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Hybrid Deep Learning Model for Multilingual Sentiment Analysis

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Abstract- **The usefulness of understanding public opinion across linguistic boundaries cannot be overstated. Sentiment analysis is a great method for learning more about users' opinions and their opinions on social networks, such as movie review sites. Natural language processing (NLP) challenges jeopardize sentiment analysis' efficiency and accuracy. It has been demonstrated that hybrid models can utilize some of the advantages of classical models as long as deep learning models are capable of overcoming the obstacles connected with NLP. We want to look at this hybridization in this study.**

Keywords- **DeepLearning, Sentiment Analysis, LSTM, CNN**

INTRODUCTION

The approach for multilingual sentiment analysis is based on employing a sentiment dictionary to translate words for words in any native language. A text is analyzed in three stages: morphologically, using a sentiment dictionary to extract verbal sentiment from each word, and finally utilizing word sentiments to analyze the text. On tweets in English and Hindi, we did a sentiment categorization experiment. We used the assessment standards "Accuracy," "Precision," "Recall," and "F1 score" to evaluate our classifier's performance to that of different preceding classifiers. The experimental results suggest that our classifier may be utilized for sentiment analysis in multilingualism since its performance is unaffected by language variations.

Deep learning hybrid models have been suggested for analyzing social network data for sentiment analysis. We investigate the performance of combining SVM, CNN, and LSTM on eight datasets of tweets and reviews using two-word embedding approaches, Word2vec and BERT. Following that, we contrasted four hybrid models that had been created with single models that had been reviewed. These tests were carried out to explore if hybrid models could be applied to a wide range of dataset types and sizes. The impacts of various datasets, feature extraction methods, and deep learning models on sentiment polarity analysis were investigated. The findings of our sentiment polarity analysis studies demonstrate that hybrid models beat all other models examined. Deep learning models paired with SVM give better sentiment analysis findings than when used alone. The dependability of hybrid models employing SVM is greater than that of models without it in most of the datasets evaluated; however, the computational time for hybrid models using SVM is substantially longer. We also discovered that the algorithms' efficacy is heavily influenced by the datasets' features and quality. We recognise that the context of the dataset has a substantial impact on the sentiment analysis algorithms we employ. We intend to examine the efficacy of hybrid approaches for sentiment analysis on hybrid datasets and multiple or hybrid settings in order to get a deeper knowledge of a particular topic, such as business, marketing, or medicine. The capacity to relate feelings to relevant context in order to give consumers specific individualized feedback and suggestions drives its adoption.

We provide a multilingual sentiment analysis method that uses a sentiment dictionary to do word-for-word translation in any native language. The phases in this technique are as follows: text morphological analysis, sentiment dictionary-based word sentiment extraction, and sentiment-based text sentiment extraction. On English and Hindi tweets, we conduct a sentiment classification experiment. Using the assessment standards "Accuracy," "Precision," "Recall," and "F1 score," we compare the performance of our classifier in the experiment to the performance of several preceding classifiers. The experimental findings show that our classifier is suitable for sentiment analysis in multilingualism since its performance is unaffected by language variations.

Using social network data, hybrid deep learning models for sentiment analysis were built. The performance of integrating SVM, CNN, and LSTM with two-word embedding methods, Word2vec and BERT, was assessed on eight textual datasets comprising tweets and reviews. Then we compared four hybrid models to single models that had previously been studied. These research are being conducted to determine if hybrid models and hybrid techniques can adapt to a broad variety of dataset types and sizes. Using a range of datasets, feature extraction approaches, and deep learning models, we assessed the reliability of sentiment polarity analysis. Combining deep learning models with the SVM approach produces better results than using a single model when performing sentiment analysis. In terms of dependability, hybrid models that use SVM outperform models that do not in the majority of datasets tested; nevertheless, the computational time for hybrid models that include SVM is much longer. Furthermore, we discovered that the quality and quantity of the datasets had a significant influence on the performance of the algorithms. The context of the dataset has a significant impact on sentiment analysis methodologies. We propose to examine the usage of hybrid methodologies for sentiment analysis on hybrid datasets and numerous or hybrid contexts in order to gain a more comprehensive knowledge of a particular topic. Its usefulness arises from its capacity to relate attitudes to relevant facts in order to deliver Clients are provided with individualized feedback and suggestions. Sentiment analysis is difficult to do without considering a range of semantic and syntactic limitations as well as the terminology of the input text. This research led to the creation of a sentiment analysis deep learning model that consists of one-layer CNN architecture and two layers of LSTMs. Word embedding models can be used as the input layer in this approach. Research indicates that the proposed model can enhance accuracy by up to 11.6 percent and outperform existing techniques on many benchmarks. The proposed model makes use of CNN for feature extraction and LSTM for recurrence.

