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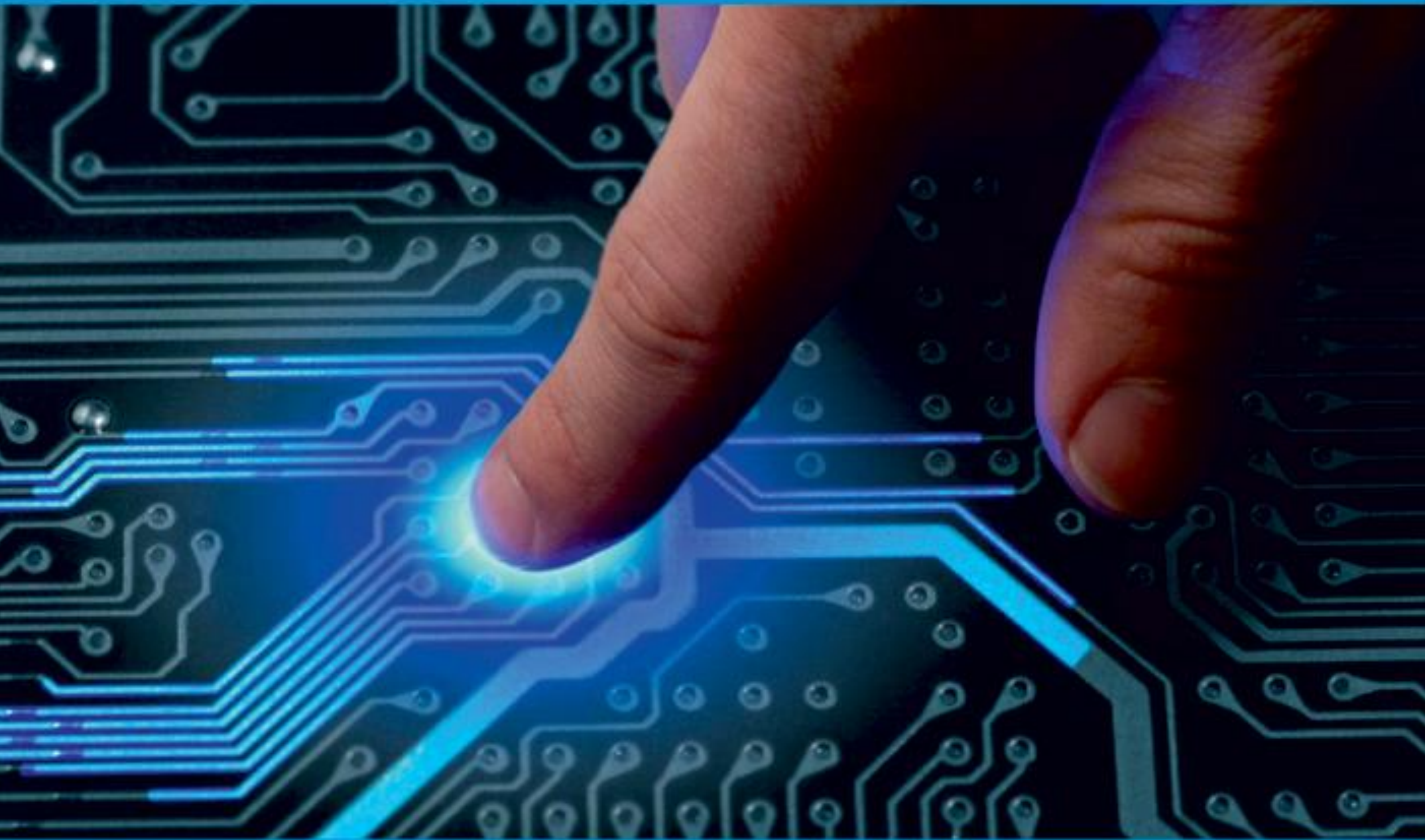

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Sentiment Analysis of Movie Review Using Deep Learning Techniques

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ABSTRACT: Text mining is a process of identifying meaningful information from text-based data. A large amount of data in the form of reviews and tweets is available on the web. It is difficult to manually read these reviews and assign sentiments to them, so an automated system can be created that analyses the text and extracts the user precepts. In this system, sentiment analysis is performed on collected restaurant reviews. The implemented system performs sentiment analysis on data available for restaurant review data. This result can provide an opinion that is positive or negative.

