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Children's Sentiment Analysis From Texts by Using Weight Updated Random Forest Classification

Dr D V Nagarjana Devi[1], P Rama Venkata s s Durga[2]

[1]Department of computer science and engineering, RGUKT
Nuzvid,India, *devi.duvvuri@rguktn.ac.in*
[2]Department of computer science and end engineering, RGUKT-RK Valley
Idupulapaya, India, subhashpalisetti@gmail.com

Abstract

The sentiment analysis of children is fundamental to understand the emotional responses in literary narratives, where significant implications are made in terms of educational and therapeutic use. Traditional text classification models, which include Bi-LSTM, Decision Tree, and ensemble models, are often characterized by reduced accuracy that can be explained by low data quality, overfitting, and inadequate optimization of hyperparameters. This paper uses a sentiment-annotated 4,000 short stories dataset. The preprocessing pipeline included the cleansing of the text, the process of breaking down into sentences and the removal of unnecessary symbols to standardize the inputs. An eight-layer LSTM network was used to perform feature extraction followed by dimensionality reduction using PCA and Truncated SVD. Classical machine learning models were trained simultaneously with a transformer-based ELECTRA model using weighted cross-entropy loss to counter class imbalance, including Random Forest and Decision Tree. The accuracy, precision, recall, and F1-score were used to evaluate the performance of the model, with ELECTRA achieving the best scores in each of the measures (93.4%). Flask-based web interface was created to enable interactive user input, prediction and presentation of sentiment results. The explainable AI approaches, LIME and SHAP were used to clarify predictions at the feature level, providing transparency and actionable insights. This approach has a significant improvement in anticipated precision and interpretation as opposed to traditional methods.

Keywords:*Sentiment Analysis, Children's Narratives, Deep Learning, Explainable Artificial Intelligence (XAI), LSTM, Web-based Deployment.*

I. INTRODUCTION

Narrative text reading in young children is important for central cognitive and emotional functions. Reading narratives promotes understanding of complex social and moral environments, empathy, critical thinking and emotional intelligence, helping children to comprehend complex social and moral scenarios. The growth of online reading platforms is offering young people a wide range of textual content, raising the need for digital tools for measuring emotions. Sentiment analysis is a valuable tool for analysing subjective text, allowing us to understand the emotional states and emotions that underline a text. This feature enables applications in learning, psychology and personalisation, to improve the understanding of the impact of narratives on children.

Despite significant advancements in natural language processing and ML, current approaches currently have significant limitations for the analysis of complex storytelling. Existing approaches often rely on hand-crafted features, have difficulty in modelling long-term contextual interdependencies and encounter problems with high-dimensionality data and class imbalance [4], [5]. Additionally, some methods show a reduced level of generalization on different narrative corpora, resulting in inconsistent interpretation of emotions and poor classification performance [6], [7]. The challenge of identifying relevant emotional features from intricate narrative structures, the variety of language usage and the vagueness of semantics are a gap in current sentiment analysis methods [8].

In this study, we seek to provide a robust framework for automatic sentiment analysis in children's stories, addressing these problems. This technique will focus on enriched semantics, reduction of feature redundancy, as well as improved stability in classification, while preserving interpretability [9]. The technique will accurately recognise and pinpoint emotions in stories, considering different types of stories and the nuances of language. The method will effectively prevent overfitting, improve feature selection and provide a reliable sentiment analysis approach that can support a holistic analysis of emotions in narratives.

The anticipated outcomes of this research are significant to education, psychology and society. Sentiment analysis can help to develop new curricula, track child emotional development and implement interventions that support the development of social and empathetic skills. A transparent and scalable method for sentiment analysis can help researchers, teachers and policy makers to understand the effects of narratives and inform decisions to enhance educational environments and child welfare programs.

II. LITERATURE REVIEW

The latest sentiment analysis techniques have combined lexicon-based and DL approaches for an improved understanding of emotions and contextual interpretation of text. Kumar and Uma [11] proposed an advanced lexicon that used neural networks for the classification of sentiment based on contextual information, showing better performance using data from social media. The proposed approach enabled contextual understanding and interpretation, but relied heavily on the lexicons, which limits the domain-specific applications. Mishra et al. [12] have used DL for sentiment analysis and topic modeling of tourism text during the pandemic with promising results in discovering patterns of community sentiment. However, their approach was limited to multidomain or narrative-driven text.

