20]. This model aims at using LSTM-based approach and combine with opinion mining for reducing ABSA complexity, and keeping the same high accuracy performance as suggested by previous CNN-based ABSA systems. The performance of these LSTM based systems can also be improved via the use of position context-aware attention-based LSTMs as discussed in [21], which provide accuracies in the range of 80% to 90% depending upon the dataset being evaluated. Performance of LSTM can be improved via the use of Bayesian Networks as suggested in [22], wherein Dynamic Bayesian Network (DBN) is used along with Gaussian Process Regression. This combination improves overall ABSA accuracy to around 92%, with low complexity, and thus can be used for real-time ABSA systems. Transformer based networks as suggested in [23] are also a good candidate for real-time application due to its high accuracy and moderate complexity, but these systems are only applicable for small to medium scale systems, and their accuracy reduces exponentially as dataset sizes are increased. This accuracy can be improved via the use of target dependent BERT model training as suggested in [24], but then as this training is target dependent, this results into a highly complex system, with large memory and energy footprints. Therefore, the work in [22] can be considered as a base line for any kind of ABSA system that requires high accuracy with low complexity for real-time applicability. Extensions of these algorithms are mentioned in [25], [26], [27], [28], [29], [30], [31] and [32], wherein GRU models, Pretraining and Multi-task learning model based on Double BiGRU models, Multi-Layer Dual Attention Deep Learning Model, Interactive Gated Convolutional Networks, rating & recommendation prediction model, Interactive Multi-Head Attention Networks and Frequent Pattern Mining with Graph Traversal Algorithm respectively are mentioned. All these algorithms have similar workings as suggested in [1-15], but suggest different ways in which CNNs, GRUs, LSTMs and other deep learning entities can be applied to ABSA systems. But all these systems have an issue of increased complexity, which is due to the extensive use of CNN models. Reducing this complexity results into an exponential reduction in overall ABSA accuracy, which is a major drawback. In order to reduce the probability of this drawback, the underlying work suggests a dynamic aspect-based sentiment analysis model using ensemble deep learning. A detailed description of this model is mentioned in the next section, which is followed by its result analysis on different datasets.

3. Proposed Aspect-Based Sentiment Analysis Using Ensemble Deep Learning (ABSA-EDL).

In order to improve the efficiency of current ABSA systems, a low complexity and high accuracy aspect classifier & sentiment analyzer is needed. In this section, design details of aspect classification and sentiment analysis are given in different sections. Initially, design of an ensemble sentiment analyzer is described, which is followed by the design of CNN based aspect classification & aspect-based sentence extraction engine. This engine is based on semi-supervised learning, wherein a part of learning is done by standard ontologies, while dictionary-based sentiment analysis uses customized dictionary. Overall flow of the system can be observed from figure 4, wherein results from the aspect-based sentence extraction engine are given to the ensemble sentiment analysis engine for high accuracy ABSA. The architecture works using the following components,

- *Aspect based sentence evaluation using convolutional neural network.*

The aspect-based sentence evaluation engine uses a deep learning based convolutional neural network (CNN) architecture which can be observed from figure 5 and is taken directly from the work in [33] for standardization purposes. In this architecture, input data is processed using the following steps,

  - Input sentences are given to a word embedding layer and to an aspect map extraction network.
  - The word embedding layer, performs feature extraction operations, wherein the values of term frequency, and inverse document frequency is evaluated using the following equation,

$$TF = \frac{W_c}{N_w} \dots (1)$$

$$IDF = TF * \log\left(\frac{N}{df}\right) \dots (2)$$

Where, TF is the term frequency, W_c are number of occurrences of the given word in the document with N_w number of words. IDF is the inverse document frequency, N total number of sentences being input to the system and 'df' are the total number of sentences containing the given word.