In the baseline system, we demonstrate two different feature extraction techniques. First, the bag of words model is used for feature extraction. The second technique used is the term frequency-inverse document frequency scores. We examined the effectiveness of several N-gram ranges using Naïve Bayes Classifier. We analyze the results of the baseline system and scope of improvement in the results using the word embedding technique. The CNN model efficiently extracts higher level features using convolutional layers and max-pooling layers. The LSTM model is capable of capturing long-term dependencies between word sequences. We propose a hybrid model using LSTM and CNN model named as Hybrid CNN-LSTM Model to overcome the sentiment analysis problem.

KEYWORDS: Sentiment Analysis, NLP, RNN, LSTM model, CNN

I. INTRODUCTION

Natural language processing (NLP) is the ability of a computer program to understand human language as it is spoken. Sentiment analysis is one of the most popular applications of NLP. The term sentiment analysis first appeared in (Nasukawa and Yi, 2003), and the term opinion mining first appeared in (Dave, Lawrence, and Pennock, 2003). However, research on sentiments and opinions appeared earlier (Das and Chen, 2001; Morinaga et al., 2002; Pang, Lee and Vaidyanathan, 2002; Tong, 2001; Turney, 2002; Wiebe, 2000) [2]. A sentiment analysis system for text analysis combines natural language processing and machine learning techniques to assign weighted sentiment scores to the entities, topics, themes, and categories within a sentence or phrase [1]. There are also many names and slightly different tasks, e.g., sentiment analysis, opinion mining, opinion extraction, sentiment mining, subjectivity analysis, effect analysis, emotion analysis, review mining, etc. [2].

In this study, we propose a hybrid model using LSTM and CNN model named as Hybrid CNN-LSTM Model to overcome the sentiment analysis problem. First, we use embedding layer to train initial word embeddings. The Word embedding translates the text strings into a vector of numeric values. Afterword embedding is performed in which the proposed model combines set of features that are extracted by convolution and max-pooling layers with long term dependencies. The proposed model also uses dropout technology for accuracy improvement. Our results show that the proposed Hybrid CNN-LSTM Model outperforms traditional deep learning and machine learning techniques in terms of precision, recall, f-measure, and accuracy. We have proposed a system that performs sentiment analysis on IMDB movie review dataset based on into two categories: Positive and Negative.

II. METHODOLOGY

Step 1: Define the Objective
Identify exactly what you want to achieve with the sentiment analysis. For movie reviews, this often involves classifying reviews as positive, negative, or neutral. You might also be interested in more fine-grained analysis, such as different levels of positivity or negativity.

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Step 2: Data Collection and Preparation
- **Dataset:** Obtain a dataset of movie reviews. A popular choice is the IMDb dataset, which is widely used for sentiment analysis and is available on platforms like Kaggle.
- **Preprocessing:**
- **Cleaning Text:** Remove HTML tags, special characters, and numbers. Convert all text to lowercase to maintain consistency.
- **Tokenization:** Convert sentences into words or tokens to simplify analysis.
- **Stopword Removal:** Eliminate common words that may not contribute to sentiment analysis (e.g., "the", "is", "at").
- **Lemmatization/Stemming:** Reduce words to their base or root form.
- **Vectorization:** Since deep learning models work with numerical data, convert text to vectors using techniques such as:
- **Word Embeddings**: Pre-trained models like Word2Vec, GloVe, or fastText provide a dense representation of words and capture semantic meanings.
- **Embedding Layer:** Use an embedding layer in your neural network to learn an embedding for all words in the dataset.