Duong [13] has explored methods to address resource scarcity of low-resource languages and has shown the effectiveness of natural language processing methods even with limited labeled data. Razali [14] has been successful in the understanding of figurative language through the realization of the importance of contextual feature selection and DL for the recognition of metaphorical language. However, these techniques often lack the ability to cope with different language style variations and large feature spaces. Wang and associates. [15] explored the use of adversarial training to enhance neural language models, thus enhancing model generalization and robustness. Despite their advanced text generation and prediction techniques, the approach was not well tailored for improving sentiment detection.

Recurrent structures have been explored to best model the sequences. Wang et al. [16] developed the NEWLSTM, an advanced model of LSTM for sequence prediction with a high level of accuracy for predicting temporal correlations in sequences. Behera et al. [17] proposed Co-LSTM, a combination of convolutional and LSTM layers to perform sentiment analysis on large social data sets, achieving better results on large data sets. Despite these achievements, challenges remain in handling complex narrative data, the balance of feature representation and overfitting in widely diverse data. Geetha et al. [18] improve multimodal emotion recognition by incorporating text, image and audio features, highlighting the benefits of multimodal fusion features, and issues concerning interpretability and complexity.

Ensemble learning and feature reduction have been used to make sentiment classification better. Wall et al. [19] have demonstrated the merits of SVD and PCA for reducing feature redundancy in high-dimensional data. Noroozi et al. [20] explored voice-based emotion recognition using random forests and decision trees, which have been shown to be very effective in detecting audio sentiments, but less successful in text-based cases. The above studies point to the current shortcomings in capturing subtle emotional cues in narrative-rich and prejudiced textual content, enabling cross-domain predictions, and providing interpretable and reliable predictions.

To address these limitations, the current study aims to build a holistic approach to sentiment analysis of narrative text, by improving semantic representation, dimensionality and category consistency. The proposed methodology seeks to enhance the accuracy and interpretability of the predictions by addressing the problems of redundancy, lack of context, and inability to distinguish among emotions in order to establish reliable automated analysis of complex narrative text.

III. METHODOLOGY

The suggested technique aims to classify emotions of children based on a carefully curated collection of 4,000 narratives, each accompanied with sentiment labels, which can be used to identify emotional indicators in the narrative text. The technique involves massive data ingestion, preprocessing and feature extraction to produce high-quality representations, followed by dimensionality reduction using Principal Component Analysis and Truncated Singular Value Decomposition so as to reduce feature redundancy and enhance computational speed. The deep LSTM neural network captures temporal information, while traditional ensemble classifiers, such as RF and DT, carry out sentiment prediction to improve prediction accuracy and robustness. The ELECTRA transformer embeddings are also employed to address semantic contextuality and to better understand text nuances. Additionally, XAI tools, LIME and SHAP, enhance interpretability, both locally and globally, and thus model transparency. The web implementation of Flask is used to provide online inference and display for real-time and interactive sentiment analysis on children's stories so that they are dependable, scalable and interpretable.

Dataset Collection

A. Pre-Processing

The pre-processing framework provides a methodical process of cleansing and standardising narrative text to enable accurate labelling of sentiments, extracting features, and training models, which leads to enhanced classification accuracy and interpretability.

Data Pre-processing:pre-processing of input text involves a systematic approach to cleaning and normalising unprocessed text for improved model accuracy and reliability. Unwanted elements like URLs, emojis, punctuation and unnecessary whitespace are removed to prevent feature distortion. Text normalization is done via tokenization and sentence breakage enabling a consistent input format and improving the ability to learn from sequential data. Appropriate pre-processing ensures that the sentiment analysis that follows is able to detect important semantic and contextual patterns, reduces variability and computational complexity, and so enhances the feature extraction and model interpretability.

