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A Composite Approach in Sentiment Analysis using Random Multimodal Deep Learning

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Abstract: An essential job in natural language processing is aspect-centered sentiment evaluation, which entails classifying the opinion represented in a text into positive, negative, and neutral categories with regard to particular features or attributes of a given entity. While traditional sentiment analysis techniques have shown success, they often struggle with capturing the nuances and complexities present in real-world text. A unique deep neural learning method for Aspect-Based Sentiment evaluation is proposed in this research. To assign a negative, positive, or neutral sentiment polarity to every extracted aspect, a neural network model called random multimodal deep learning is used. The capability of neural networks is intended to automatically learn and capture intricate relationships between textual content and corresponding sentiments associated with various aspects. Deep learning model is trained with a hybrid approach called Dwarf Mangoose Chimp Optimization algorithm to get better classification accuracy. The proposed approach introduced an innovative hybrid strategy which combines the strength of deep learning with meta heuristic methods for training the model for sentiment analysis, resulting in improved accuracy and robustness. In comparison to current methodologies, the strategy produces competitive and outstanding results.

Keywords: *Aspect Based Sentiment research, Natural language processing, Random multimodal deep computing, Meta heuristic method*

1. Introduction

Sentiment analysis is referred to as an NLP, and it is frequently used to evaluate social media and extract user opinions about products while taking reviews into account. NLP was first introduced in 1950 and has recently become increasingly popular. Using user-assisted content, the NLP enables computers to read, analyse, identify imperative sections, measure sentiment, and extract knowledge from texts. It depends extensively on how computers and people communicate with one another. In the business domain, sentiment analysis applied to large data sets can help producing associations make timely decisions about their production and marketing.

Sentiment is the emotional tone, attitude, or sentiment that is communicated through writing, speech, or other forms of communication. It represents the overall sentiment or viewpoint expressed through the language employed. Typically, sentiments can be divided into a number of categories, including positive, negative, neutral, or even more complex ones like happiness, rage, sadness, and surprise. Opinion mining, often known as sentiment or opinion analysis, is an artificial intelligence technique that includes examining and identifying the sentiment present in a text or other piece of content. The analysis of sentiment is frequently employed in many different areas, including financial forecasts, market research, customer feedback analysis, political analysis, social media monitoring healthcare, brand monitoring and content creation.

Aspect-based sentiment analysis is a specialised method in natural language processing (NLP) that tries to identify, evaluate, and extrait sentiments or views directed towards particular elements or aspects of a text. Traditional sentiment analysis categorises an entire text as positive, negative, or neutral, providing an overall sentiment score. However, aspect-based sentiment analysis goes further by breaking down the analysis into individual component. This approach delivers more granular insights into the sentiment distribution and enables for a deeper knowledge of user opinions.

The automated process of evaluating a product review's sentiment for a certain product or service is known as sentiment assessment [1]. A study area in artificial intelligence called "sentiment assessment" uses text mining to take into account user opinions, emotions, and behaviour. The sentiment assessment is applicable to a variety of contexts, including news articles [2], stock markets [3], [4], travel and tourism [5], in addition to product reviews. This process can be broken down into three steps: first, detection of polarity, in which the label of sentiment is detected as positive, neutral, or negative; second, selection of aspect; third, classification, in which machine learning is applied and lexical technique is modified for text classification [6]. Deep learning assisted classification techniques have demonstrated crucial results that outperform traditional methods which encompasses numerous domains like

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computer vision and natural language processing (NLP), it is currently being used for sentiment evaluation tasks. RNN and CNN are two widely used primary models.

Deep models have received a lot of attention recently, greatly improving classification accuracy [7]. Deep learning has been extensively utilized in customer feedback analysis for sentiment analysis in the commercial area because it produced amazing outcomes while processing NLP [8]. Deep learning does not need human interaction features, in contrast to traditional machine learning models, but it does need a lot of data to support it. The features are extracted using various neural network approaches, and the model assists in learning from the error itself [9].

Main goal is to provide an efficient sentiment categorization technique with mobile phone review data. To separate the reviews obtained from the inputted review, the BERT tokenization is modified. Additionally, ATE is used to create aspects. The feature extraction procedure follows that. The TF-IDF is extracted in this case and is regarded as the first output. Then, features from the Wordnet ontology are extracted and designated as the second output. Additionally, the third output of BERT tokenization includes features like N-gram, statistical, and sarcasm linguistic features. The three outputs are provided to Random Mutimodal Deep Learning(RMDL), whose sentiment classification training is carried out using Dwarf Mongoose Chimp Optimization(DMCO) which is a recent metaheuristic algorithm.

The major contribution of this work is using a Radom Multimodal deep learning(RMDL) for categorising sentiment and the model is trained using Dwarf Mongoose Chimp Optimization(DMCO). DMCO is a combined technique using two algorithms, which are Dwarf Mongoose Optimization algorithm(DMO) and Chimp Optimization Algorithm(ChO).

1.1. Motivation

The requirement to derive insightful information from massive volumes of textual data and use those insights to improve decision-making, customer experiences, and business outcomes typically motivates sentiment analysis research. Businesses may improve their offers, better match their goals, and meet customer expectations by understanding sentiment. The primary contribution of our work is the use of an RMDL hybrid model for sentiment classification, which performs better than an RMDL model trained without a hybrid approach.

