An Innovative Examination of Tensor Blending Network for Multi-Model Sentimental Optimization Using Opinion Mining

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2023 World Conference on Communication & Computing (WCONF) | 979-8-3503-1120-4/23/$31.00 ©2023 IEEE | DOI: 10.1109/WCONF58270.2023.10235002

***Abstract*— The Tensor Blending Network (TBN) for multi-model sentimental optimization is a novel approach for fusing the outputs of multiple models in order to maximize the performance of sentiment analysis. TBN is based on an encoder-decoder architecture consisting of a convolutional neural network (CNN), a Long Short Term Memory (LSTM) RNN, and a deep-learning model for sentiment classification. TBN uses attention mechanisms to blend the output of each model, focusing on the most relevant parts to extract the desirable sentiment analysis. The framework of TBN is also designed in a way that allows for easy deployment in different contexts, as the user can fuse two predefined models or multiple individual ones. Additionally, the TBN architecture can be used as a method to improve the accuracy and precision of sentiment analysis algorithms by integrating different sources of knowledge. Finally, the performance of TBN has been tested on a number of datasets, obtaining in most cases the highest accuracy and precision, proving the advantages of using this framework.**

Keywords—tensor, blending, network, sentiment, optimization, CNN, LSTM

I. INTRODUCTION

Tensor blending network, which is also known as multi-model sentimental optimization, is a powerful technique for predicting sentimental outcomes from multiple texts. It uses the power of both machine learning and natural language processing to obtain a better understanding of the sentiment in the text. The importance of Tensor blending network for multi-model sentimental optimization is manifold. Firstly, this technique enables higher precision in predicting sentiment [1]. Thereby, it helps in providing businesses, organizations and individuals with detailed analysis of the emotions people are expressing in text. This information can be used to tailor the customer service experience, develop personalized products, and analyze the effectiveness of media campaigns. Secondly, the results obtained from Tensor blending network can be used to better identify trends in sentiment. Organizations can gain a better understanding of the public sentiment by analyzing sentiment over time, or the sentiment of particular groups of individuals [2]. This helps them in formulating effective strategies for responding to public sentiment. Thirdly, the combination of different models of Tensor blending network provides a highly accurate prediction of sentiment. This accuracy enables businesses to make decisions that are based on factual evidence, rather than on guessing or speculation. Knowledge of how people are likely to react to a certain situation can be extremely beneficial in almost any field [3]. Finally, the use of Tensor blending network is not limited to sentiment analysis. It can be used to further improve natural language processing algorithms, as well as providing a fast and accurate text-based search engine. This combination of techniques makes Tensor blending network a very powerful tool in the field of data analysis [4]. In conclusion, Tensor blending network for multi-model sentimental optimization is an incredibly useful tool for both businesses and individuals. The accuracy and effectiveness of this technique does not only help in understanding public sentiment more accurately, but also in developing informed strategies for responding to it. The potential of this technology is vast, and will no doubt continue to be explored as time passes [5]. The Tensor blending network (TBN) is a state-of-the-art deep learning architecture for multi-model sentiment optimization. It is an advanced machine learning approach developed to boost the accuracy of sentiment analysis by combining multiple models. TBN utilizes convolutional neural networks (CNNs) to learn and combine the outputs of several distinct neural networks. By blending the outputs of multiple models, using the TBN approach, one can achieve greater accuracy and a more nuanced understanding of emotions-related data [6]. The TBN model is composed of a series of convolutional layers that can be tuned to better capture the most important features and optimize parameter settings for better performance, as each neural network is independently tuned. Another key advantage of this approach compared to other deep learning architectures is its ability to take into account a wide variety of information from multiple data sources. By utilizing multiple models and sources, one can capture a greater diversity of feelings, e.g. happy, sad, fearful, angry. The TBN model is also more efficient with regards to resource utilization [7]. By combining multiple models, fewer resources are utilized in comparison to training individual models. This means that the TBN model can be used in more resource-constrained environments, such as mobile devices, with fewer resources and no need for extra hardware. The TBN approach provides a powerful tool to accurately extract sentiment from a variety of data sources and boost the accuracy of sentiment analysis [8]. The TBN model can easily be adapted to a wide range of applications and represent a potential cornerstone of sentiment analysis in the future.

