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MOVIE REVIEW ANALYSIS USING LSTM AND CNN

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ABSTRACT:

Movie review analysis plays a crucial role in understanding audience sentiments and preferences towards various films. In this study, we propose a novel approach utilizing Long Short-Term Memory (LSTM) and Convolution Neural Networks (CNN) to analyze movie reviews for sentiment classification. By combining the strengths of LSTM in capturing sequential dependencies and CNN in extracting local features, our proposed system aims to achieve accurate and robust sentiment analysis of movie reviews. This project delves into an examination of different learning algorithms through the sentiment analysis of movie reviews. Currently, sharing opinions on films via reviews is a popular method for expressing assessments and criticisms regarding box office performance or audience feedback received.

Sentiment Analysis, which is likewise called opinion mining, is the sphere of having a look at which analyses human beings' reviews as thoughts to understand if the character was “glad”, “unhappy”, “angry” and so on.

Keywords: LSTM, CNN, Movie reviews, Sentiment Analysis.

INTRODUCTION :

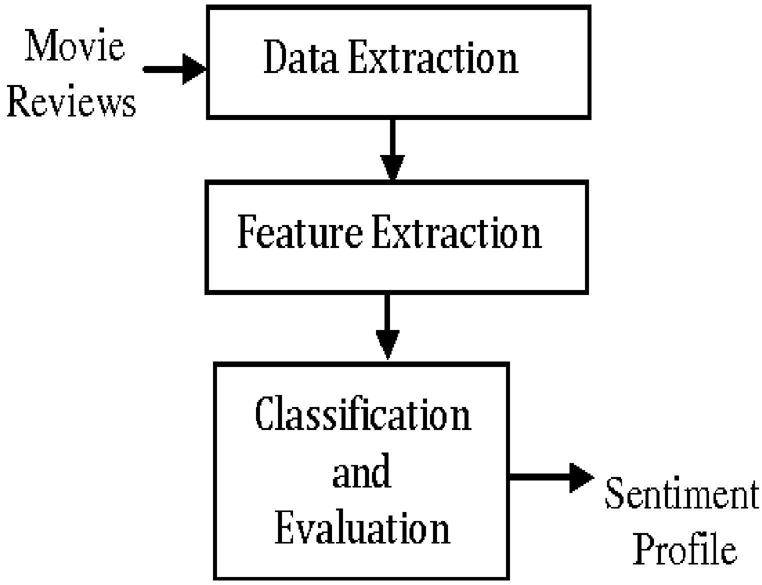
Expressing opinions and posting reviews about places visited or movies are seen has become really popular nowadays. This has influenced to the hunger to automatically derive the sense of this tremendous amount of data. The human interpretation is complex appropriately teaching a machine to study the distinctive grammatical nuances, cultural variations, buzzword and misspellings that turn out in reviews provided by users is a deep process.
The surge in expressing opinions and reviewing places visited or movies watched has led to a massive influx of data. Consequently, there's a growing need to automatically extract meaning from this vast pool of information. Teaching machines to grasp the intricate nuances of human interpretation, including grammatical subtleties, cultural disparities, buzzwords, and even misspellings found in user reviews, is a profound endeavour. However, advancements in machine learning and natural language processing have made it feasible to analyze user reviews and discern their sentiments accurately. These sentiment analysis techniques find utility across various domains, from business to politics.

LITERATURE WORK :