The remaining content in this article is organised as follows. We review the earlier studies that helped to establish the foundation for our method in Section 2. A thorough structure for our suggested model, using Random Mutimodal deep Learning, has been provided in Section 3. Datasets, implementation specifics, and a result analysis are portrayed in Section 4. The final section of the article offers a summary of our study as well as a potential path for future investigation.

2. Background and Related Work

A study of the available research on aspect-based sentiment analysis using deep neural networks claims that, a thorough amount of research has been done on employing neural network designs to analyse feelings expressed towards particular features of text. Here is a summary of some significant studies and developments in this area:

This research by Wang et al in [10] used LSTM networks' attention mechanisms to do aspect-based sentiment analysis. The study demonstrates that a sentence's sentiment polarity is strongly correlated with the concerned aspect in addition to being decided by the content. The approach highlights the most significant words for each aspect's sentiment classification by using attention weights. In order to make the suggested models more competitive for aspect-level categorization, when various elements are given, they concentrate on distinct portions of a text. Results demonstrate that the suggested models, both the attention-based LSTM with aspect embedding (ATAE-LSTM) and the long short-term memory network with aspect embedding (AE-LSTM) perform better than the original models. Despite the proposals' demonstrated potential for sentiment analysis at the aspect level, various elements are input independently.

Ma et al in [11] propose an Interactive Attention Network (IAN) that targets the component and simultaneously attends to words in the surrounding context. In this study, researchers assert that contexts and targets require unique attention and must be taught their own representations through interactive learning. The IAN model's ability to accurately depict a target and its collocative context attributed to this design is beneficial for sentiment classification. Results from experiments on SemEval 2014 Datasets show how effective model is. The way the model captures the relationships between attributes and context increases sentiment categorization accuracy. The IAN model is able to focus on the relevant target and context elements in order to generate target and context representations in an efficient manner.

Target dependent twitter sentiment classification utilising rich automated features based on distributed word representations has been researched by Zhang et al. [12]. The approach eliminates the possible drawback of the syntax-based approach by using an automatic syntactic analyzer to reduce the impact of noise. The results of the research show that sentiment lexicons, several pooling functions, and numerous embeddings are valuable sources of feature information, which significantly improves accuracy. Compared to the best previous solution using syntax, this method performs better and doesn't rely on external syntactic analyzers.

A deep memory network is presented in the Tang et al. article [13] for aspect-based opinion analysis. This model employs a memory module to retain crucial data on many components in order to enhance sentiment prediction. When determining the emotion polarity of an aspect, this method clearly considers the significance of every context word, as compared to sequential neural models like LSTM and feature-based SVM. To compute the text representation and importance degree, multiple computational layers are employed; an external memory with a neural attention framework is present in each layer. This approach performs on parity with the most advanced feature-based SVM algorithms and significantly better than LSTM and attention-based LSTM designs, according to experiments conducted on laptop and restaurant datasets. It is demonstrated on both datasets that the performance could be enhanced by using numerous computing layers.

Huang et al.'s research [14] introduced an attention-over-attention (AOA) neural network based aspect level opinion classification system. By representing aspects and phrases jointly, this method accurately represents the connection between aspects and context sentences. This model automatically focuses on significant portions of sentences after learning the representations for aspects and sentences together with the AOA module. This approach surpasses earlier LSTM-based architecture, as demonstrated by using datasets from restaurants and laptop assessments.

The work by Sun et al.[15] creates an auxiliary sentence from the aspect of ABSA in order to convert it into a sentence-pair classification job, such as question answering (QA) and natural language inference (NLI). By enhancing the BERT pre-trained model, they were able to generate new innovative findings using the SentiHood and SemEval2014 Task 4 datasets. The contextualised embeddings in BERT enhance the model's ability to understand nuanced differences in sentiment and intricate context.

For aspect-based sentiment categorization, Convolutional Neural Networks (CNNs) and attention techniques are frequently utilised because of their innate capacity to semantically match aspects with their context words. But because these models don't have a way to take into consideration pertinent syntactical constraints and long-range word dependencies, they could incorrectly identify contextual words that aren't syntactically important as indicators of aspect sentiment. To deal with the problem using syntactical and word dependencies, Chen et al. [16] developed a graph convolutional network (GCN) on top of a sentence's dependency tree. A unique aspect-specific sentiment categorization system is suggested based on it. Tests conducted on three benchmarking sets demonstrate that the suggested model is as effective as a number of cutting-edge approaches.

Schmitt et al. [17] proposed an alternative method for sentiment evaluation based on features. Unlike other methods, this model is a trainable neural network from end to end, that simultaneously represents aspect recognition and polarity identification. Using the most recent GermEval 2017 dataset, they experiment with various word models and neural structures. When comparing the joint modelling technique to pipeline alternatives in all circumstances, they were able to demonstrate significant improvements in performance. A convolutional neural network and quick text embeddings outperformed the top submission for the shared task in 2017, establishing a new benchmark in the discipline.

The overview of aspect based sentiment evaluation, which emphasises the extraction of the product feature, is explained by Ravi K et al. in [18]. The non-ontological approach and the ontological approach are the two categories into which the methods for extracting product features fall. The reviews of ontological approaches are presented in this part because they outperform non-ontological methods in sentiment categorization, particularly when related to product aspect extraction. The method known as the fuzzy domain sentiment ontology tree (FDSOT), which emphasises the attributes of product, sentimental terms, and the associations between those components, is utilised to reinforce the innovative aspect level SA, as demonstrated by Liu et al in [19]. Product reviews from 360buy.com, a Chinese website, were taken into consideration when evaluating computers for the two fold propagation method of producing FDSOT. The study's findings demonstrate that the accuracy of the polarity forecasts is significantly higher than in earlier studies without FDSOT.