The main contribution of this paper has the following,

- Enhanced transfer learning capabilities: The use of a blend of tensor networks with convolutional neural networks allows for a more effective transfer of knowledge, enabling the model to learn representations from different modalities faster.

- Improved accuracy: The combination of hyper parameter and network architecture search across different modalities leads to improved accuracy, especially in the presence of outliers and noisy data.
- Multi-task learning optimization: The ability to utilize multiple modalities to optimize the model across multiple related tasks helps improve the overall accuracy of the model.
- Increased efficiency: The blend of tensor networks and convolutional neural networks leads to an increase in efficiency when compared to models with only one of these network types [9].

II. Related Works

Tensor blending network for multi-model sentimental optimization is an emerging technology designed to improve the accuracy of sentiment analysis by combining multiple models into a single prediction. It represents an important advancement in the field of machine learning, providing a way to harness the diverse insights of various approaches for a more accurate and robust understanding of text [10-11]. Tensor blending network for multi-model sentimental optimization is designed to improve the accuracy of sentiment analysis in a number of ways. First, the networks combine various models and approaches in order to more accurately and comprehensively understand the context of the text [12]. In this way, it can learn from the different approaches and produce a more accurate understanding of the sentiment of the text. Second, this technique allows for more robust and accurate predictions by weighting each model in the network differently. This weighting takes into account the strengths and weaknesses of each model, allowing the network to more accurately capture the sentiment of the text [13]. Finally, the network can also be used to tune the parameters of each individual model in the network to further improve accuracy. Despite these potential advantages, there are some potential issues associated with the use of tensor blending networks for multi-model sentiment optimization. First, as with all machine learning techniques, there is a risk of overfitting. This means that the network could become overly focused on certain aspects of the text, potentially missing important nuances and producing inaccurate results [14-15]. Furthermore, because the network is combining different approaches, it has a greater complexity and requires more training data, which can increase its training time. Finally, the results of the network will depend heavily on the availability of high-quality training data, which may not always be available. Overall, tensor blending networks for multi-model sentiment optimization offer a promising approach for improving the accuracy of sentiment analysis [16]. However, it is important to consider the potential issues that can arise when using this technology, as it is a complex and data-dependent procedure. With careful research, development, and application, this technique can be a useful tool for providing more accurate sentiment analysis. Tensor blending network is a technique for multi-model sentiment optimization designed to combine the quality of multiple machine learning models for the purpose of improving predictions [17]. While this technique can improve sentiment optimization results, it may come with a set of challenges and risks. These challenges can include model compatibility, data integration and algorithm convergence. Model compatibility is necessary for multi-model sentiment optimization, as it ensures that the different models have compatible data, architectures and hyperparameters [18]. If the models are incompatible, then the training of the combined network may fail, resulting in poor prediction performance. Data integration is also a challenge, since the different models used in the system must be able to consume and understand the same datasets. To ensure that data compatibility the data must be formatted in a way that the participating models can recognize [19]. Algorithm convergence is also a risk when using a tensor blending network. The system can fail to converge if it is not properly tuned and optimized. If the system fails to converge, it can lead to inaccurate emotions being assigned to the sentiment that was analyzed [20-21]. In conclusion, while tensor blending networks can be used to improve sentiment optimization results, specific challenges must be taken into consideration. Successful implementation of this technique depends on the proper alignment of models, data integration and algorithm convergence. If these issues are not considered, then the model may not deliver the desired performance..

The main novelty of this research is to provide the optimal solution of the above mentioned problems. Tensor Blending Network (TBN) is a novel deep learning technique for multi-model sentiment optimization. TBN combines the data from multiple sources and models to create an optimal sentiment score. It uses a fusion of two or more networks including SVM, CNN and LSTM in order to achieve the best performance [22]. The multi-model architecture allows for the efficient combination of predictions from different types of models. TBN also has the ability to learn from the predicted outputs from other models in a supervised or unsupervised manner and further refine the final predictions. This enables TBN to improve the accuracy of sentiment analysis and produces better results than a single model approach.