Step 3: Choose a Model Architecture
- **Recurrent Neural Networks (RNN):** Good for sequence data like text.
- **Long Short-Term Memory (LSTM):** Variants of RNNs, better at capturing long-range dependencies and avoiding the vanishing gradient problem.
- **Convolutional Neural Networks (CNN)**: Though traditionally used for image processing, CNNs can be effective for sentence classification tasks.

Step 4: Model Training
- **Split the Data:** Typically, split the data into training (80%) and validation sets (20%).
- **Model Configuration:** Set up the neural network architecture. If using LSTMs or GRUs, configure the number of layers and units per layer.
- **Compile the Model**: Choose an optimizer (like Adam), a loss function (typically binary cross entropy for binary classification or categorical cross entropy for multi-class classification), and evaluation metrics (like accuracy).
- **Training**: Train the model on the training data using batch processing and validate it using the validation set. Use techniques like early stopping and model checkpointing to avoid overfitting.

Step 5: Evaluation
- **Testing:** After training, evaluate the model on a separate test dataset to assess its real-world performance.
- **Metrics:** Use accuracy, precision, recall, F1-score, and perhaps ROC-AUC to evaluate performance.
- **Confusion Matrix:** Helps in understanding the true positives, false positives, true negatives, and false negatives.

III. PROPOSED WORK

A. Baseline System

We propose a baseline model for this system's first load of data. Then next we perform the pre-processing task. After that convert text to vectors using a bag of and transform the vector in TF-IDF vectorization. In this used different classifier algorithm to classify the reviews.

In this figure.1 we have seen how to build a baseline model for sentiment analysis following a few simple steps:

• First is the pre-processing step. the only thing we need to do is remove punctuation, special characters, tokenization and convert everything to lowercase.
• Then comes the vectorization step, which produces numerical features for the classifier. For this, we used a bag of word and TF-IDF, a simple vectorization technique that consists of computing word frequencies and downscaling them for words that are too common.
• Applying this method on the Restaurant Reviews dataset, finally to train a sentiment analysis classifier that uses Multinomial Naïve Bayes.

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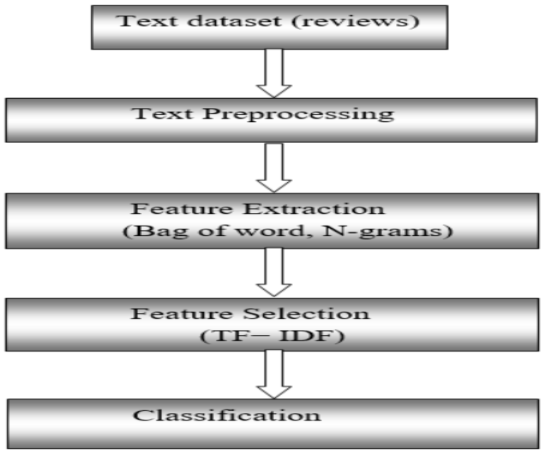

Fig.1 Abstract baseline system approach

Machines cannot understand the text. Machines can work with numbers. Machine learning can only work with numbers. Therefore, we need to convert our text into numbers. In this, we use the bag of word model to convert our text to numbers.

The script above uses CountVectorizer class from the sklearn. feature_extraction. Text library.

Some important parameters are required to be passed to the constructor of the class. The first parameter is the max_features parameter, which is set to 1500. This is because when we convert words to numbers using the bag of words approach; all the unique words in all the documents are converted into features. All the documents can contain tens of thousands of unique words. But the words that have a very low frequency of occurrence is unusually not a good parameter for classifying documents.

Therefore, we set the max_features parameter to 1500, which means that we want to use 1500 most occurring words as features for training our classifier.The fit_transform function of the CountVectorizer class converts text documents into corresponding numeric features.To convert values obtained using the bag of words model into TFIDF values.We have divided our data into 70 training and 30 testing set. We use the Naive Bayes Algorithm to train our model.