A method for locating dependency parsing rules to extract opinion expressions was proposed by Bhattacharyya et al. [20]. In product reviews with a range of characteristics and conflicting feelings, they offer an innovative method to find opinion expressions related to a certain aspect. The goal can be achieved by determining a number of probable characteristics in the review and using their associations to extract opinion expressions about those aspects. The system picks up the set of important relationships that dependency parsing will use, together with a threshold value that will allow us to combine closely related opinion expressions. Less data is required because these domain-independent factors only need to be learned once. To acquire the opinion expression that most accurately characterises the attribute that the user has specified, the associations are shown as a divided graph. Despite its limited data, we demonstrate that the system operates on par with complex systems and achieves exceptional accuracy across all areas. To build improved aspect-based opinion mining systems, the majority of recent research works employ hybrid approaches that combine statistical or machine learning techniques with Natural Language Processing techniques. The system's capacity to assess implicit sentiment that is dependent on a particular domain is constrained because it was not trained on any domain-specific data.

According to authors Xu et al. [21], the secret to company risk management and decision support is competitive intelligence, which is the capacity to comprehend and assimilate the attitudes of the external environment in order to boost business among competitors. As a result, following the release of web 2.0, customer product evaluations frequently include information about rival companies, and numerous academics began diligently working to mine competitive intelligence. This facilitates the detection of entity relationships, which is useful for competitive intelligence. For a variety of reviews, the authors created a model based on Conditional Random Fields (CRF) that abstracted proportionate relations more precisely than benchmark techniques. The extraction process was divided into three stages: (i) entities; (ii) a graphical model that used the CRF to show how relationships and objects are interdependent; and (iii) the belief propagation algorithm. An extensive corpus of Amazon customer reviews was used for the experiment.

Pontiki et al.[22] increasingly viewed sentiment analysis as an essential task from an academic and business perspective. Most existing methods, on the other hand, try to determine the overall polarity of a word, paragraph, or passage of text, independent of the objects that are included (like laptops) that are referenced or their characteristics (like battery, screen). The goal of SemEval2014 Task 4 was to advance aspect-based sentiment analysis research, in which characteristics of given target entities are detected, and each aspect's sentiment is represented. The assignment produced datasets containing manually annotated evaluations of restaurants and computers, along with a standard grading process. 32 teams submitted 163 entries to it. They provide a synopsis of SemEval2014 Task 4. The goal of the task was to promote research on aspect-based sentiment analysis (ABSA). They produced and released manually annotated ABSA benchmark datasets from the restaurant and laptop categories. A total of 32 teams submitted 163 entries for the task, which were assessed in four subtasks that concentrated on aspect words (finding aspect terms and their polarities) as well as aspect classes (assigning aspect classes and aspect class polarities to sentences). SemEval-2015 will replicate the challenge, adding more datasets and a domain-adaptation subtask. As mentioned by Pavlopoulos and Androutsopoulos (2014a), in the future, they intend to include an aspect term aggregation subtask.Together, these works demonstrate the evolution of aspect-based sentiment evaluation through the application of deep modelling techniques. Advancements in memory networks, models based on transformers, such as BERT, and attention mechanisms have been enhanced the understanding of sentiment nuances in complex text data. Recursive structures and graph neural networks are also employed, emphasising the ongoing exploration of increasingly intricate architectures to represent intricate relationships between traits and emotions.

By extracting and quantifying the aspect level sentiments, a hybrid methodology combining the deep learning method and the rule-based method has been introduced for aspect level sentiment analysis[32]. For this, a seven-layer-specific deep neural network architecture has been constructed. The suggested method yields improved classification accuracy, and sarcastic sentences are not taken into account.

2.1. Literature Gap

Deep learning-based aspect-level sentiment analysis has advanced significantly in the last several years. Scholars persistently design increasingly intricate methodologies for achieving fine-grained sentiment analysis, hence enhancing efficacy and furnishing a more comprehensive comprehension of sentiments regarding certain attributes within textual data. These methods include transformer-based designs such as BERT and attention-based models.

The above-mentioned results show that by using deep learning algorithms for aspect extraction and sentiment classification, there is space for improvement in this research area. By contrasting and assessing how the aforementioned changes impact the effectiveness of random multimodal deep learning which is trained using a hybrid metaheuristic approach, this effort seeks to bridge the gap. Understanding the effectiveness of sentiment analysis based on aspects for mobile product reviews is the aim of this study. In the present study, we use a suggested hybrid model to examine the effectiveness of aspect-based sentiment analysis for reviews of mobile products and a deep learning model without using hybrid approach, and the proposed hybrid model outperforms in various performance measures.

3. Proposed Method

The objective is to develop an efficient model to categorise sentiment using mobile phone review data and the suggested DMCO method. The Amazon phone review document must first be obtained from the necessary dataset [23] and fed into the BERT tokenization method as an input. The first output is created by performing aspect term extraction, which leads to the creation of TF-IDF. Following the extraction of Wordnet ontology features from BERT tokenization to produce TF-IDF, the second result is obtained. Statistical features, count vectorization, elongated units, numeric data, sentence to sentence similarity, negation, punctuation, sentence length, emoticons, hashtags, bag-of-units, sarcasm linguistic features like exclamation mark, sarcasm indicators, mixed indicators, and laugh indicators are also extracted from BERT tokenization, and which will be the third ouput. Following that, RMDL, which was trained with DMCO, is used to classify sentiment using all three of these outputs. A sample sentiment categorization scenario using the suggested DMCO-based RMDL is shown in Figure 1.