- Results of the word embedding layer are given to a convolutional layer, wherein comparisons are made between the features of every word, and word indexes are evaluated.
- These indexes allow to evaluate similarity measures between given aspect word and the sentence being checked.
- All this information is combined with an aspect extraction map, wherein aspect's relative information is checked, and using an 'n' gram approach, its features are compared with other parts of the sentence.

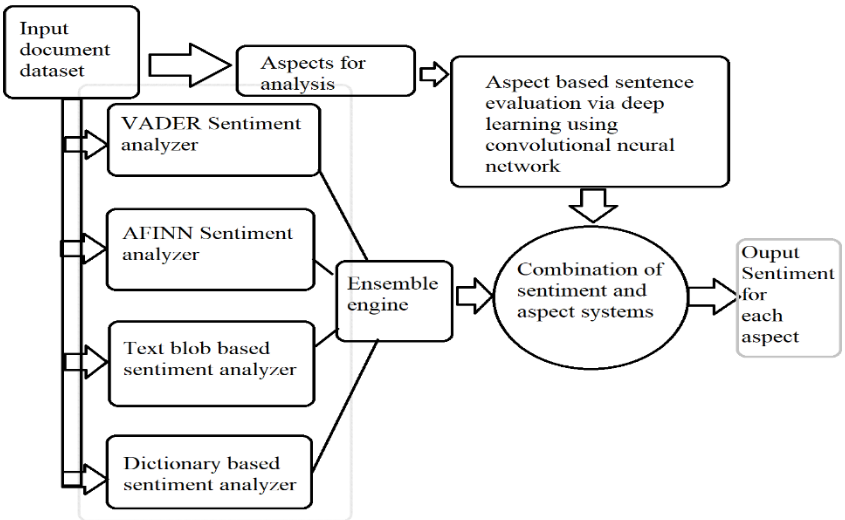

Fig 4. Architecture of the proposed ABSA system

- The combined information is given to a fully connected convolutional layer, that evaluates confidence scores between input sentence and each word related to that sentence.

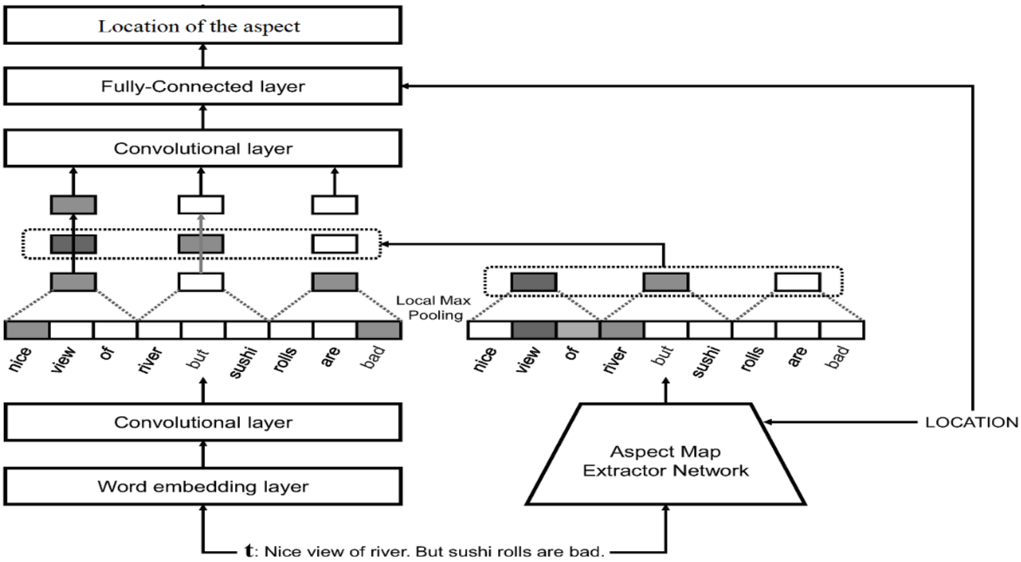

Fig 5. Internal working architecture of the used CNN layer for aspect-based location analysis [33]

