Leveraging AI for Adaptive Narratology in Children's Literature: Enhancing Reader Engagement through Interactive Storytelling

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Abstract: A vital component of children's development is literature. Children's literature is an effective means of promoting kids' societal, emotional, and mental growth. It helps kids to recognize legal and moral quandaries by seeing the lifestyles, encounters, and moral difficulties of others. Outside the traditional position of passive individuals, interaction elements in visual storytelling encourage people to thoroughly engage with the narrative. Engagement and emotions are two important factors that greatly impact a reader's perspective throughout a reading job. One statistical technique that aids in determining and evaluating an individual's emotions through written material is sentiment evaluation. Various instruments and approaches were used to analyze text data employing artificial intelligence methods to identify mixed emotions. Employing the Random Forest (RF) method, a 5-fold cross-validation method was used to distinguish between optimistic and sad emotions. In the end, the grid-search strategy was used to adjust the hyperparameters, and the outcomes were contrasted with those of five standard methods: AdaBoost, XGBoost, Support Vector Machine (SVM), LSTM, and Naïve Bayes (NB). According to the research results, the suggested framework outperformed all five cutting-edge techniques with corresponding margins of 4.64%, 10.80%, 19.45%, 21.1%, and 56.6%, achieving an accuracy percentage of 99.64% on the 4000 stories database. It's noteworthy to note that the suggested approach also produced better outcomes in terms of additional traditional efficiency criteria, including temporal complication, recall, precision, and specificity. All things considered, the suggested framework has enormous possibilities for use in academic settings, child psychology studies, and the monitoring of kid-friendly material, typically aiding in the comprehension of kids' emotions and activities in the electronic sphere.

Keywords: Children's literature, Storytelling, Emotions, Sentiment analysis, and Artificial intelligence.

I. INTRODUCTION

Children benefit from the fresh information and emotional assistance that children's literature provides, which aids in their societal, psychological, and emotional growth [1]. Stories that mostly use graphical elements, such as images, graphics, and photographs, to tell their story are referred to as graphical stories in children's literature. Via engaging components in these graphical stories, readers can take a leading position in the story and move beyond the conventional role of the passive spectator [2, 3]. This paper examines the relationship between reader engagement and graphical storytelling in children's literature, with the primary emphasis on postmodern interaction components. Graphical stories greatly enhance children's literature since they captivate kids and facilitate their comprehension of the story [4].

Reading literature regularly alters people's capacity to think and causes many other alterations in people. This is since people are engrossed in the personalities and lessons presented in stories [5], and when kids start reading, their feelings will vary according to the kind of literature they like. People experience a range of feelings when they read, including joy, grief, abandonment, detachment, and trauma, which results in the development of a connection between the stories that are told in literature and people [6].

Given that literature is thought of as a means of expressing emotions, the web has used semantic assessment (SA) to decipher the feelings that a person has after completing a novel. SA uses machine learning (ML) and deep learning (DL) techniques to identify, extract, and characterize emotions from regular text [7]. To extract useful features particular to a group and apply suitable categorization procedures, several methods were used in SA. Algorithms identify the useful aspects of input text in the feature extraction process to enhance interpretation and system performance [8]. This stage is essential because it converts unprocessed statistics into an additional useful and compact type for simulation and evaluation. Finding and separating important characteristics from the raw data allows us to reduce its difficulty, get rid of interruptions, and find important trends or characteristics that are crucial for sentiment statistics simulation [9].

Hence, this study aims to investigate the adaptive narratology and emotions in children's literature using AI algorithms.

II. Literature Review

A strategy for adaptable aspect-based vocabulary for sentiment categorization was proposed in the paper [10]. The researchers created two methods for creating flexible dictionaries and enhancing categorization accuracy: (1) data, and (2) genetic algorithms (GA) [11]. The flexible vocabulary in this study was modified autonomously and offered more accurate context-based conceptual ratings. Numerous industries, like the stock markets, travel, tourism, and medical treatment, have utilized sentiment analysis [12].