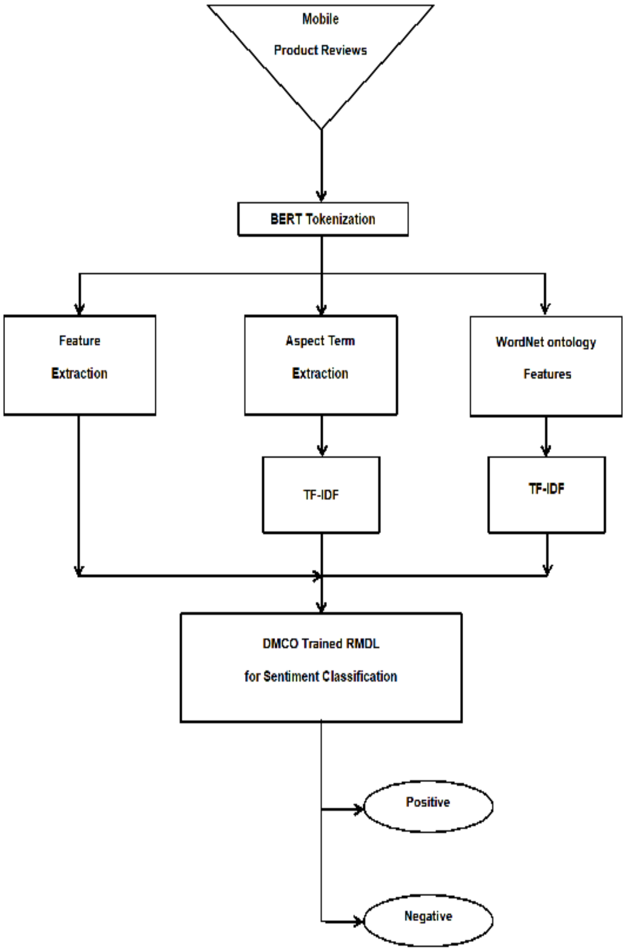


Fig 1: DMCO based RMDL for sentiment analysis

3.1. Gathering reviews and Tokenization

Many different sentiment evaluation approaches are used to evaluate large databases, but it is unknown which technique should be used. Here, the evaluation takes into account the data from the mobile reviews. Examine a review dataset K that is annotated by the total number of samples from K_1 to K_r wherein, $\boldsymbol{r}$is total reviews. Tokenization is done using BERT [24] to separate the generated review into individual words. BERT is made to use unlabeled texts to pre-train the representations of deep bidirectional models by combining left and right context in all layers. Two steps are involved, namely pretraining and finetuning. In the pre-training stage, the model is trained with unlabeled data while accounting for various pre-training techniques. When it comes to fine-tuning, BERT starts with pre-trained attributes and uses labelled data to refine them while taking downstream processes into account. BERT's generic approach, which can perform a variety of jobs with either a single text or a group of texts, is its unique characteristic. Therefore, the output of BERT tokenization is indicated by F and provided to ATE.

3.2. Aspect Term extraction and feature extraction using TF_IDF

While aiding with the learning of aspect features and the reluctant extraction of aspects from texts, the ATE [25] saves time and work. ATE uses user-provided seed words to enable the simultaneous extraction and grouping of aspects for many classes of aspects.

The ATE result, which is given to extract characteristics, is indicated as T. The ATE outcome, designated as T, is used to derive the TF-IDF characteristic. The TF-IDF is a numerical statistic that illustrates a word's significance to a document inside a corpus or collection [26]. This approach is specifically employed as a weighting factor while getting texts and retrieving data. The TF-IDF score rises in direct proportion to how frequently a word appears in the data on average. The term "frequency" describes how often a term appears in a document in its raw form. Furthermore, the term taking into account the inverse document frequency indicates how common or uncommon a phrase is within an article.

Hence, the model for the TF-IDF is, in equation 1:

$$TF - IDF = t_f * i_f \tag{1}$$

The output obtained from the TF-IDF is denoted byV_1.

From the BERT tokenized reviews, features such as count vectorization, numeric data, sarcastic linguistic feature, statistical feature, elongated words, N-gram features, sentence-to-sentence correspondence, sentence length, emoticons, hashtags, and bag of units are also extracted. The corresponding model for the feature vector is as follows in equation 2 :

$$V_2 = \{L_1, L_2, \dots, L_{16}\} \tag{2}$$

3.4. Features using Wordnet Ontology

The relationship between the terms can be obtained with the help of WordNet ontology [27]. The WordNet is an English language thesaurus that was developed based on research in psycholinguistics. The various semantic relationship retrieved using wordnet ontology features are: hyponymy, hyperonymy, and synonymy. Hyponymy shows how a concept-1 and a more distinct concept-2 are related. A relationship connecting an idea-1 to a broader concept is represented by hyperonymy. Synonymy referred to as a symmetrical relation since it shows the relationship that unites two notions that are similar or equal. The obtained Synonymy, Hyperonymy, and Hyponymy are used to adjust the TF-IDF and produce the feature vector. Additionally, this functionality is indicated as V_3.