Sentiment Annotation:Sentiment annotation labels narrative texts with polarities based on the cumulative sentiment scores computed on a sentence level. The two narratives are analysed for sentiment, producing binary labels that correspond to major sentiment classes. This approach produces a systematic ground truth to train supervised learning models. This approach converts narrative data into quantitative labels of sentiment, ensuring that the data is consistently categorised, enabling standardised evaluation metrics, and allowing for successful training of MLand DL models, thereby improving the quality of predictions and understanding of the prediction outcome.

Exploratory Data Analysis (EDA):To inform feature engineering and model design, exploratory data analysis provides information on the statistical and linguistic properties of the texts. Word clouds and distribution graphs show commonly used words, biases in the emotions and class imbalances. This research implies the naturalness of stories and emotional likes and dislikes. Exploratory data analysis can help to identify relevant features and potential biases, improving the feature representation and guiding the dimensionality reduction techniques as well as simplifying the design of future model in accordance with the data.

Feature Extraction:Converting data to numerical values for modeling is called feature extraction. A method using LSTM is applied to learn temporal features which can help understand the temporal and spatial connections in narratives. This approach maintains the narrative and semantics of the story, which is important for sentiment analysis. The creation of high-dimensional features that store relevant information helps the model learn, generalise and classify faster by increasing sensitivity to subtle changes in emotions.

Dimensionality Reduction:This is the process of reducing high-dimensional representations of features into useful, low-dimensional vectors. The methods used to remove redundancy and reduce computing costs are PCA and truncated SVD. This process enhances the model's ability to adapt to different situations, reduces overfitting and optimises the classifier. The fewer number of features optimises predictive models and improves classification for the prediction of the sentiment category while maintaining interpretability and usefulness by simplifying the selection of informative features and enabling an emphasis on relevant features.

B. Training & Testing:

Training and testing involves the selection of predictive features from the feature set, and the examination of the predictive model using unseen data. The reduced feature sets are trained using the traditional ML algorithms RF and DT, and the performance of the predictive models is evaluated using accuracy, precision, recall and F1-score. This process evaluates the generalizability of the system across different narratives, prevents overfitting, and provides a benchmark to judge how effective the preprocessing, feature extraction and dimensionality reduction algorithms are in capturing the important emotional characteristics of the narrative texts.

C. Algorithms

Random Forest Classifier: RF is a classification learning model that boosts the efficiency and robustness of sentiment analysis. The model cleverly identifies non-linear relationships between the text and sentiments by generating multiple decision trees from randomly selected subsets of features and aggregating the results.This averaging approach reduces variance and overfitting issues of single tree models. The use of a controlled tree depth and sufficient number of estimators improves generalization performance whilst keeping computational cost low. Moreover, Random Forest is robust to noise and irrelevant features, and thus suitable for use with lower-dimensional representations of complex textual inputs.

$$Gini=1-\sum_{i=1}^{C}(P_i)^2 \qquad (1)$$

Decision Tree Classifier:The classification uses a DT, a simple interpretable model to predict emotions. It is based on the recursive division of the feature space into more homogeneous regions based on suitable split criteria, thus enabling the explicit specification of decision boundaries. The tree-like structure of the algorithm permits it to capture basic non-linear relationships with little preprocessing required. The model addresses growth of the tree by controlling the number of samples required for splitting and over-fitting the tree. Decision Trees empower comparative assessment by introducing transparency and speedy inference, thus explaining the role of each feature in the decision of sentiment classification.

$$I(i)=1-\sum_{i=1}^{k}p_i^2 \qquad (2)$$

ELECTRA Transformer Model:The ELECTRA transformer is used to obtain in-depth contextual and semantic understanding of textual stories. This model uses bidirectional attention to capture

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global dependencies, thus increasing sensitivity to contextual clues for sentiment, unlike traditional sequence models. During training, the use of class-balancing, weighted loss and adaptive learning algorithms are applied to address data imbalance and enhance training stability. The training process is affected by the learning rate and early stopping, thereby preventing overfitting. All these approaches enable ELECTRA to achieve improved generalisation, stability and higher prediction accuracy in sentiment classification.