One of the well-liked RNN variations that addresses the disappearing gradients issue, which is a prevalent one in NNs, is LSTM [13]. When analyzing sequential statistics, this improvement enables the algorithm to efficiently acquire and maintain trends over extended durations of time. The number of tiers in an LSTM system is a critical factor in improving the effectiveness of serial data evaluation, according to research findings [14]. In a constrained setting, a network's capacity to identify complicated trends and descriptions from the data rises with the number of tiers it contains. Deep LSTM (DLSTM) can reflect stronger links and may perform better in complicated operations because it can interpret patterns and associations in the information [15].

III. Materials and Methods

A. Data Collection

This research uses a collection of 5,000 kids' stories to do the sentimental evaluation. The collection of 5000 brief stories was divided into groups according to their semantic architecture and emotional depth. This real-time database was created for the study on sentiment evaluation. The database consists of the following areas: tale URL, valence, stimulation, authority, width, etc., feature vector properties. Every text is categorized as a 300-dimensional vector in a semantic structure that was developed using the doc2vec method. The database was produced by a researcher as a component of an investigation on the effects of storytelling fiction on psychological wellness.

B. Text Pre-Processing

To improve the standard of the input text, several pre-processing techniques were first used after loading the pre-existing collection of kids' stories. Before extracting features, the initial stage involves processing the non-standardized features and missing data with the appropriate scaling measurements. The Word embedded technique was used to find semantic connections between terms in a vector area to do. In this case, this study used the assumption that terms with comparable meanings usually have similar embedded data. In this case, the correct substitute for the missing term was identified using a cosine analogy metric. Additionally, among the most widely used NLP collections, which contains packs to assist systems in understanding human language and responding to clients correctly, was used to preprocess the database to eliminate disturbance and get it ready for categorization. In this rule-based sentiment tester, words are typically classified as either good or bad depending on their semantic direction. According to this research, a happy narrative is one with a polarity value higher than 0.5; a bad (sad story) is one with a polarity value far below 0.5.

C. Feature Extraction

An important phase in AI-based study is extracting features. To produce a representative, condensed collection of the material, language, and textual components are extracted from a particular collection. Various groups have been allocated to various language "features" in a text based on how important those pieces are to the material of the text. A measure vector is one feature that transforms text input into a set of token values. It is a language development feature that lists the frequency value of instances of a term for every file in the collection, displayed as a row, and every term in the file is indicated by a column. The product of the number of documents in the matrices or thesaurus determines its overall dimension. One often utilized aspect in text evaluation is Term Frequency-Inverse-File Frequency, or TF-IFF. It demonstrates the significance of a term to a file inside an archive or group. To accommodate often appearing terms by assigning them fewer scores compared to uncommon phrases, the TF-IFF score rises with the number of occurrences a word occurs in the file and is lowered by the number of files in the collection that comprise the term.

D. Hyperparameter Adjustment

One of the most important steps in successfully deploying the LSTM framework for categorization is hyperparameter adjustments. Bayesian optimization is a highly useful instrument among the many approaches for this problem. By taking into account an established goal operation, Bayesian optimization intelligently selects the best combo while traversing the hyperparameter domain with efficiency. By striking the right equilibrium between search and extraction, this approach may quickly identify viable regions with strong efficiency measurements without consuming a lot of processing power.

E. Dimension Reduction

PCA and bio-orthogonalization SVD (Solitary Value Distortion) techniques can be used to minimize the size of the retrieved characteristics. To improve PCA and SVD for feature size minimization, the features extracted from the Deep LSTM framework are provided as a single linear collection of characteristics. While some sizes collect trends or meaningful linkages in the information, others comprise noisy and useless data. PCA helps manage these issues by reducing the input data to just a few primary elements and detecting the most important sizes. The ML method receives the primary elements that are produced. Reducing distortion and understanding unimportant data are two further advantages of utilizing PCA in SA, which significantly increases accuracy. Using the SVD approach, the linear collection of features was once more decreased to low-dimensional features. Classification takes place after the selection of linear characteristics. In the RF method, the majority of categories from each DT are categorized. Any DT that made inaccurate predictions had their factor weights rise and were put into the subsequent DT. Each feature's weights allocated by the LSTM tiers were modified to reflect the feature category of the RF algorithm tree data. Thus, the LSTM NN is used to achieve the variable adjustment. Using a novel collection of categorized linear characteristics, SVD enhances the system's performance and raises the precision of sentiment forecasts. Comparative evaluation and measures are used to evaluate the algorithm's efficiency.