Endsuy utilized Twitter datasets to perform exploratory data analysis on the 2020 US Presidential Election. They conducted a comparative analysis between the sentiment expressed in location-based tweets and the sentiment of on-the-ground public opinion. The study incorporated features such as latitude, longitude, city, country, continent, and state code, obtained using the OpenCage API and sciSpacy Named Entity Recognition (NER). Two datasets from Kaggle, concerning Donald Trump and Joe Biden, both dated November 18, 2020, were employed. For lexicon-based feature extraction, the study employed a valence aware dictionary for sentiment reasoning (VADAR), while logistic regression machine learning approaches were utilized for classification purposes.
Bibietal developed a Cooperative Binary-Clustering Framework for sentiment analysis on Indigenous datasets from Twitter. They employed majority voting to partition the data and integrated single linkage, complete linkage, and average linkage approaches. Utilizing the confusion matrix, they categorized the clusters into positive and negative sentiment categories. For feature selection, the study employed uni-gram, TF-IDF, and word polarity mechanisms. Results of the analysis indicate that the cooperative clustering approach outperforms individual partitioning techniques, achieving a 75% accuracy rate.
Rodrigues et al. devised a pattern-based methodology for extracting aspects and analyzing sentiment. This approach leverages pattern analysis to extract explicit aspect syntactic patterns from product sentiments. It utilizes bigram features extraction and integrates Senti-Wordnet to ascertain the sentiment polarity of sentences. The study found that the multi-node clustering approach surpasses the single-node clustering approach in terms of performance.

Cekik et al. employed a filter-based feature selection technique known as Proportional Rough Feature Selector (PRFS) for feature selection. They evaluated PRFS with multiple classifiers including SVM, Decision Trees (DT), K-Nearest Neighbors (KNN), and Naive Bayes. PRFS utilizes rough set theory to ascertain document classification into specific classes. The study demonstrated an enhancement in classifier performance at a 95% confidence level.

Imran et al. utilized tweets from Twitter along with the sentiment140 dataset. They employed the Long Short-Term Memory (LSTM) model to estimate sentiment polarity and emotion. In a similar vein, for sentiment analysis, Li et al. developed lexicon-integrated CNN family models. They introduced a sentiment padding approach to ensure consistent input data sizes and increase the percentage of sentiment information in each row. This method effectively addresses the gradient vanishing problem during neural network learning between the input layer and the first hidden layer.



METHODOLOGY :

- Data Collection: Gather labelled training data for the deep learning model. This could include images, text documents, sensor data, etc.
- Pre processing: Clean and pre process the data to ensure it's in a suitable format for the deep learning model. This may involve tasks like resizing images, tokenizing text, or normalizing numerical data.
- Model Architecture Design: Choose an appropriate deep learning architecture (CNN, LSTM) based on the nature of the data and the task at hand.
- Model Training: Feed the pre processed data into the deep learning model and train it on a portion of the labelled dataset
- Model Evaluation: Evaluate the trained model's performance on a separate validation dataset to assess its accuracy, precision, recall, etc.
- Features and Opinion Words Extraction: All opinion words are selected from the sentence. The system extracts all nouns, noun phrases, verbs and adjectives from the movie review and compares with the existing list of words. These words are classified on basis of their polarity. For Example “good” word is of positive polarity. For this system API is trained only for movie reviews with keyword and phrases dictionary which includes “good acting”, “solid story” and “awesome action”.

MACHINE LEARNING MODEL :

CNNs are primarily used for processing grid-like data, such as images. They consist of convolution layers, pooling layers, and fully connected layers. Convolution layers apply filters to extract features, while pooling layers reduce spatial dimensions. Fully connected layers perform classification/regression. Workflow: Input images undergo convolution and pooling operations to extract relevant features. The process involves flattening these features, followed by passing them through fully connected layers for tasks involving classification or regression. Convolution Neural Networks (CNNs) undergo training in a manner similar to Feed-forward Neural Networks (FNNs), employing back-propagation and optimization algorithms.