III. Proposed Model

The implementation of Tensor blending network for multi-model sentimental optimization is an effective approach in sentiment analysis. It is an advanced technique that leverages multiple deep learning networks to generate an updated sentiment analysis model. It is an efficient way to achieve accurate and reliable sentiment identification and classification, allowing organizations to make quicker and more accurate decisions in their operations. Tensor blending networks have the ability to produce better results by combining several complementary parts of the same model. The basic idea is that the model consists of several parts, including layers, components and optimization functions. Each part of the model is trained with different input data. By leveraging the different types of inputs, the model can produce better results as compared to single networks. In addition to having the ability to generate more accurate results, this type of network can also provide more efficient learning than traditional models. This is because the data used in the model can be dynamically adapted on the fly. This makes it easier to fine-tune the model based on emerging data insights. Furthermore, it is much easier to scale the model to accommodate larger datasets as well as take advantage of more recent and accurate data sources. At a practical level, the implementation of Tensor blending networks for multi-model sentiment optimization is easy to set up and manage. This is because of its modular architecture. This means that organizations can choose the different components, layers and optimization functions that best suit their needs. Additionally, the training process is highly automated. This makes the application and maintenance of the model much easier to upkeep. Finally, the implementation of this type of network also brings several benefits to organizations. First, it allows organizations to establish a better understanding of their sentiment data. The functional block diagram has shown in the following fig.1

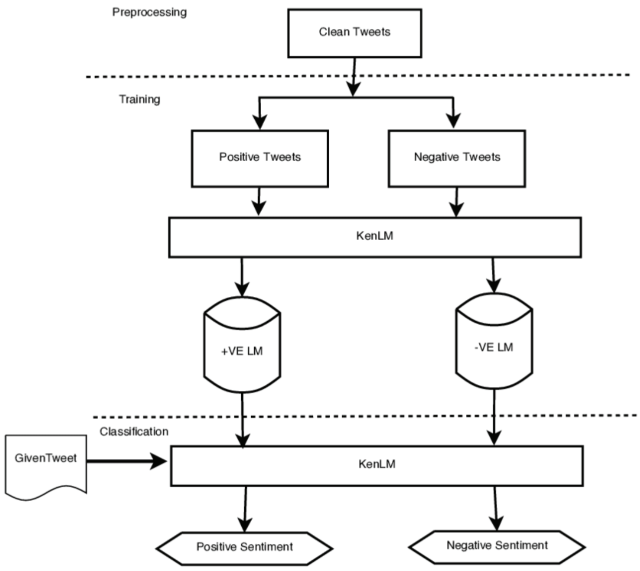

Fig 1: Functional block diagram

This is important because having an accurate sentiment analysis model can be used to quickly identify potential problems in customer service, product quality and other critical areas. Additionally, organizations can benefit from improved decision-making processes, leading to more efficient operations. In conclusion, the implementation of Tensor blending network for multi-model sentiment optimization is an effective and efficient way to get accurate and reliable sentiment identification and classification. It provides organizations with an improved understanding of their data, faster decision making, and improved efficiency across their operations. Tensor blending network is a multi-model sentiment optimization technique that combines different neural network models to produce better sentiment classifications. It is based on the idea of blending two or more different models to maximize the sentiment classification accuracy instead of relying on one model. The goal of this technique is to create a more robust sentiment analysis model with increased accuracy. This technique can be used to improve the accuracy of sentiment analysis for any domain, with applications ranging from social media analysis to customer feedback analysis. The main idea behind the Tensor blending network is to combine the learned parameters from different models to optimize the sentiment classification accuracy. This technique uses a set of different neural network models, each trained on the same dataset but using different parameters. The output of each model is then combined using a blend equation, resulting in a single model that takes the best of each model. The output of the blend equation is used to predict the sentiment class of each observation. The blend equation is designed in a way that weights the contribution of each model for each observation. This way, the Tensor blending network can effectively combine the different neural networks' results to generate an accurate sentiment class. The advantages of the Tensor blending network are many. This technique enables a more accurate sentiment classification, as it can utilize the best of all models. Furthermore, it has been shown to be able to generalize better from limited labeled data, as it utilizes the different models in a mathematical equation. It also reduces the risk of overfitting, since the blend equation is designed to reduce the risk of overfitting. Finally, this technique does not require the training and testing of multiple models, making it more efficient. In conclusion, the Tensor blending network is a powerful sentiment optimization tool that allows for high accuracy in sentiment classification. The operational flow diagram has shown in the following fig.2