F. Implementation of AI Algorithms

Adaboost is an ensemble-based ML algorithm that creates a robust algorithm by combining several inadequate models. Adaboost's weakened algorithms are single-split DTs, often known as decision stumps. Every statistic in the training collection is given a mass by Adaboost, which then modifies the scales at the end of every repetition to give incorrectly categorized values greater value so that the next repetition can concentrate on them.

In the realm of adaptive ML, XGBoost has emerged as a leading method. One kind of DT method with boosted gradients is called XGBoost. Its rapid operation pace, system efficiency, and storage capacity make it superior to alternative gradient-boosting devices. This method is a composite method that corrects faults triggered by current algorithms by adding novel types. Throughout the training, XGBoost uses all of the CPUs to build trees due to simultaneous processing. It greatly increases the computing efficiency and rapidity of XGBoost by using the "maximum level" variable in place of the conventional halting criterion and beginning to cut trees from the reverse path. Learning percentage, number of trees, maximal tree extent, and type weighting are among the adjusted hyperparameters.

Support vector machines (SVMs) convert data into a more easily separated format by using kernel techniques. Sequence Minimum Optimization (SMO), the kernel in the instance, builds polynomials by multiplying characteristics and giving the goods modifiable values. Support vectors are the data examples that are nearest to the hyperplanes; novel events are categorized according to how far away they are from the hyperplanes. In this study, the radial foundation kernel is used to generate the SVM-RBF, which is used to estimate the results of non-linear statistics using SVM by translating the input characteristics into a higher-dimensional characteristic space. Another supervised ML method for regression and classification problems is the SVM. This approach is flexible in terms of employing various kernel operations (decision procedures) and is very effective in statistics with a higher-dimensional characteristic area.

A DL method is used in this investigation to forecast the yoga poses. A reliance that spans arbitrarily extended periods is learned by the LSTM. An LSTM solves the reducing gradients issue by replacing a traditional neuron with a challenging LSTM unit architecture. The LSTM block expands when connected points are used.

G. Performance Assessment

To assess every AI method's precision, recall, accuracy, and F-value, a performance assessment was conducted. Every variable was calculated using the following equations (1-4).

$$Accuracy = \frac{TN + TP}{FN + FP + TN + TP} \tag{1}$$

$$Recall = \frac{TP}{FN + TP} \tag{2}$$

$$F - value = \frac{2 \times Precision \times recall}{Recall + Precision} \tag{3}$$

$$Precision = \frac{TP}{FP + TP} \tag{4}$$

Accuracy is the percentage of instances that the classification algorithm correctly classifies.

Numerous statistical metrics, such as F-score, recall, and precision, were introduced to assess the efficacy of different AI techniques. When the implemented ML paradigm requires to be tested employing actual and expected outcomes, precision is a trustworthy metric. It establishes the percentage of expected assertions that happen. As a result, it depends on the FP and TP values. The proportion of correctly classified affirmatives is measured by the recall, an essential evaluation statistic that is crucial for figuring out how many positives may be fairly anticipated. Recall is assessed using FP and TP measures. A classification outcome, recall, and precision are monitored by the F-score.