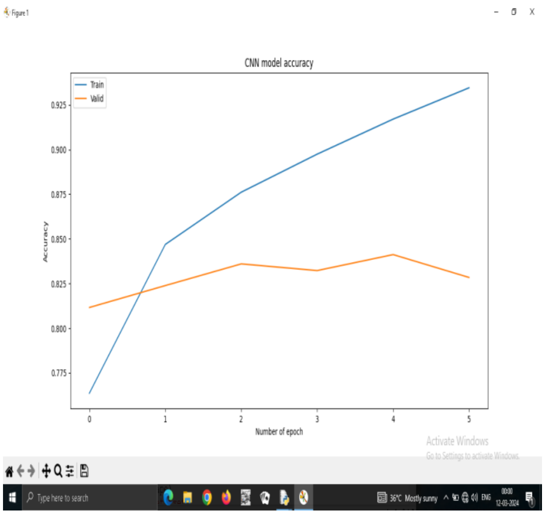
Long Short-Term Memory networks (LSTMs), a subtype of Recurrent Neural Networks (RNNs), are engineered to mitigate the vanishing gradient problem. They integrate specialized memory cells and gating mechanisms, enabling selective retention or omission of information across extensive sequences. Workflow: LSTMs maintain a cell state that can carry information across time steps, allowing them to capture long-term dependencies more effectively than traditional RNNs. They are widely used in tasks requiring memory of past inputs, such as natural language processing and speech recognition.

RESULT AND DISCUSSION :

Deep Learning, a subset of Machine Learning, utilizes algorithms to analyze data and emulate cognitive processes or construct abstractions. In Deep Learning (DL), multiple layers of algorithms are employed to process data, interpret human speech, and recognize objects visually. Data flows through each layer successively, with the output of one layer serving as the input for the next. The initial layer in a network is termed the input layer, while the final one is designated as the output layer. Intermediate layers are commonly known as hidden layers, each typically comprising a uniform algorithm featuring a specific activation function.

The result of such analysis would typically include metrics such as accuracy, precision, recall, and F1 score, which indicate how well the models perform at classifying the sentiment of the reviews. These metrics are calculated on a test dataset that the models haven't seen during training to ensure unbiased evaluation.

1. Accuracy measures the proportion of correctly classified instances, out of all instances considered. It provides a straightforward assessment of a model's overall correctness.
2. Precision: The proportion of true positive instances (correctly classified positive instances) out of all instances classified as positive.
3. Recall: The proportion of true positive instances out of all actual positive instances.
4. The F1 score, on the other hand, represents the harmonic mean of precision and recall. This metric offers a balanced evaluation of a model's performance, considering both how precise its positive predictions are (precision) and how many actual positives it can correctly identify (recall). Hence the result may be seen as the following figure:



The above graph represents the Accuracy model for the CNN algorithm.

CONCLUSION AND FUTURE WORK :

In conclusion, deep learning algorithms have revolutionized the field of artificial intelligence by enabling computers to learn complex patterns and representations directly from raw data. From feed forward neural networks to specialized architectures like convolution neural networks (CNNs) algorithms have demonstrated remarkable capabilities in various domains, including computer vision, natural language processing, and speech recognition.

Future work could focus additional data uploading into the model and implement with high performance.

REFERENCES :

1. M. Govindarajan conducted a study titled "Sentiment Analysis of Movie Reviews using Hybrid Method of Naive Bayes and Genetic Algorithm" published in the International Journal of Advanced Computer Research (ISSN (print): 2249-7277 ISSN 2277-7970), Volume-3 Number-4 Issue-13 in December 2013.
2. Apoorv Agarwal, Boyi Xie, Ilia Vovsha, Owen Rambow, and Rebecca Passonneau contributed to a paper on "Sentiment Analysis of Twitter Data."
3. Apoorv Agarwal and Jasneet Singh Sabharwal presented a paper on "End-to-End Sentiment Analysis of Twitter Data" at the Proceedings of the Workshop on Information Extraction and Entity Analytics on Social Media Data during COLING 2012 in Mumbai, in December 2012.
4. V.K. Singh, R. Piryani, A. Uddin, and P. Waila authored a paper titled "Sentiment analysis of movie reviews: A new feature-based heuristic for aspect-level sentiment classification," presented as a conference paper in March 2013.
5. Alexander Pak and Patrick Paroubek conducted research on "Twitter as a Corpus for Sentiment Analysis and Opinion Mining."
6. Ajinkya Ingle, Anjali Kante, Shriya Samak, and Anita Kumari explored "Sentiment Analysis of Twitter Data Using Hadoop," published in the International Journal of Engineering Research and General Science Volume 3, Issue 6, November-December 2015 (ISSN 2091-2730).