The feature vector V unifies these features such that

$$V = \{ V_1, V_2, V_3 \} \quad (3)$$

3.5. Sentiment Categorization by RMDL based on DMCO

Utilising the feature vector, a hybrid technique used for training RMDL and that deep learning model is used to categorise sentiment. In this case, RMDL training is carried out with DMCO(Dwarf Mangoose Chimp Optimization) and is acquired through the combination of Dwarf Mangoose Optimization Algorithm (DMOA)and Chimp Optimization Algorithm(ChOA).

The method known as RMDL [28] is used to any dataset in order to carry out an efficient sentiment assessment. The RMDL accepts as its input feature vector V. The RMDL model has multiple classifiers, including Deep CNN, Deep RNN, and Deep Neural Networks (DNN). By simultaneously enhancing accuracy and resilience through an ensemble of deep models, RMDL addresses the challenge of identifying the optimal deep model. It has the capacity to handle massive amounts of data with extreme precision. Every model is defined uniquely in accordance with RMDL. *w* CNN, *x* RNN, and *y* DNN models are included in the RMDL. The result that RMDL produced is l_{out}.

3.6. DMCO training with RMDL model

The DMOA and ChOA partnership produces and implements the RMDL training in collaboration with DMCO. DMOA [29] draws inspiration from dwarf mongoose behaviour. It works well for finding new search regions and prevents premature convergence as well as local optima trapping. It balances exploration and exploitation and offers solution uniformity. In the meantime, chimpanzee hunting behaviour serves as the inspiration for ChOA [30]. ChoA is designed to prevent the local optimal trap and address the problem of slow convergence speed. It is helpful in resolving high-dimensional problems, such as learning algorithms for high-dimension neural network problems. Chimpanzee entities fall into four categories: barrier, attacker, chaser, and driver. It has been modified to mimic several forms of intelligence As a result, DMOA and ChOA are combined to increase effectiveness and find the best possible global solutions.

The DMCO steps are enlisted below:

Step 1: Population Initialization

The following is how the DMCO solution is initiated:

$$M = \{ M_1, M_2, \dots, M_k, \dots, M_n \} \quad (4)$$

Where *n* is the total solution M_k specifyκ^{th}solution.

Step 2: Computing Fitness function

It is written as follows in equation 5 and is described with error using mean square error:

$$f = \frac{1}{v} \sum_{0=1}^{v} \psi 0 - l_{out} \quad (5)$$

where *f* is the fitness function, v represents the total samples in such a way that, $\psi 0$ is the intended output, and l_{out} represents the RMDL result.

Step 3: Alpha set Initialization

The solution efficacy is acquired once population is commenced, according to DMOA [31]. It indicates the likelihood value and determines which alpha female is most likely, and is indicated by in (6)

$$A_l = \frac{P_Z}{\sum_{Z=1}^{i} P_Z} \quad (6)$$

Where A_l is the alpha female set, the number of mongooses *i* such that, $1 \le z \le i$ and P_z represents fitness value.

The solution modification is therefore notated as:

$$M_{Z+1} = M_Z + R_Z \times S \quad (7)$$

Here, R_z represents a distributed random number, S is the leading female's vocalisation, and M_z the current solution.

Thus, the representation of the sleeping mound is,

$$V_c = \frac{(P_{Z+1} + P_Z)}{(\max [|P_{Z+1} - P_Z|)} \quad (8)$$

The sleeping mound's average count is shown as,

$$\emptyset = \frac{\sum_{c=1}^{i} V_C}{I} \quad (9)$$

Step 4: Scout set Allocation

The scout mongoose is recognised as:

$$M_{Z+1} = \begin{cases} M_Z - Y \times q \times rand\left[M_Z - \vec{C}\right], if\ \emptyset_{Z+1} > \emptyset_Z] \\ M_Z + Y \times q \times rand\left[M_Z - \vec{C}\right], Otherwise \end{cases}$$
(10)

The random value *rand* is in the range of [0,1]. The mongoose's relocation to the new sleeping mound is the result $\vec{C}$. Therefore, the control parameter for collective volitive movement (CF) is illustrated as:

$$Y = \left(1 - \frac{h}{h_{max}}\right) \left(2 \times \frac{h}{h_{max}}\right) \quad (11)$$

$$\vec{C} = \sum_{Z=1}^{i} \frac{M_Z \times t_Z}{M_Z} \quad (12)$$

Consider criterion if $\emptyset_{Z+1} > \emptyset_Z$,

$$M_{Z+1} = M_z[1 - Y \times q \times rand] + Y \times q \times rand\ \vec{C} \quad (13)$$

As to ChOA [32], the update expression appears as follows:

$C(\beta+1) = C_{prey}(\beta) - \chi \times \delta$ (14) $\delta = \left| \varsigma \times C_{prev}(\beta) - ћ \times C(\beta \right|$ (15)

By assuming $\varsigma \times C_{\text{prey}}(\beta) > ћ \times C(\beta)$

$C(\beta+1) = C_{\text{prey}}(\beta) \times (1-\chi\times\delta) + \chi \times ћ - C(\beta)$ (16)

Assume $C(\beta+1) = M_{Z+1}$, $C(\beta) = M_Z$ and $Cprey(\beta) = M_{Zprey}$

$$M_z = \left(\frac{M_{z+1} - M_{Zprey}(1-\chi *^{\varsigma})}{\chi \times ћ} \right) \quad (17)$$