IV. Results and Discussion

The performance assessment of the suggested emotion categorization in the sentiment evaluation for many measures is demonstrated in the next part, which also explains the comparison assessment part. Employing a 5-fold cross-validation method, the initial database was divided into five equal-sized categories to verify the research configuration described aforementioned. The validation collection and mean accuracy values have been released after the framework was trained and assessed five times, every attempt employing a distinct fold. By fusing ML and mathematical methodologies, SVD and PCA with RF algorithms offer a practical approach for sentiment assessment by streamlining the data and producing precise predictions. Additionally, the relevance of the features extracted was demonstrated using a chi-squared examination, and the top 10 characteristics were displayed in decreasing sequence of value (Fig.1). RF algorithms were used to classify the chosen characteristics, and the documented categorization accuracy was 99.2%.

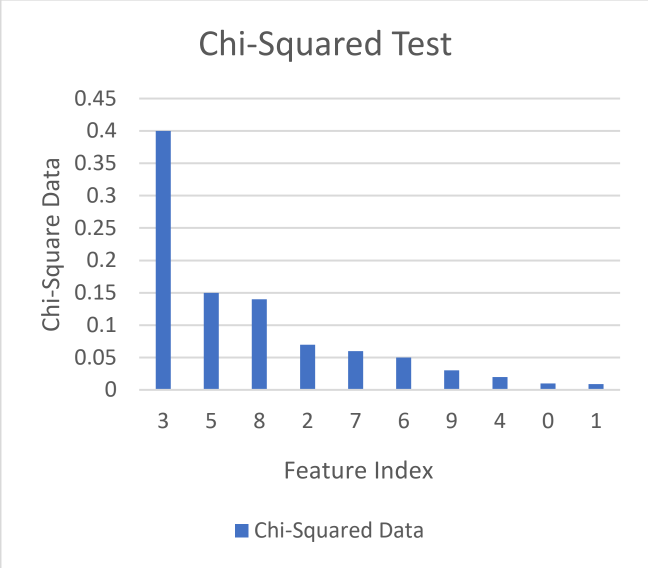

Fig.1. Chi-Squared Test

There are several hyperparameters in the RF technique that may be changed to find the greatest efficiency. The number of branches in the forest is determined by the n_calculators measure; large numbers may result in better efficiency, but they can additionally raise the computational complexity. Each tree's maximum length is determined by the max_depth factor; deep trees are known to detect intricate trends and have the drawback of overfitting. This study changed the max_depth variable to 10 to reduce overfitting. Finding the ideal equilibrium, however, is crucial for min_samples_division, which establishes the bare minimum of specimens required for splitting a node's inside. A threshold that has been established too low could lead to overfitting, while a value that is placed too high could cause underfitting. In this case, this study set the basic value of the parameter to 5.

The five benchmark categorization methods, NB, XG-Boost, SVM, LSTM, and AdaBoost, were outperformed by the stated mean categorization accuracy of 99.2 percent. This study combined benchmark categorization algorithms with two distinct characteristic categories to expand the focus of the planned study. The sentiment characteristic, which is the initial kind of characteristic, combines the emotion, power, and pole from a thesaurus, if one is accessible. The National Taiwan Institute Sentiment Dictionary (NTISD) and the Dalian Institute of Innovation Sentiment Dictionary (DIISD) are the vocabularies employed in the assignment. Unprocessed, fragmented terms are also employed as the 2nd type of characteristic because these dictionaries have the drawback of not including every sentiment term. A standard bag-of-terms format is used for extracting features. A set of terms and keywords with sentiment ratings allocated for sentiment evaluation is one of the many characteristics provided by the initial dictionary. Conversely, a feeling dictionary depending on the lexicon (terms) created by the NTI scientists is referred to in the subsequent section. It represents a collection of terms with sentiment spectrum values that fall into one of three categories: unbiased, unfavorable, or favorable. Due to the binary nature of the classification issue, this study disregarded neutral characteristics in the study.