MOTIVATION AND BACKGROUND

Sentiment analysis, which aims to extract subjective information from texts, is an important machine learning issue. Sentiment analysis is intrinsically tied to text mining and natural language processing. This helps you understand the overall polarity of the review or how the reviewer felt about a specific topic. Based on sentiment analysis, we might be able to determine whether the reviewer felt "glad," "sad," "angry," etc. when writing the review. In assessing the performance of a film, movie reviews are crucial.

Although numerical/star ratings provide a quantitative indication of a film's success or failure, film reviews provide a more qualitative analysis of the film. A textual movie review educates us about the film's good and bad points, and a more in-depth evaluation of a film review may reveal if the picture meets the reviewer's overall expectations. As a result of the project, sentiment analysis will be available in a range of languages, giving it a strong analytical tool that is not limited by linguistic limitations. In comparison to standard models, the hybrid model surpasses them by combining aspects from other models.

RELATED WORK

[1] This paper discusses the core of deep learning models and associated approaches used in sentiment analysis for social network data. Before feeding input data to a deep learning model, the words embedding are employed. To perform sentiment analysis, we examined the architectures of DNN, CNN, and RNN based on word embedding . A number of experiments have been conducted to test DNN, CNN, and RNN models using datasets ranging from tweets to reviews. There is a model comparison as well as some associated field studies. This data, together with the results of other model tests, paints a complete picture of the usage of deep learning models for sentiment analysis and their integration with text preparation.

[2] LSTM should be utilized to examine stock investor sentiments on stock swings, according to the paper. The author defines a model with seven separate phases for sentiment analysis. Participants are expected to perform tasks including data collection, data cleansing, manual sorting, feature extraction, LSTM model training, sentiment classification, and sentiment analysis.

The positive group's accuracy is 80.53 percent, while the negative group's accuracy is 72.66 percent, both of which are greater than the accuracy of the Cheng and Lin model, which used a sentiment dictionary to assess investor sentiment and stock return in the Chinese stock market. The paper expressly states the benefits of LSTM over a vanilla RNN network in sentiment analysis, and it is proposed that LSTM be utilized instead to get higher accuracy in analysis. Because the computing cost and time required for the analysis are not factored into the model, the result of using LSTM for sentiment analysis is confusing. Following the examination, DNN, CNN, and hybrid approaches were discovered to be the most often utilized models for sentiment polarity analysis. The study also discovered that typical techniques like CNN, RNN, and LSTM were separately analyzed and judged to have the best accuracy.

[3] Based on our findings, we show that convolutional neural networks can outperform data mining in stock sentiment analysis. Documents are represented as bag-of-word vectors in the standard data mining approach for text categorization. These vectors represent the existence of words in a text but not their order in a sentence. In certain circumstances, it's clear that word order influences the tone of a comment. You can utilise n-grams to efficiently extract a document's sentiment and solve this problem with CNN. According to the investigation in this article examining and comparing a number of standard Deep Learning techniques, convolutional neural networks outperform logistic regression for sentiment analysis. Convolutional neural networks outperform other models in terms of accuracy. The study fails to discuss the use of a combination of models to increase overall performance by leveraging the characteristics of each model.

[4] As a benchmark for Sentiment Analysis on Twitter, the authors used data from the SemEval-2013 competition. Both terms and messages were classified in this project. Subtask b, which consisted of classifying a message into three categories: good, negative, and neutral, received the most attention (message-level polarity classification). Using lexical and machine learning approaches to evaluate Twitter sentiment, this study examines how negation handling impacts performance and how SWN-based feature computation compliments it. To avoid misclassification by the SVM classifier, we created exceptions in cases where a negation cue is present but no negation sense is present. The research asserts unequivocally that hybrid deep learning models are employed for improved analysis, and that utilizing hybrid models considerably increases analysis accuracy.