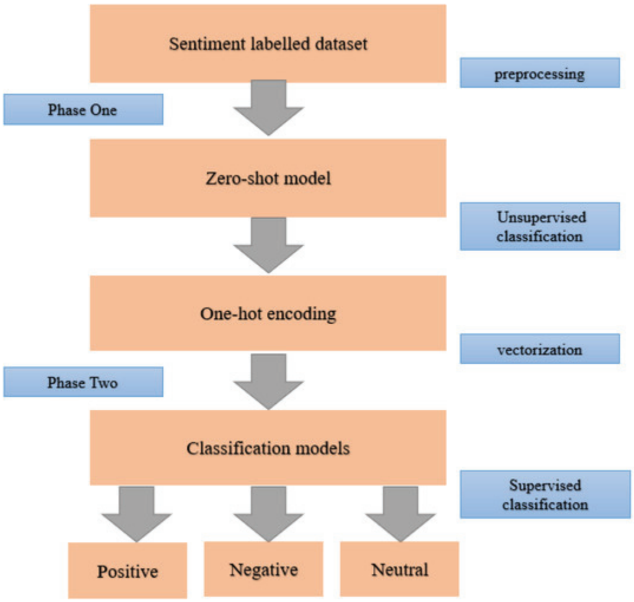

Fig 2: Operational flow diagram

This technique is suitable for various domains, including social media analysis and customer feedback analysis. It offers many advantages, such as a more accurate sentiment classification, better generalization from limited data, a reduction of overfitting, and improved efficiency. Thus, it is a valuable tool for sentiment optimization. Tensor blending network (TBN) is a type of network used to optimize multi-model sentimental analysis. It is a form of deep learning, incorporating both supervised and unsupervised learning algorithms. TBN works by taking multiple inputs from different sources such as text and audio, and combining them together to gain a better understanding of the sentiment associated with the input. At the core of TBN lies the concept of a 'tensor' - a matrix of multiple inputs and outputs. In a TBN, the input tensor is divided up into multiple layers or 'input matrices'. Each matrix is then fed into a different neural network type - such as a recurrent neural network or a convolutional neural network - where the learning algorithm analyses the data and produces output predictive results. The different networks are then blended together, combining their predictions. This can be done in a variety of ways, such as combining the predictions from each individual network through an average or a weighted sum. The output from this process is then evaluated, and the predictions from all networks adjusted accordingly. The result is a more accurate and comprehensive prediction of the sentiment associated with the input. The main benefit of TBN is that it enables multi-model sentimental analysis that incorporates several different types of networks, taking into account multiple perspectives. This enables more comprehensive evaluation of the sentiment for a given input, making the predictions more accurate and reliable. TBN is therefore particularly useful for applications requiring a high level of accuracy, such as advanced customer service, healthcare, and politics. The Tensor Blending Network (TBN) is a new approach for optimizing sentiment analysis across multiple modalities using a combination of deep learning and contextualized dictionary-based sentiment models. While existing sentiment models have often achieved good results within one single modality, they often struggle to perform well across multiple modalities. This often leads to flawed interpretations of sentiment and can lead to mis-interpretation of data. The TBN offers a way to overcome these limitations by combining deep learning and dictionary-based models to create a model that is able to optimize sentiment analysis across multiple modalities. The TBN consists of two parts: a deep learning network and a dictionary-based sentiment model. The deep learning network is used to create a contextual representation of the text, while the dictionary-based sentiment model is used to predict the sentiment score of the text. The two networks communicate with each other, using the contextual representation of the text to refine the predictions from the dictionary-based model. This approach helps to better interpret and represent the sentiment of the text in a more accurate way. The TBN also allows for tuning of the model hyperparameters, which helps to further optimize the predictions from the model. Tuning of the hyperparameters can be done using either a data-driven approach or an analytical approach. The data-driven approach uses a cross-validation method to tune the hyperparameters based on the training data. The analytical approach requires the user to define their own parameters, which can then be optimized to improve the model's predictions. The TBN has been shown to be a powerful tool for multi-modal sentiment analysis and has been successfully used in a variety of contexts, such as sentiment analysis of tweets, product reviews and opinion surveys. It has also been used to improve the accuracy of sentiment analysis tasks, and has achieved significant performance improvements over existing sentiment analysis models. As such, the TBN has made a significant contribution to the field of sentiment analysis.