To train our machine learning model use Multinomial Naïve Bayes classifier from class the sklearn.naive_bayes library. The fit method of this class is used to train the algorithm. We need to pass the training data and training target sets to this method. Finally, to predict the sentiment for the documents in our test set we can use. The prediction method of the Naïve Bayes Classifier class. To evaluate the performance of a classification model such as the one that we just traine methods and transfer learning approaches are also considered to leverage pre-trained models and enhance the system's predictive capabilities.

Convolution neural network for text classification CNN is a class of deep, feed-forward artificial neural networks. Image Classification and the text analysis method based on CNN can obtain important features of text through pooling [4].

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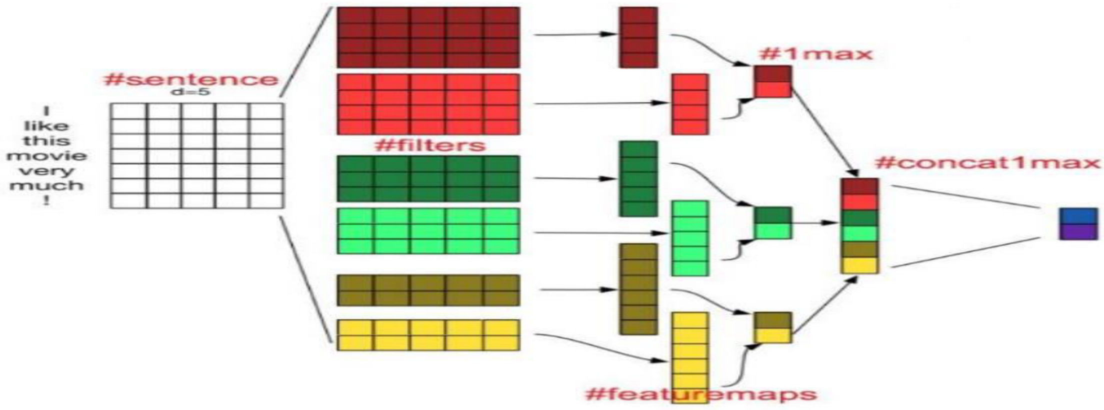

Fig.2 CNN for text classification

In the figures below you can see how such a convolution works. It starts by taking of input features with the size of the filter. With this take the dot product of the multiplied weights of the filter, multiply its values element wise with the original matrix, then sum them up.

The one-dimensional convnet in that certain sequences can be recognized at a different position. This can be helpful for certain patterns in the text classification. to get the full convolution, do this for each element by sliding the filter over the whole matrix [3].

Instead of image pixels, the input to most NLP tasks are sentences or documents represented as a matrix. Each row of the matrix corresponds to one token, typically a word. That is, each row is vector that represents a word. these vectors are word embeddings that index the word into a vocabulary. For a 10-word sentence using a 100-dimensional embedding we would have a 10×100 matrix as our input [4].

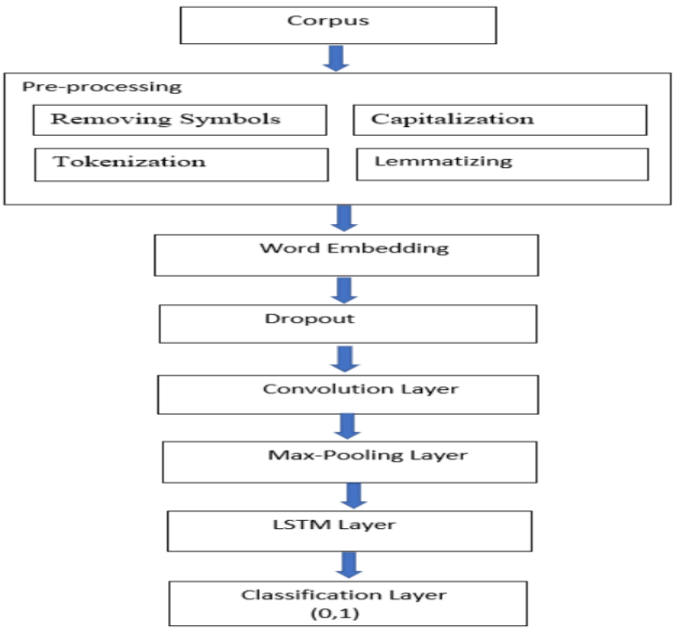

Fig .3 Methodology of Proposed Hybrid CNN-LSTM Model

In NLP we typically use filters that slide over the full rows of the matrix (words). Thus, the width of our filters is usually the same as the width of the input matrix. The height, or region size, may vary, but sliding windows over 2-5 words at a time is typical [3]. Recurrent neural networks can obtain context information but the order of words will lead to bias, the