Replace M_Z value from equation (17) in equation (13)

$$M_{z+1} = (M_{z+1} - M_z(1-\chi) \times \varsigma)$$

$$M_{z+1} = \left(\frac{M_{z+1} - M_z prey(1-\chi \times \varsigma}{\chi \times ћ} \right) \times (1 - Y \times z \times rand) + Y \times q \times rand\, \vec{C} \quad (18)$$

The DMCO final update is noted as ,

$$M_{z+1} = \frac{[M_{zprey}\left(\chi \times^{\varsigma} -1\right)[1 - Y \times q \times rand] + \chi\, ћ \times Y \times q\, rand\, \vec{C}]}{\chi\, ћ - 1 + Y \times q \times rand} \quad (19)$$

Step 5) Re-compute fitness

The optimal solution is obtained by recalculating the fitness.

Step 6) Termination

The aforementioned procedures are followed until an increased iteration count is achieved.

4. Results and Discussion of the Study

To evaluate the performance of DMCO-based RMDL, training data and K-fold in the x-axis are obtained. The evaluation is carried out using particular measures.

4.1. Experimental set-up

Python is used to script the DMCO-based RMDL.

4.2. Dataset description

The dataset from Amazon Cell Phones Reviews [22] is used to conduct the analysis. This information includes reviews from Amazon and ratings for unlocked phones. The product's ASIN, brand, title, URL, and other information are included.

4.3. Measures used

The DMCO-based RMDL's potential is examined using specific metrics, which are detailed below and performed using various equations from 20 to 25.

(i)Accuracy:

It indicates how close an observational group is to its actual value and is indicated as,

$$acc = \frac{T^{-ve} + T^{+ve}}{T^{+ve} + T^{-ve} + N^{+ve} + N^{-ve}} \quad (20)$$

Here the terms, T +ve denote true positive, T -ve express true negative, N +ve signifies false positive, and N -ve articulates false negative.

(ii) TPR

It displays the percentage of genuine positives to overall positives, which is often defined as,

$$TPR = \frac{T^{+ve}}{T^{+ve} + T^{-ve}} \quad (21)$$

(iii) TNR

It provides the negative ratio and is accurately calculated and represented as,

$$TNR = \frac{T^{-ve}}{T^{-ve} + N^{-ve}} \quad (22)$$

(iv) Precision

It is the percentage of genuine positives to total positives.

$$Pr = \frac{T^{+ve}}{T^{+ve} + N^{+ve}} \quad (23)$$

(v) Recall

It is the measure of the model correctly identifying True Positives.

$$rec = \frac{T^{+ve}}{T^{+ve} + N^{-ve}} \quad (24)$$

(vi) F1-Score

It is the Precision and Recall Harmonic Mean and it is measured as,

$$F1 - score = \frac{pr * rec}{pr + rec} \quad (25)$$

4.4. Performance Analysis

Figure 3a to 3f shows how performance is assessed using training data by changing metrics.