[5] The author proposed a model that incorporated characteristics from different social context levels in the paper. This approach evolved from previous systems that only categorized users at the individual level. It also used community detection to find weak ties between users who were not directly connected in the network. The combination is projected to outperform at various levels of confidence in the labels in the context and with diverse degrees of social network sparsity. In a variety of situations, the proposed method has been proved to work for both types of categorisation. Several datasets are examined in order to evaluate the model. The amount of datasets that could be included in the evaluation was limited due to the requirement for a social context. Because it comprised a more densely linked network of users, the RT Mind dataset appeared to be the most suited of the three. When CRANK was compared to other baseline models in that dataset, the findings were mixed. The model was created by combining data from many levels of social settings, and it was not confined to user-level categorization for community identification, and it also discovered weak relationships between users. There is no comparison between various community models and various graph traversal strategies, leaving the topic of model efficacy with other community techniques wide open and ambiguous.

[6] This article's authors describe numerous deep learning models and suggest that hybrid models are the best option for sentiment analysis. Among the hybrid models, the authors highlight the CNN-LSTM hybrid.

CNN can assist you in determining how to extract data characteristics. Long-term interactions, on the other hand, necessitate the inclusion of more convolution layers, and capturing dependencies gets more challenging as the duration of an input sequence in a neural network increases. The convolutional neural network layer is quite deep in practice. Associations between word sequences can be represented using LSTM models.

A CNN-LSTM hybrid model for sentiment analysis is presented in the study. The suggested hybrid CNN-LSTM model outperformed CNN and LSTM models independently in two benchmark movie review datasets. By 91 percent, the suggested Hybrid CNN-LSTM model outperformed traditional machine learning and deep learning models. The study examines a number of individual and hybrid sentiment analysis models, such as CNN-LSTM, which are projected to be more accurate than their rivals.

[7] Based on a one-layer CNN architecture and two LSTM layers, the study developed an Arabic sentiment analysis deep learning model. Based on this architecture, FastText supports word embedding. The results of a multi-domain dataset show that it is quite successful, with scores of 89.10 percent precision, 92.14 percent recall, 92.44 percent F1-Score, and 90.75 percent accuracy, respectively. The effect of word embedding methodologies on Arabic sentiment categorization was comprehensively explored in this work, revealing that the FastText model is a more acceptable choice for extracting semantic and syntactic information. The performance of the proposed model is also evaluated using NB and KNN classifiers. SVM is the top performing classifier, according to the statistics, with an accuracy improvement of up to 3.92 percent. Due to the effectiveness of CNNs in feature extraction and LSTM's recurrent nature, the proposed model outperformed state-of-the-art approaches on a number of benchmarks with a +11.6 percent accuracy increase. The study specifies explicitly how accurate and effective the hybrid deep learning model is with layers and compact architecture. Multidomain datasets make the model more adaptable and accurate.

[8] The author's major focus in this study is on comprehending the text's mixed linguistic character, which includes both formal and informal textual material. Because user-generated material frequently incorporates localized slangs as a means of expressing genuine emotions. The author employs a variety of methods to examine the data's subjectivity and polarity. This study considered not just formal languages, but also informal and limited-resource languages. The author also suggested using a hybrid architecture to create sentiment analysis resources. The final methodologies applied in the different components, as well as the quality of resources accessible, are critical to the correctness of the suggested framework.

[9] Bing, Google, and Moses are three distinct machine translation (MT) systems used by this author. The authors discovered that SMT systems can collect training data for languages other than English, and sentiment analysis systems can perform similarly to English. Here, the author carried out a number of tests. In the first experiment, the data is translated from English to three other languages: German, Spanish, and French, and the model is trained separately for each language. In the second experiment, the author combined all of the translations of the training data obtained for the same language using the three different MT systems. SMO, AdaBoost M2, and Bagging classifiers are used by the author. However, combining all of the translated training data significantly raises the training data's noise level.