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text analysis method based on CNN can obtain important features of text through pooling but it is difficult to obtain contextual information.

IV. EXPERIMENTAL RESULT

We conducted several experiments to compare the performance of this model. We can use metrics such as the confusion matrix, F1 measure, and the accuracy. To find these values, we use classification report, confusion matrix, and accuracy score utilities.

Model	**Optimizer**		**Accuracy**
LSTM	RMSprop		87.86%
	Adam		85.14%
LSTM with Dropout	RMSprop	0.2	87.12%
		0.3	87.33%
	Adam	0.2	83.10%
		0.3	86.65%
CNN with LSTM	RMSprop		88.70%
	Adam		88.32%

Table I: Performance of Model

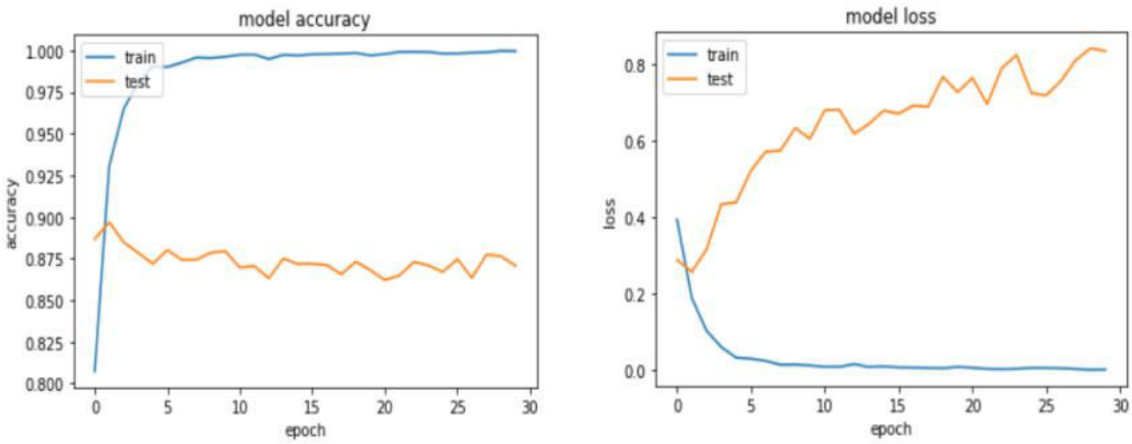

Fig.4 Hybrid model Adam optimizer

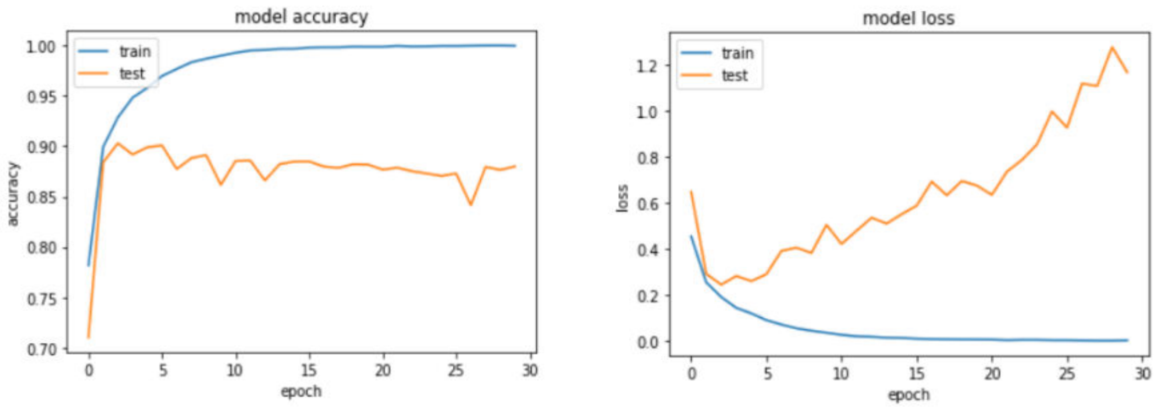

Fig.5 Hybrid model RMSprop optimizer

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We compare the training and test accuracy, see that the testing accuracy for CNN with LSTM model approach which is greater than the testing accuracy of the LSTM.

Analysis of Misclassified Reviews form test data
Here analysis the Misclassified Reviews from test data is a Word ambiguity problem for sentiment analysis.

actual output: 1
predicted output: 0.00012990832

wow this wa a great italian zombie movie by two great director s fulci zombie and bruno mattie hell of the living dead lucio started this movie and wa ill so the great bruno took over and it turned out surprisingly better than i expected it to turn out so if you have seen hell of the living dead directed by bruno mattie and if you saw zombie directed by lucio fulci and liked both or one of theme then this is a movie you must watch it ha great zombie make up witch equal great looking zombie ha a funny zombie flying head and zombie bird that spit acid at you and turn you into a zombie that only to two people but they are mainly just the great toxic zombie like in bruno hell of the living dead so if you like italian zombie movie or just zombie movie s in general than check this one out it a great italian zombie movie

actual output: 1
predicted output: 0.004727751
one of the more sensible comedy to hit the hindi film screen a remake of s malayalam hit boeing boeing which in turn wa a remake of the s hit of the same name garam masala elevates the standard of comedy in hindi cinema akshay kumar ha once again proved his is one of the best super star of hindi cinema who can do comedy he ha combined well with the new hunk john abraham however john still remains in shadow and fails to rise to the occasion the new gal are cute and do complete justice to their role a mustwatch comedy leave your brain away and laugh for hr after all laughter is the best medicine ask priyadarshan and akshay kumar