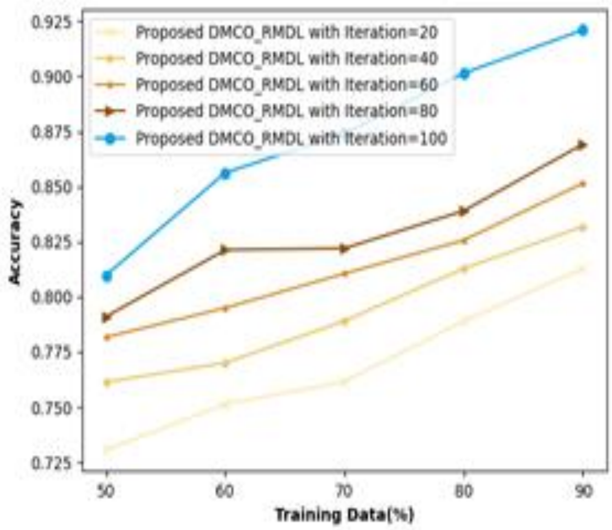


Fig 3a: performance evaluation using Accuracy

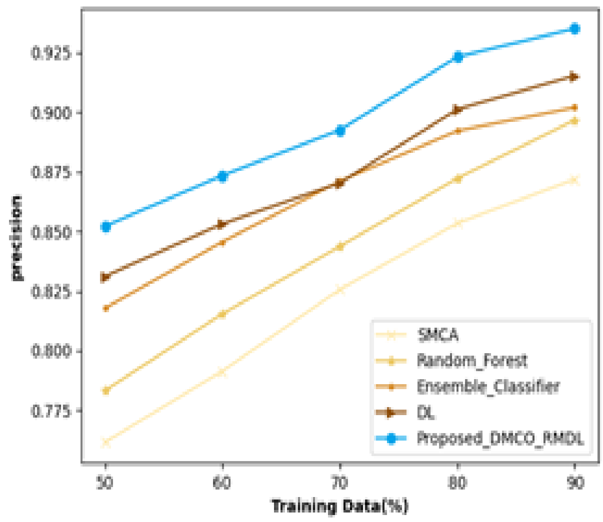


Fig 3d: performance evaluation using Precision

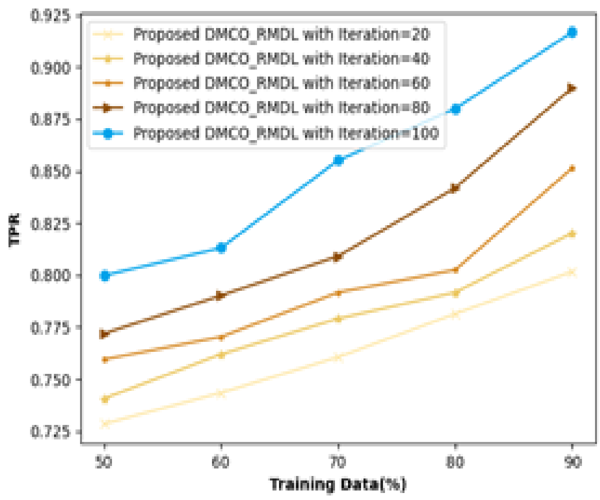


Fig 3b: performance evaluation using True Positive rate

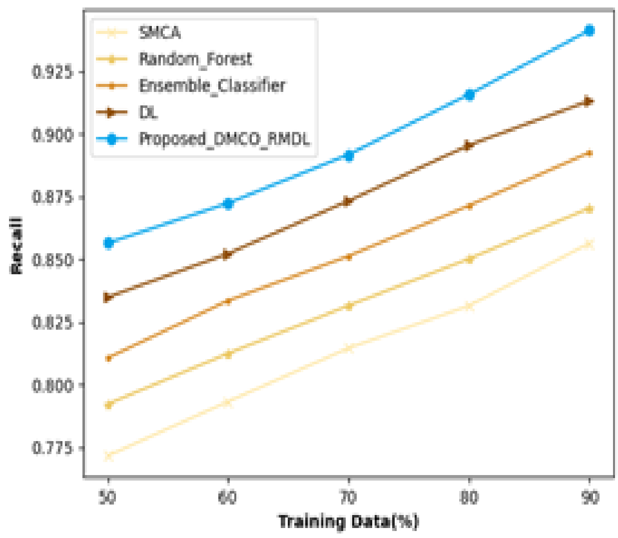


Fig 3e: performance evaluation using Recall

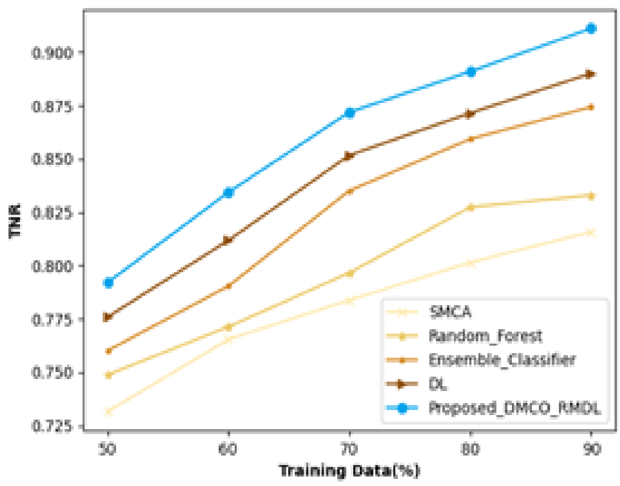


Fig 3c: performance evaluation using True Negative rate

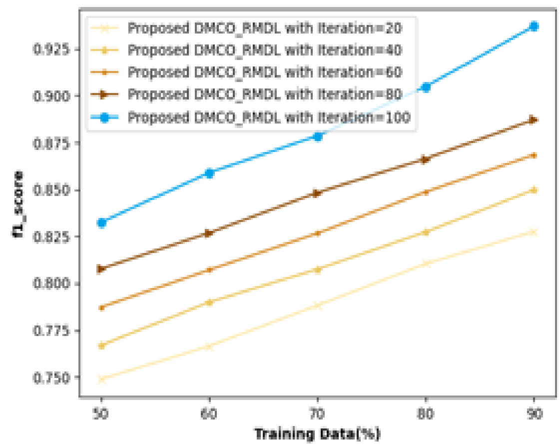


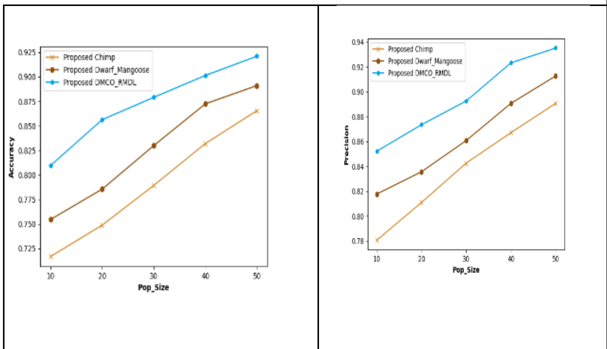
Fig 3f: performance evaluation using F1-Score