[10] The author tries to do sentiment analysis on languages with the greatest datasets, such as English, and then reuse the model for languages with low resources. The authors use RNN to build a sentiment analysis model based on English reviews. The robust technique of utilizing a single model trained on English reviews beats the baseline considerably in various languages. As a result, it can deal with a variety of languages. The author created a sentiment analysis model tailored to a particular domain just for this article.

[11] The author of this article examines the feasibility of building sentiment detection and classification models in languages with fewer/no resources than English, emphasizing the importance of translation quality on sentiment classification performance, using machine translation and supervised methods. In the training phase, the author could see that improper translations result in an increase in features, sparseness, and greater difficulty in recognising a hyperplane that separates the positive and negative instances. The extracted features are insufficiently informative for the classifier to learn when the translation quality is poor. The results of the testing can be used to assess the quality of the translation. In this case, poor translation quality causes a decline in performance.

[12] The author introduces a unique hybrid deep learning model in this research that purposefully integrates multiple word embedding strategies (Word2Vec, FastText, character-level embedding) with various deep learning methods (LSTM, GRU, BiLSTM, CNN). The proposed model incorporates information from several deep learning word embedding algorithms and classifies texts based on their emotional content. Several deep learning models known as basic models were also built in order to conduct a series of experiments to evaluate the proposed model's performance. When comparing the suggested model's performance to that of previous research, it is clear that the new model outperforms the others. To test the suggested model's performance. The author carried out two separate trials. In the first experiment, twelve basic deep learning models were created. There are four types of deep learning. Twelve basic deep learning models were built in the first experiment. Four deep learning models (CNN, LSTM, BiLSTMGRU) were combined with three distinct text representation methods (Word2Vec, FastText, and character-level embedding). FastText and Word2Vec embedding, both word representation approaches, performed better with RNNs models in the trial. The combination of BiLSTM and FastText in a word embedding technique yielded the highest classification accuracy of 80.44 percent. With a mix of CNN and character-level representation, accuracy was 75.67 percent. With our suggested combination of CNN and BiLSTM with fastText and character embedding, we achieved an accuracy of 82.14 percent classification success. As a consequence, the suggested model's performance is superior to that of existing basic models. The suggested model's performance was compared to that of a prior research on the same dataset in the second experiment. The M-Hybrid author obtained 82.14 percent, compared to 69.25 percent in earlier research on the dataset. The author categorized the dataset used in this work with various significant deep learning algorithms in order to confirm the correctness of our model. In light of the presented strategy, the author suggests combining several text representation methods for a higher classification accuracy rate.

[13] CNN and LSTM are used in this study to build information channels for Vietnamese sentiment analysis. This scenario gives an innovative and efficient method for combining the benefits of CNN with LSTM. The author also assessed their method on the corpus and the VLSP corpus. On the two datasets, the suggested model outperforms SVM, LSTM, and CNN, according to the experimental findings. The author also gathered 17,500 reviews from Vietnamese social media platforms and labeled them as good, neutral, or negative. This method combines the benefits of CNN and LSTM into a single model. In comparison to other models, which produces the best results? There is room for improvement in performance on unambiguous scenarios as well as cases with both positive and negative attitudes.

[14] The purpose of this research is to develop a semi-automated sentiment analysis learning system that can be changed in response to language changes in order to remain current. This is a hybrid strategy that employs both lexicon-based and machine learning methods to detect the polarity of tweets. Several datasets were chosen to put the suggested approach to the test. The accuracy for a 3-class classification challenge was 73.67 percent, while the accuracy for a 2-class classification problem was 83.73 percent. The semi-automated learning component was proven to improve accuracy by 17.55 percent. The author offers a hybrid approach for Arabic Twitter sentiment analysis that gives high accuracy and dependable performance in a dynamic setting where language analysis systems must intelligently cope with these ongoing changes.