Table II and Fig.2. provides a thorough comparison of the suggested classification approach with the most advanced techniques. As could be shown, the suggested method (DLSTM characteristic + RF) outperformed other competing methods with an optimal categorization accuracy of 99.2%. It's important to note that, when contrasted to the original LSTM technique (without any modification), the driven hybridization technique greatly improves the classification efficiency (4.7%). It demonstrated RF and DLSTM characteristics of remarkable coherence as well as their capacity to distinguish intricate textual trends. Furthermore, the worldwide outcomes suggest abandoning AdaBoost in text categorization since it was discovered that this approach occasionally overfits throughout training. In a similar vein, the suggested method classified "Happy" and "Sad" moods with good precision and recall values (0.99). It shows that, out of all the data provided, our approach accurately detected FN and FP cases. Additionally, it results in a high F1-value that demonstrates an equitable compromise between both favorable and adverse classifications, offering a more thorough evaluation of its performance in problems involving unbalanced categorization. The confusion matrix in Table II makes it simple to calculate these metrics. Four of the six algorithms (LSTM+RF, NB, SVM, and AdaBoost) achieved favorable Cappa scores in various assessments, whereas the other two calculated unfavorable scores.

TABLE I: PERFORMANCE EVALUATION OF VARIOUS ALGORITHMS

Accuracy						
S.No	**NB**	**XGBoost**	**SVM**	**LSTM**	**AdaBoost**	**LSTM+RF**
NTISD	87.4	91.4	90.1	93.2	84.7	-
DIISD	80.9	87.2	92.6	91.4	78.6	-
DLSTM Features	81.8	83.1	89.7	94.9	63.4	99.2
Precision						
S.No	**NB**	**XGBoost**	**SVM**	**LSTM**	**AdaBoost**	**LSTM+RF**
NTISD	0.60	0.63	0.59	0.74	0.70	-
DIISD	0.65	0.87	0.53	0.65	0.56	-
DLSTM Features	0.73	0.67	0.69	0.79	0.59	0.99
Recall						
S.No	**NB**	**XGBoost**	**SVM**	**LSTM**	**AdaBoost**	**LSTM+RF**
NTISD	0.43	0.59	0.65	0.61	0.55	-
DIISD	0.59	0.75	0.53	0.63	0.63	-
DLSTM Features	0.83	0.69	0.73	0.63	0.67	0.99
F1-Value						
S.No	**NB**	**XGBoost**	**SVM**	**LSTM**	**AdaBoost**	**LSTM+RF**
NTISD	0.50	0.61	0.61	0.66	0.61	-
DIISD	0.61	0.80	0.53	0.63	0.59	-

DLSTM Features	0.78	0.68	0.70	0.70	0.63	0.99
Implementation Duration						
S.No	**NB**	**XGBoost**	**SVM**	**LSTM**	**AdaBoost**	**LSTM+RF**
NTISD	34.3	20.6	32.5	72.2	22.9	-
DIISD	44.2	22.9	18.9	48.7	36.4	-
DLSTM Features	38.9	28.6	16.4	51.7	36.3	103