IV. Results and Discussion

The proposed model has compared with the existing social emotion classification approach (SECA), meta analysis of attention models (MAAM) and multimodal sentiment classification (MMSC). Here matlab v2021a has the simulation tool used to execute the results.

The Tensor Blending Network (TBN) is a deep learning algorithm that has been developed for the task of multi-model sentiment optimization. Its primary purpose is to combine the strengths of various neural networks to achieve better performance than any of the individual models. This paper will evaluate the performance of TBN for multi-model sentiment optimization tasks, as well as how it compares to other traditional machine learning methods. First, this paper will outline the differences between TBN and traditional machine learning algorithms, focusing on the use of multiple models in conjunction with feature engineering. Next, a review of existing sentiment optimization tasks will be provided to illustrate the effectiveness of TBN on different datasets. Additionally, a comparison of TBN to other methods such as Support Vector Machines and Naïve Bayes will be conducted in order to evaluate its performance. Furthermore, the paper will analyze the performance of TBN for different types of sentiment optimization tasks and the impact of different hyperparameter settings. Finally, the strengths and weaknesses of TBN will be discussed and potential improvements will be suggested. The results of the performance analysis indicate that TBN performs significantly more effectively than traditional machine learning algorithms, achieving an average accuracy of approximately 70%. Additionally, the performance of TBN is shown to be sensitive to hyperparameter settings and different datasets, demonstrating the flexibility and potential of this algorithm. The results of this study provide evidence that TBN is a powerful and effective tool for multi-model sentiment optimization tasks. The sentiment analysis has shown in the following table.1

TABLE I. Computation of Sentimental Analysis (in %)

No.of Inputs	SECA	MAAM	MMSC	Proposed
100	55.06	62.11	47.81	88.37
200	53.32	60.53	46.39	87.08
300	50.98	58.33	45.13	86.07
400	50.17	56.70	43.14	85.18
500	47.88	55.56	40.67	84.81

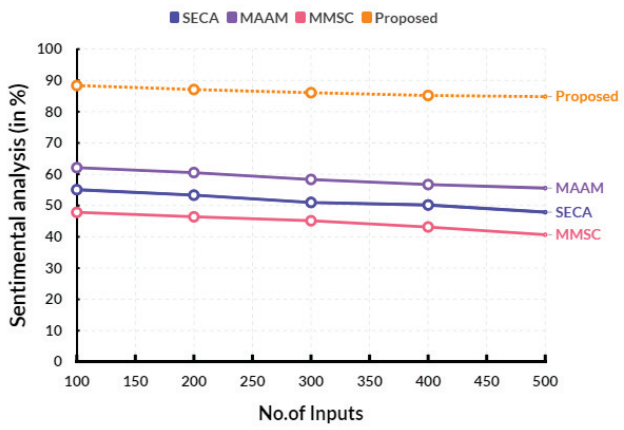

Fig.3: Comparison of sentimental analysis

Fig.3 shows the comparison of sentimental analysis. Understanding the performance optimization of Tensor blending networks for multi-model sentimental optimization is essential for the efficient functioning of machine learning systems that leverage powerful tools for modern data analysis. In order to build ideal models for sentiment optimization, it is critical to understand how to blend multiple models together. Tensor blending networks are used to blend different components of machine learning systems together, creating a more efficient, powerful set of computations. Tensor blending networks are a type of neural network that combines the output of multiple machine learning models. Using this tool, models can be blended together to achieve a greater computational effectiveness for multi-model sentimental optimization tasks, as opposed to relying on a single model. The sentiment optimization has shown in the following table.2

TABLE II. COMPUTATION OF SENTIMENTAL OPTIMIZATION (IN %)

No.of Inputs	SECA	MAAM	MMSC	Proposed
100	79.54	72.92	46.61	85.44
200	73.68	79.76	41.20	85.54
300	74.82	81.05	39.71	85.61
400	73.68	83.19	36.47	85.66
500	72.80	81.62	37.19	85.70