- Using this combined information, aspect-based sentence modification is done, and the underlying aspect is marked as the primary action word in the given sentence.
- The aspect-based sentences are located and given to ensemble sentiment engine.
- Word embedding is done using the following formula,

$$p(W_o|W_i) = \frac{\exp\left(v_{w_o}, T_{v_{w_i}}\right)}{\sum exp\left(v'_w, T_{v_{w_i}}\right)} \ldots (3)$$

Where, v_{w_i} is the input word vector, v_{w_o} is the output word vector, and 'T' is the distance metric between the words, which is evaluated using TF and IDF values.

- This architecture is a toned-down version of existing CNN, and thus has lower complexity when compared to the original CNN VGGNet based architectures.
- This architecture is termed as a toned-down version because it doesn't use the entire CNN stack, but only uses intermediate convolutional layers and fully connected layers. Layers like softmax, max pooling and Rectilinear Unit (ReLU) are skipped from this architecture.

• *Ensemble sentiment analysis engine using a combination of multiple sentiment analysers.*

- This engine consists of 4 different algorithms, each of which is selected for solving a particular issue in sentiment analysis.
- The VADER sentiment analyser allows for word-by-word sentence checking, wherein the polarity score of each word is evaluated, and then added to form the final sentiment score. This method has high efficiency for independent sentences but doesn't work well for mutually related sentences.
- The AFINN sentiment analyser is similar to VADER but uses a different language processing engine and classification process. The AFINN engine utilizes hidden Markov model-based sentiment evaluation, which works good for related sentences, but has moderate level of accuracy.
- Text-blob sentiment analysis uses customized features for sentiment evaluation. It uses a n-gram approach for finding out sentence polarity, and processes the complete sentence at one go, instead of using one word at a time. This allows for a singular polarity of the sentence, irrespective of word positioning. Moreover, this method also has good efficiency in case of negative or dual negative words.
- Finally, a custom dictionary-based analyser is used which is trained as per the given application. This analyser uses the same concepts as used by AFINN and VADER but applies them over a customized dictionary. Which allows the system to evaluate sentiments for any kind of application.

The scores of all the 4 sentiment analyzers are normalized in the range of 0 to 1, and then combined using the following equation,

$$S_f = {(w_v * S_v + w_a * S_a + w_t * S_t + w_d * S_d)}/{N} \quad \ldots (4)$$

Wherein, 'w' terms are the weights for VADER, AFINN, Text Blob and Dictionary based approaches, while 'S' terms are their individual scores. Weights are decided based on the given application, and must follow the given equation to be applicable,

$$w_v + w_a + w_t + w_d = N \ldots (5)$$

Using this algorithm aspect-based sentiment analysis is done, this algorithm is also represented in a pseudo code format, so that is easier for readers to implement the same with ease. The following figure 6 showcases the pseudo code for this algorithm, and assists in observing overall implementation details for the proposed aspect-based sentiment analysis engine.

Input: Sentence for which ABSA is needed to be executed (S)

Output: Aggregated aspect-based sentiment for the given sentence (S_{out})

Algorithm:

(a) Evaluate aspects for the given sentences using toned-down version of CNN as observed from figure 5, let this list of aspects be ($A_1, A_2, A_3, etc.$)

(b) Divide sentence into multiple parts depending upon the extracted aspects let these parts be ($P_1, P_2, P_3, etc.$)

(c) Find aspect-based sentiments for each of these parts, let these sentiment values from VADER be ($VAS_1, VAS_2, VAS_3, etc.$)

(d) Find aspect-based sentiments for each of these parts, let these sentiment values from AFINN be ($AAS_1, AAS_2, AAS_3, etc.$)

(e) Find aspect-based sentiments for each of these parts, let these sentiment values from Text Blob be ($TBAS_1, TBAS_2, TBAS_3, etc.$)

(f) Find aspect-based sentiments for each of these parts, let these sentiment values from Dictionary be ($DAS_1, DAS_2, DAS_3, etc.$)

(g) Find aspect-based sentiments for each of these parts, let these sentiment values from CNN be ($CAS_1, CAS_2, CAS_3, etc.$)

Fig 6. Pseudo code for the proposed algorithm

Based on this architecture, the standard laptop, restaurant, and twitter dataset's accuracies were evaluated, and compared with standard CNN architectures. This analysis can be observed in the next section.