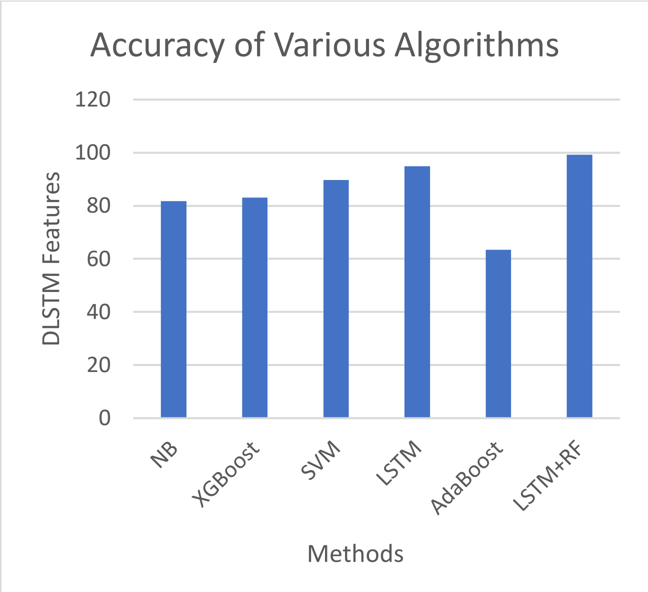

Fig.2. Accuracy of Various Algorithms

TABLE III OUTCOMES OF PROPOSED CLASSIFICATION METHOD

Predicted Label			
P	**N**		
985	6	**P**	**True Label**
3	6	**N**	

In this case, the suggested categorization algorithm's significant cappa value (0.83) suggested a high degree of concordance between class tags. The suggested technique's extremely long implementation duration (103 secs) in the most recent comparison is another significant drawback of the technique. SVM finished the contest in this instance, computing stable outcomes in 17 secs. The lengthy hyperparameter adjustment process in the RF algorithms and the DLSTM algorithm (8 hidden layers) employed for extracting features are the main causes of this constraint. This restriction can be overcome in the future by combining novel techniques like system evaluation, batch analysis, TL, and GPU speed.

Even though the 4000 kids' story database is a useful resource for emotional evaluation, certain procedures may limit the framework's potential. The database's emphasis on kids' literature may be biased and lead to a greater reliance on a single emotional representation and language kind, which may restrict the system's applicability to other age categories and areas. Furthermore, the majority of the semantics in children's stories are emotional, which presents another difficulty for sentiment evaluation methods [16,17]. It becomes considerably more complex when these difficulties are combined with the reality that sentiment evaluation programs struggle to accurately capture nuances and figures of words. Particular consideration must be given to database diversity and system adaptability to address the issues raised [18,19]. Preprocessing is yet another important factor. Each of these factors influences how the sentiment evaluation approach is applied and how successful it is.

V. CONCLUSION AND FUTURE STUDIES

Children's literature that uses graphical storytelling that combines contemporary and traditional elements enhances reader perception and engagement. While the combination of creative images and graphical cues allows for the construction of individual significance, interactive features promote active participation. Young learners' focus is vitally captured by graphical stories, which foster their vision and creativity and enable them to effectively construct significance while reading. A key technique for gaining insight is sentiment categorization, which evaluates the viewpoints, thoughts, and feelings gleaned from speech, text, and large data using a variety of techniques. Large database extracting features is laborious and may include human prejudices, which might influence feature integrity and ultimately the categorical operation. Greater misclassification could come from the extraction of unnecessary and redundant traits. As a result, the study proposed an effective sentiment evaluation framework that combines an improved Adjusted RF classification system with Deep LSTM extracting features. The categorization of exact results from pen-ultimate system tiers is aided by the extraction of important characteristics acquired by numerous LSTM tiers for learning the primary traits.

The mass-modified hyperparameter RF model can accurately categorize emotional characteristics since it trains intricate multi-variate operations in each phase to choose pertinent pathways. With the inner system results, the performance evaluation of the suggested paradigm explains an outstanding 0.99 accuracy, recall, precision, and F1-value. Additionally, a comparison of the suggested approach with alternative algorithms reveals that the system is efficient, producing better results with 99.20 percent accuracy. In light of ongoing complications and the growing volume of big data, duration and dependability appear to be important factors, particularly in other vital structures that demand quick reactions. To handle a greater range of linguistic elements and intricacies in further research, the current investigation can be expanded by combining data from several resources, including social media articles, product evaluations, and client input. Furthermore, in the future, SA may be included in a variety of uses, including chatbots, tailored advertising, and suggestion systems. Additionally, when evaluating sentiment assessment, scientists may investigate ensemble approaches and data augmentation to lower the misclassification percentage. By altering a few of the numerous versions of the train collection to have more syntax and others to possess more emotional expressiveness, the data variation enhances the collection. Nonetheless, ensemble approaches make use of a variety of techniques by integrating the predictions of numerous models that have been developed on various data groups or by employing several methods. Such system diversity improves forecast consistency and accuracy. By integrating the methods into the sentiment evaluation pipeline, the algorithm's generalization and resilience may be enhanced, resulting in more accurate predictions throughout assessment and a certain amount of misclassification. For managing languages besides English, the suggested method may additionally be improved. The performance of the suggested approach can also be increased in the future by using improved methods like multi-semantic feature extraction and merging technologies.

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