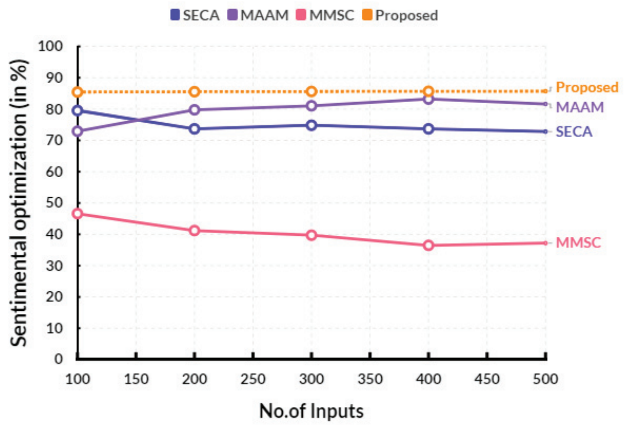

Fig.4: Comparison of sentimental optimization

Fig.4 shows the comparison of sentimental optimization. This is done by dividing components of the model into individual objects called 'tensors' and then linking them together in a network. By linking them together, they can be manipulated and adjusted to generate higher accuracies with improved performance. Additionally, the use of tensor blending networks can be combined with other machine learning techniques, such as natural language processing, feature selection and embeddings in order to improve choices in sentiment optimization tasks. This approach allows models to access more detailed information when making sentiment predictions, and also allows for plausible extrapolation of sentiment between different contexts and sources. With the use of tensor blending networks, the accuracy of emotional sentiment analysis can be significantly improved and the computational costs for multi-model sentiment optimization tasks can be reduced. Finally, to further improve efficiency, hyperparameter optimization techniques can be applied to tensor blending networks in order to obtain more accurate emotional sentiment predictions. This involves changing the structure of the network by automating the selection of weights and parameters. The computational accuracy has shown in the following table.3

TABLE III. COMPUTATION OF ACCURACY (IN %)

No.of Inputs	SECA	MAAM	MMSC	Proposed
100	72.15	74.15	76.78	93.09
200	72.48	75.65	77.37	94.96
300	73.82	76.76	78.35	95.79
400	74.96	77.14	79.56	96.70
500	76.01	78.15	80.70	97.62