[15] The author presents a hybrid sentiment classification model that incorporates a Manhattan LSTM (MaLSTM) based on a recurrent neural network (RNN), also known as long-short term memory (LSTM), and support vector machines (SVM). The suggested technique uses LSTM to learn the hidden representation before employing SVM to identify attitudes. SVM-based representations of the LSTM are used to determine attitudes from an IMDB movie review dataset based on the learned representations. In comparison to existing hashtag-based models, the proposed model outperforms them. The proposed system (MaLSTM) shows that merging Siamese LSTM with SVM yields an outstanding text classification model. When there are a lot of sentences, a pooling layer is created, and then the SVM is used to categorize them. Because it can detect hidden unit representations of sentences, the model may be employed in real-time applications. According to the findings, the approach is competitive with state-of-the-art algorithms on a variety of text classification tasks. Regularization strategies can improve classification in neural network models with dropout.

[16] In this research, the author presents a novel hybrid deep learning architecture for sentiment analysis in resource-constrained languages. Convolutional Neural Networks were also used to train sentiment embedding vectors (CNNs). To choose the improved qualities, a multi-objective optimization (MOO) framework is employed. Finally, the sentiment enhanced vector acquired is utilized to train the SVM for sentiment classification. An assessment of the suggested approach for coarse-grained (sentence level) and fine-grained (aspect level) sentiment analysis on four independent Hindi datasets. He also validated the proposed technique on two benchmark English datasets. According to a performance evaluation, Across all datasets, the suggested technique outperforms existing state-of-the-art systems. When a sentence lacks a distinct sentiment identifier, the algorithm has a more difficult time properly predicting the sentiment.

[17] This study presents a hybrid learning system that incorporates both deep and shallow learning aspects. Not only can a hybrid technique classify single language text sentiment, but it can also classify bilingual text sentiment. Recurrent neural networks with long short term memory (RNNs with LSTM), Naive Bayes Support Vector Machine (NB-SVM), word vectors, and bag-of-words are among the models investigated. Experiments demonstrate that accuracy may reach 89 percent, and that the hybrid technique outperforms any other method alone. The hybrid technique for multi-language text sentiment classification is a novelty in this work since it includes both generative and discriminative models.

[18] The author suggests utilizing convolutional neural networks to classify sentiments. Experiments with three well-known datasets show that employing consecutive convolutional layers for relatively long texts works well, and that our network beats state-of-the-art deep learning models. The author showed in his research that using many convolutional layers in a row increased performance on reasonably long texts. The suggested CNN models obtained around 81 percent and 68 percent accuracy for binary and ternary classification, respectively. Despite the lengthy content, the convolutional layers helped to improve performance. The suggested CNN models had a ternary classification accuracy of 68 percent, which isn't extremely good.

[19] The author of this study discusses and contrasts previous work in the subject of multilingual sentiment analysis. The goal is to see if the approaches allow for precise implementation and reliable replication of the claimed result, and whether the precision seen by the author is less than that defined in the original methodology publications. Author used several ways using SVM classifierI, such as lexicon-based, corpus-based, hybrid, supervised learning, and so on, and compared the reported accuracy with the accuracy that author obtained. The paper offers insights into the authors' various methodologies as well as his research, which paints a clear picture of the accuracies of various approaches.

[20] The author of this study mixes many models into one. We've observed that the hybrid method beats all other models, whether single or multiple languages, or both, and to evaluate each model's contribution, we combine two models at a time to build the hybrid model. Time. Experiments have shown that each model works in a distinct way. Although different languages are handled differently, they all contribute to the overall image. This model is a mix of the two. As the penalty coefficient drops, over-fitting becomes more prevalent and dangerous. The accuracy of the models is affected by many iterations. As the number of iterations grows, the hybrid model that matches the training data gets increasingly accurate. The accuracy of training data, on the other hand, significantly improves. The precision of test results is deteriorating.

CONCLUSION

We conclude that using TF-IDF rather than combining deep learning with word embedding is optimal. Moreover, CNN provides a good balance between accuracy and processing time, compared to other models. The reliability of RNN is higher than that of CNN on most datasets, but its computation time is much longer. At long last, a decision was reached. The study found that the algorithm's effectiveness is highly reliant on the input data. The datasets' characteristics allow testing deep learning algorithms with bigger datasets simpler. When compared to solo CNN and LSTM models in two benchmark movie review datasets, the suggested Hybrid CNN-LSTM model performed surprisingly well.

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