Here another problem is people express their negative sentiments using positive words or vice versa.

actual output: 0
predicted output: 0.99998474

despite the excellent cast this is an unremarkable film especially from the aviation perspective it may be somewhat better than the egregious von and brown but not by much blue max remains the best of a small market over the last year while darling lilli is fun if not taken seriously it s interesting to speculate what ilm could do with zeppelin and in a new high quality ww i film

actual output: 1
predicted output: 0.00018617511

this is simply the funniest movie i ve seen in a long time the bad acting bad script bad scenery bad costume bad camera work and bad special effect are so stupid that you find yourself reeling with laughter so it s not gonna win an oscar but if you ve got beer and friend round then you can t go wrong

V. CONCLUSION

In this work, we first studied about basic concepts and techniques related to sentiment analysis. We analyzed various datasets and selected one of the datasets for the experiment. Baseline system was implemented with N gram and TF-IDF features with Naïve Bayes classifier. In proposed model combining CNN and LSTM. Due to convolution layer and pooling layer, the CNN makes it easy to automatically extract local features and reduce the computation complexity. and LSTM is learning sequence characteristics. we proposed a Hybrid CNN-LSTM model for sentiment analysis it solve word negation problem. Therefore, our model achieves good performance on sentiment classification.

VI. FUTURE WORK

Considering the result of this work, we believe that the pre-trained embeddings (Word2vec and Glove) method would be applying this model to the task of sentiment analysis with the hope of improving the classification performance. GloVe algorithm is an extension of the word2vec. It is a vector space model representations of words were developed

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using matrix factorization techniques. This is an unsupervised learning algorithm developed by Stanford to generate word embeddings by aggregating the global word-word co-occurrence matrix from a corpus.

In our proposed model Improve by Training on Large Data sets. For future work, it would be used to improve systems by using other variants of RNN Architectures like GRU and Bi-LSTM.

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