4. Result Evaluation

In order to evaluate performance of the proposed system, the standard datasets of restaurant, laptop and twitter are used. These datasets were compared with the ensemble engine, and without it with CNN & GA [10] and DBN [22], because both of these algorithms have high performance, and use the standard datasets for evaluation. The following table 1 showcases these accuracy results on different number of sentences, and for restaurant,

Number of sentences	**CNN with GA [10]**	**DBN [22]**	**Proposed without ensemble sentiment analysis**	**Proposed with ensemble sentiment analysis**
10	60.00	50.00	40.00	60.00
20	63.00	61.00	55.00	71.60
50	71.00	65.00	54.40	76.16
70	82.00	72.16	61.66	86.33
100	85.00	76.56	64.62	90.47
150	89.00	82.70	68.68	90.71
200	91.00	87.75	71.50	94.43
250	91.00	83.25	69.70	92.06
300	91.50	85.98	70.99	93.76
350	91.70	85.69	70.96	93.72
400	91.90	83.97	70.35	92.91
450	92.10	84.09	70.47	94.87
500	92.20	83.55	70.30	94.64
600	92.20	82.85	70.02	94.26
700	92.23	82.51	69.90	94.09
800	92.30	82.05	69.74	93.88
900	92.40	83.13	70.21	94.52
1000	92.50	84.86	70.94	95.50

Table 1. Accuracy results evaluated on the restaurant dataset.

This accuracy can be represented using the following figure 7, wherein the proposed model is found to be highly effective when compared with other models.