The figure 3a shows the accuracy graph. The accuracy of the suggested DMCO-RMDL with iterations 20, 40, 60, 80, and 100 during training with 90% data is 0.81, 0.83, 0.85, 0.87, and 0.92. Figure 3b shows the results of the TPR study. Assuming 90% of the training data, the TPR of the proposed DMCO-RMDL with iteration=20 is 0.80, iteration=40 is 0.82, iteration=60 is 0.85, iteration=80 is 0.89, and iteration=100 is 0.92. In figure 3c, the TNR analysis is explained. The suggested DMCO-RMDL with iteration=100 measures the greatest TNR of 0.91, whereas the proposed DMCO-RMDL with iterations of 20, 40, 60, and 80 measured TNR of 0.79, 0.80, 0.83, and 0.88 for 90% training data. The figure 3d shows the precision graph. The precision of the suggested DMCO-RMDL with iterations 20, 40, 60, 80, and 100 while training with 90% data is 0.82, 0.84, 0.86, 0.88, and 0.93. The figure 3e shows the recall analysis. With iteration=20, iteration=40, iteration=60, iteration=80 and iteration=100, the recall of the proposed DMCO-RMDL is 0.83, 0.88, 0.87,0.89 and 0.94, assuming 90% training data. In figure 3f), the F1-score analysis is explained. For the proposed DMCO-RMDL with iterations of 20, 40, 60, and 80, the highest F1-score of 0.94 is measured, whereas for 90% training data, the F1-scores of 0.82, 0.85, 0.87, and 0.89 are measured.

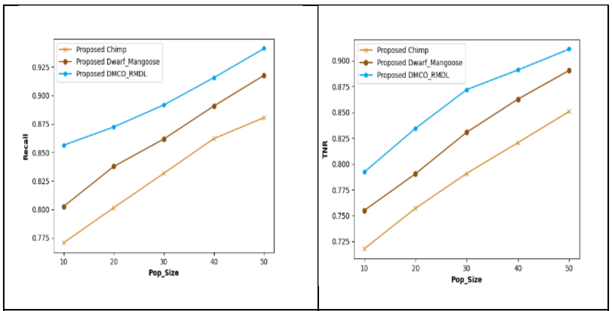
4.5. Comparative analysis

ChO_RMDL, DMO_RMDL and the suggested DMCO_RMDL are schemes used for assessment of comparative assessment.The comparison of the suggested model with DMO and ChO trained RMDL is shown in Figure 4, where the suggested hybrid strategy performs better than existing techniques.

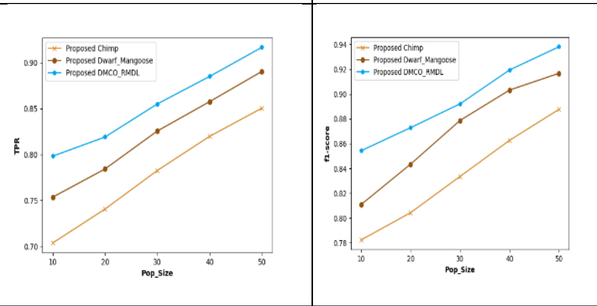
Assessment of method with definite metrics by changing training data is shown in Figure 4.



(i)	(ii)



(iii)	(iv)



(v)	(vi)

Fig.4: Comparative evaluation using pop_size based on i) Accuracy ii) TPR iii) TNR iv) Precision, v) Recall vi) F1 score.

Table 1 displays comparative analysis of methods with data considered for training and K-fold. With data considered for training, the supreme accuracy of 92.1%, TPR of 91.7% and TNR of 91.1%, precision of 93.5%, recall of 94.1%, and F1-score of 93.8% is measured by proposed DMCO-RMDL as compared to ChO_RMDL and DMO_RMDL.Using K-fold, the supreme accuracy of 93%, TPR of 92.8%, TNR of 92.2%, precision of 90.4%, recall of 95.6%, and F1-score of 94.8% is measured by proposed DMCO-RMDL compared to ChO-RMDL and DMO-RMDL.

Table 1: Comparative Analysis

Variation	Metrics	ChO_RMDL	DMO_ RMDL	Proposed DMCO_RMDL
Training data	Accuracy	0.85	0.89	**92.1**
	TPR	0.83	0.84	**91.7**
	TNR	0.78	0.81	**91.1**
	Precision	0.76	0.79	**93.5**
	Recall	0.75	0.83	**94.1**
	F1_score	0.84	0.82	**93.8**
K-set	Accuracy	0.79	0.81	**93**
	TPR	0.78	0.82	**92.8**
	TNR	0.77	0.79	**92.2**
	Precision	0.79	0.84	**90.4**
	Recall	0.74	0.81	**95.6**
	F1_score	0.83	0.85	**94.8**

5.Conclusion and Future Scope

The objective is to use the suggested DMCO algorithm to demonstrate an effective method for sentiment categorization of cell phone review data. The initial stage involves obtaining the Amazon phone review document from the designated dataset, which is then used as an input for the BERT tokenization process. The first output is then acquired by doing aspect term extraction to create TF-IDF. After that, BERT tokenization is used to extract Wordnet ontology features, which produces TF-IDF and yields the second result. Additionally, features like negation, punctuation, sentence length, emoticons, hashtags, bag-of-units, sarcasm linguistic features like exclamation marks, sarcasm indicators, mixed indicators, and laugh indicators are extracted from BERT tokenization, along with features like N-gram based features, statistical features, count vectorization, elongated units, numerical data, and sentence to sentence similarity. Consequently, third output is obtained. Following that, RMDL receives all three of these outputs and uses the DMCO algorithm to train it.

Conflicts of Interest

The authors declare no conflicts of interest.

Author contributions:

Conception and design of the work, Minu P Abraham and Udaya Kumar Reddy K R. Data collection and methodology, Minu P Abraham and Udaya Kumar Reddy K R. Writing original draft and preparation: Minu P Abraham and Udaya Kumar Reddy K R.

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