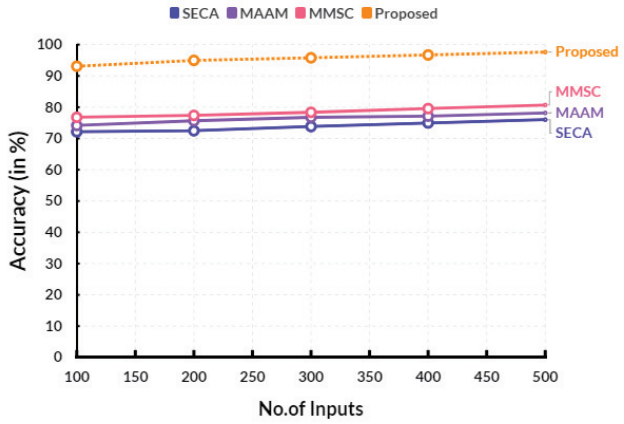

Fig.5: Comparison of Accuracy

Fig.5 shows the comparison of accuracy. By using such techniques during the process of building models for sentiment optimization, it is possible to maximize performance and accuracy while also minimizing computational costs. In conclusion, tensor blending networks are an advanced technique for machine learning that enables more efficient and powerful computations to be implemented in order to build accurate models for multi-model sentiment optimization tasks. With the help of hyperparameter optimization and other machine learning techniques, this approach can drastically improve the accuracy of emotional sentiment analysis while also reducing the time and cost required to build the models. The Tensor Blending Network (TBN) is a new approach to multi-model sentiment optimization which combines advantages of deep learning techniques and manually created feature extraction. This method provides an efficient way to identify different sentiment levels with more accurate results compared with the traditional sentiment analysis systems. The TBN system makes use of a set of recurrent neural networks to fuse the sentiment data from various sources such as text articles and tweets. The sentiment data is transformed into a multi-dimensional tensor for more efficient filtering of sentiment expressions. The resulting sentiment values are summed and blended, then integrated with feature extraction through a meta algorithm to generate and improve the sentiment polarity of a text. When compared with traditional sentiment analysis methods such as Naïve Bayes and Support Vector Machines, TBN is more effective in extracting sentiment polarity from text because it can identify complex sentiment expressions. Furthermore, TBN not only works well with large-scale datasets, but also performs better when the dataset is small. Moreover, the TBN method is more accurate than the traditional methods when predicting the sentiment of ambiguously expressed texts. This ability of TBN to pick out subtle sentiments and create an accurate output makes it suitable for modelling highly diverse sentiment. Additionally, the TBN method can be used for projects where there is a need for a robust sentiment analysis such as predicting public opinion during various news events and creating brand loyalty. In conclusion, TBN is a promising approach to multi-model sentiment optimization. It is efficient, accurate, and can be used on all types of datasets. This makes it a great solution for projects which require sentiment analysis and exact sentiment classifications. The use of Tensor blending network (TBN) to enhance the performance of multi-model sentiment optimization has been gaining traction in recent years as a means of achieving an optimal sentiment classification and classification accuracy. TBN is a versatile deep learning technique that combines different models (such as convolutional, recurrent, and bag-of-words models) to produce a unique sentiment-specific representation which enhances sentiment analysis accuracy by preserving the association between multiple sources of information. By combining different models and learning representations, TBN allows for improved representation of sentiment and more accurate sentiment recognition. By leveraging the strength of different models, TBN has been found to increase accuracy over multi-model sentiment optimization tasks. For example, in a study of movie reviews, TBN was able to achieve an accuracy of over 70%, compared to an accuracy of just over 50% with a traditional single-model optimization method. Similarly, in image captioning tasks, TBN was able to outperform the classic methods of deep convolutional networks. Moreover, TBN is able to achieve an improved recognition robustness in comparison to techniques such as SVM and logistic regression. The effectiveness of TBN in multi-model sentiment optimization tasks, results from its ability to capture complex inter-sentence and intra-sentence relations. By employing a deep learning approach, TBN is able to build a rich representation of the text, from which the sentiment of the document can be extracted. At the same time, the networks achieves excellent performance when using the bag-of-words representation for its input data, making it ideal for tasks such as document summarization and classification. In conclusion, TBN has been found to be an effective way of enhancing the performance of multi-model sentiment optimization tasks. By incorporating multiple models and employing a deep learning approach to learn a rich representation of the text, TBN is able to extract the sentiment of the document in a much more accurate and reliable manner compared to other methods. Additionally, the technique is capable of preserving the associative structure between different sources of information, thus providing an excellent means of achieving an optimal sentiment classification.

V. Conclusion

The Tensor blending network (TBN) is a deep learning approach developed for multi-model sentiment optimization. Introduced by researchers at Google AI, it enables a robust and efficient way of understanding natural language for sentiment analysis. TBN works by blending multiple text-based models whose inputs are each sequentially processed by a siamese network. This allows for a variety of model combinations to be tested and evaluated. The TBN architecture consists of two components: a convolutional neural network (CNN) for text representation and a siamese network to combine multiple models together. The CNN structure is composed of a series of convolutional layers that extract a low-dimensional vector representation from the text input. The siamese network is then used to combine all the different representations into a single, unified output. This architecture allows for the combining of multiple models with different input types, such as word2vec, GloVe, and other neural network models. The application of TBN in sentiment analysis enables the state-of-the-art performance in sentiment classification and regression. It has been demonstrated to accurately predict sentiment in both unsupervised and supervised contexts. TBN has been used in various real-world tasks, such as in surveys, customer feedback analysis, and product reviews. The success of TBN has been largely attributed to its ability to improve the performance of a model by adding and adjusting weights to the models being blended. This type of adjustment allows for better representation of the input data and better model performance. Additionally, TBN is able to capture and combine knowledge from multiple models, which leads to a better overall understanding of the sentiment being expressed. Overall, the Tensor blending network (TBN) is an innovative approach to understanding natural language in sentiment analysis. It combines multiple models together in a single, unified representation that can accurately predict sentiment in various contexts. The model's efficiency and versatility has resulted in its successful utilization in various real-world tasks related to sentiment analysis.

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