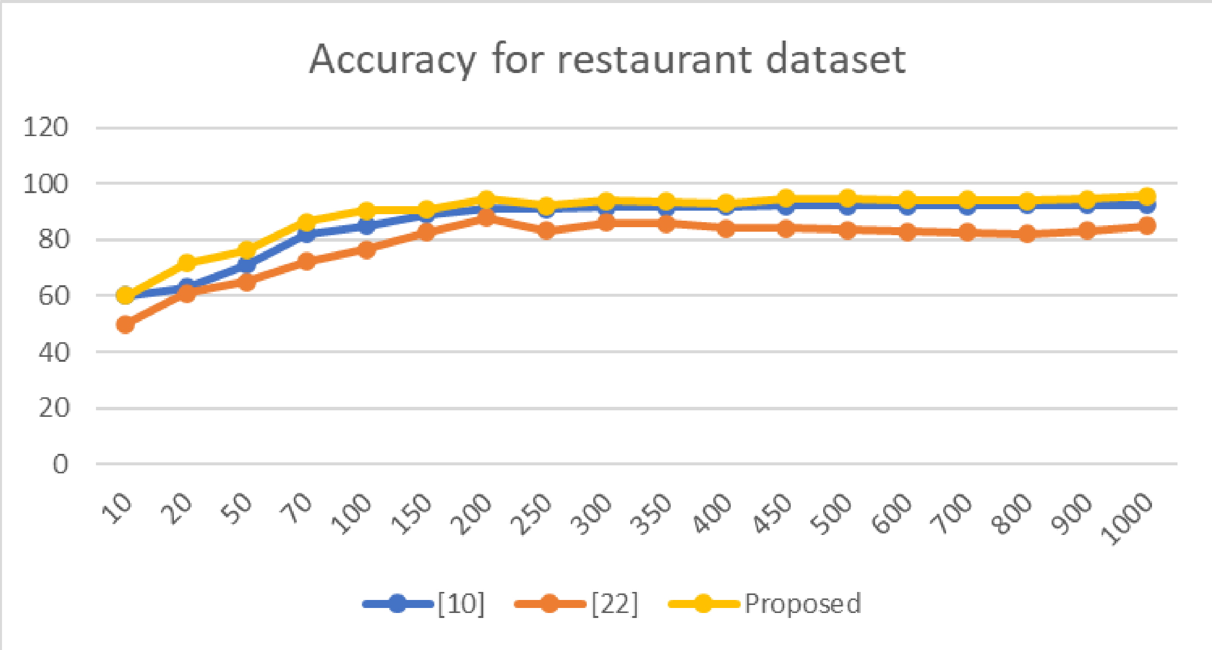

Fig 7. Accuracy of classification for different methods

Similar results were evaluated on Laptop and Twitter datasets; and their results are tabulated in tables 2 and 3 as follows,

Number of sentences	**CNN with GA [10]**	**DBN [22]**	**Proposed without ensemble sentiment analysis**	**Proposed with ensemble sentiment analysis**
10	54.00	45.00	36.00	54.00
20	56.70	54.90	49.50	64.44
50	63.90	58.50	48.96	68.54
70	73.80	64.94	55.50	77.70
100	76.50	68.91	58.16	81.43
150	80.10	74.43	61.81	81.64
200	81.90	78.97	64.35	84.99
250	81.90	74.93	62.73	82.85
300	82.35	77.38	63.89	84.38
350	82.53	77.12	63.86	84.34
400	82.71	75.57	63.31	83.62
450	82.89	75.68	63.43	85.38
500	82.98	75.20	63.27	85.17
600	82.98	74.57	63.02	84.83
700	83.01	74.26	62.91	84.68
800	83.07	73.85	62.77	84.49
900	83.16	74.82	63.19	85.06
1000	83.25	76.37	63.85	85.95

Table 2. Accuracy results for the Laptop dataset

Number of sentences	CNN with GA [10]	DBN [22]	Proposed without ensemble sentiment analysis	Proposed with ensemble sentiment analysis
10	58.46	48.72	38.97	58.46
20	61.38	59.44	53.59	69.76
50	69.18	63.33	53.01	74.21
70	79.90	70.31	60.08	84.12
100	82.82	74.60	62.97	88.15
150	86.72	80.58	66.92	88.38
200	88.67	85.50	69.67	92.01
250	88.67	81.12	67.91	89.70
300	89.15	83.77	69.17	91.36
350	89.35	83.49	69.14	91.31
400	89.54	81.81	68.54	90.53
450	89.74	81.93	68.67	92.44
500	89.84	81.41	68.50	92.21
600	89.84	80.73	68.22	91.84
700	89.87	80.39	68.10	91.68
800	89.93	79.95	67.95	91.47
900	90.03	81.00	68.41	92.09
1000	90.13	82.68	69.12	93.05

Table 3. Accuracy results for the Twitter Dataset

From these results it can be observed that as the number of samples increase, the accuracy of classification increases linearly. This accuracy saturates for other algorithms but keeps on linearly increasing for the proposed algorithm due to the combination of ensemble learning with CNN-based classification process.

5. Conclusion and future scope

Based on the analysis on different datasets, the results for the proposed architecture are improved by over 3% when compared with the standard CNN with GA architecture. The proposed architecture's performance is also improved due to the use of high-performance ensemble sentiment analysis engine, which boosts the accuracy of classification by over 20% when compared with an implementation that doesn't use it. Moreover, due to the use of a toned-down version of CNN architecture, the overall system complexity is reduced, which allows the architecture to be applied in IoT and other low-powered devices. The efficiency of this work can be further improved with the help of capsule networks, transfer learning and intelligent gated recurrent units, which will assist in efficiently finding locations of sentences containing the aspects. Automatic aspect evaluation can also be added to the system in order to make it truly dynamic.

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