D. Integration of XAI & Flask Framework

The Flask framework module increases the explainability and user-friendliness of the sentiment analysis system in XAI. XAI techniques, like LIME and SHAP, are used to provide explanations of model predictions. These approaches help to pinpoint key words, phrases and features that are important for classification of sentiments, so allowing users to understand how the AI algorithm predicts a story as being happy or sad. XAI improves model trustworthiness and supports decision-making processes, by offering local and global explanations, particularly for teachers and psychologists working with children's stories.

The Flask framework is used to build the system as a web app, enabling real-time predictions and visualizations. The user-friendly system allows users to enter stories, view predicted sentiments and explore reasons. This pairing ensures scalability, cross-device compatibility and the value of the sentiment analysis system in the classroom and the research environment.

IV. EXPERIMENTAL RESULTS

Accuracy: The test precision is the ability of a test to identify correctly patient cases and healthy cases. In order to determine the accuracy of a test, it is necessary to calculate the ratio of true positive and true negative of all the cases that were assessed. This can be mathematically thought in the form of:

Accuracy=(TP+TN)/(TP+FP+TN+FN)(3)

Precision: Precision measures the percentage of cases that are correctly classified out of the number of cases that are determined to be positive. As a result, the precision formula is given as:

Precision=(True Positive)/(True Positive +False Positive)(4)

Recall: In ML, recall is a measure that evaluates the ability of a model to identify all relevant occurrences of a particular class. The proportion of the actual positive observations correctly forecasted to the total number of actual positives, which provide information about the effectiveness of a model in recognizing events of a certain class.

Recall=TP/(TP + FN)(5)

F1-Score: The F1 score is a scale of measuring the precision of a ML model. It combines the precision and recall measures of a model. The accuracy measure is a measure of the number of correct predictions made by a model across the entire collection of examples.

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F1 Score=2*(Recall X Precision)/(Recall+Precision)*100(6)

TABLE I. Performance Evaluation

ML Model	Accuracy	Precision	Recall	F1 Score
Random Forest	0.790	0.797	0.984	0.881
Decision Tree	0.744	0.798	0.905	0.848
ELECTRA	0.934	0.934	0.934	0.934

The performance analysis (Table I) reveals that ELECTRA model outperforms the conventional classifiers, reaching the highest accuracy, precision, recall, and F1-score, thus demonstrating the improved sentiment prediction and excellent generalization to the data.

Figure 1. Comparison Graph

As Figure 1 visually shows, the ELECTRA model performs better than the Random Forest and Decision Tree classifiers in terms of accuracy, precision, recall and F1-score, which prove its effectiveness in sentiment classification.

V. CONCLUSION

The main goal of this approach is to accurately identify and classify young children's emotions through text-based stories to enable reliable emotion understanding in educational and therapeutic environments. The methodology was validated using a standard dataset of 4,000 sentiment labelled short stories. The approach was multi-faceted, involving careful pre-processing of the text, feature extraction with DL using LSTMs, and reduction in the dimensionality of the features using Principal Component Analysis and Truncated Singular Value Decomposition to enhance feature compactness and generalisation. Besides using representations to train a transformer-based ELECTRA classifier using a weighted loss function to cope with class imbalance, traditional machine learning methods such as RF and DT were also trained. The ELECTRA system has improved performance with an accuracy of 93.4% and an increase in the evaluation metrics of accuracy, precision, recall and F1-score. The explanations provided by LIME and SHAP not only improved the system performance but also improved the interpretability of the sentiment forecasts. The system's deployment and use were also enhanced by an interactive sentiment analysis and visualisation via a Flask-based web interface. The developed system can automate sentiment analysis and decision-making in real-world applications by offering a robust, understandable and accurate sentiment analysis system.

This approach could improve sentiment classification further by increasing the multi-class emotion detection and incorporating more emotions in children's stories. The system can be made even more reliable and useful in a range of language settings through the incorporation of cross-domain and multilingual data. Exploring new model frameworks such as dynamic attention and lightweight transformer models could possibly improve efficiency and speed. The system is able to adapt to changing patterns via continuous learning algorithms. Lastly, the system can be deployed through cloud and mobile applications to improve scalability and accessibility and can be used for real-time sentiment analysis in educational and psychological settings.

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