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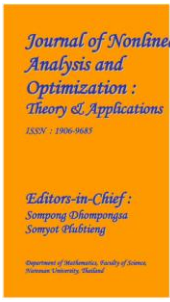

A SMART STORY TELLING MODEL WITH EMOTION-BASED ENUNCIATION

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ABSTRACT:
The tradition of storytelling, which spans through generations, has undergone significant transformation in the digital age with the emergence of interactive media and artificial intelligence. Emotion-driven narrative has emerged as a focal point, captivating attention for its capacity to enrich user engagement and immersion. This manuscript offers an extensive examination of methodologies and practical implementations in emotion-driven storytelling. Initially, we delve into the conceptual underpinnings of emotional narrative, drawing upon insights from disciplines such as psychology, narrative theory, and affective computing. Following this, we survey diverse computational strategies employed for the detection and generation of emotional content in narratives, encompassing techniques like sentiment analysis, affective computing frameworks, and natural language processing algorithms. Additionally, we explore the incorporation of emotional elements into various storytelling platforms such as virtual reality environments, video games, and interactive narrative frameworks. Conclusively, we present instances and utilities of emotion-driven storytelling across a spectrum of domains, encompassing education, entertainment, and therapeutic interventions. Our objective in this discourse is to furnish a nuanced understanding of the current landscape, hurdles, and prospective trajectories in emotion-driven storytelling research and implementation.

INTRODUCTION:

In A sophisticated storytelling model harnesses deep learning methodologies to craft narratives that dynamically adapt to individuals' emotional and behavioural cues. Through predictive analysis, this technology anticipates forthcoming emotional reactions, thereby tailoring storytelling experiences to maintain users' engagement along a dynamic trajectory of interactions.

Incorporating voice delivery systems, deep learning algorithms, and facial expression observation via cameras, the system captures pertinent data. Subsequently, this data undergoes meticulous processing, empowering the system to formulate assumptions or prognostications regarding users' emotional states. With versatile applications spanning learning, entertainment, and therapeutic domains, the software draws upon historical and real-time data to influence both narrative progression and users' emotional responses.

Employing Python programming language alongside deep learning methodologies, our research endeavours to investigate the efficacy of these emotionally enriched narratives in enhancing children's communication, attention, and overall learning experiences.

The introduction of interactivity into storytelling complicates the incorporation of interactivity into storytelling presents complexities not only at a philosophical level but also in terms of architecture and structure. In most narrative forms, authors traditionally maintain complete control over the story's structure, including its storyline or arc. This control remains consistent across various storytelling traditions, even within bardic practices where the audience occasionally influenced the tale's direction. Nonetheless, the bard retained authority over the overarching storyline, making localized adjustments without compromising the narrative's coherence. Without such meticulous control, the narrative's arc risks disruption, thereby diminishing its effectiveness.

One of the primary challenges for Interactive Storytelling (IS) systems lies in meaningful user interaction. This necessitates not only functional interfaces but also interactions that significantly impact the narrative. Research underscores that interaction should not be overly restricted by the system, as such limitations can diminish user agency and immersion in the story world. Conversely, providing users with complete autonomy complicates story generation, as every potential interaction must be accounted for by the author and IS system. Effective IS systems strive to strike a balance between these conflicting demands.

Interactive storytelling has traditionally addressed users' emotional experiences implicitly, incorporating emotional elements into story development. Typically, IS systems divide stories into smaller segments, which are dynamically assembled based on user interactions. These segments offer various narrative possibilities, with the story's progression determined by predefined logic and user interactions. However, this approach places a considerable burden on the author, who must ensure that every potential storyline elicits the intended emotional journey for users. Implicitly, authors incorporate users' emotional experiences into story creation, managing user reactions to the narrative implicitly.

We propose extending Interactive Storytelling to explicitly structure users' emotional experiences at runtime. Specifically, we suggest that IS systems should parameterize user emotions and utilize this data to dynamically construct the story. It's essential to acknowledge that this parameterization remains within the scope of the user model mentioned by Szilas. Emotional reactions vary widely based on individual, cultural, and situational factors, implying that the parameterization reflects the author's idealized expectation of the user's emotional response. By continuously considering users' emotional experiences, the story engine can intelligently select story segments to maintain narrative coherence and manage the audience's emotional journey.

Emotion research, primarily within psychology, has produced numerous theories and classifications. While the classification of emotions remains debatable, the field of emotion recognition in computers is gaining traction. This research aims to enable computers to recognize users' emotional states through various methods. Although consensus regarding which emotions to categorize or identify remains elusive, parameters such as attention or interest also hold relevance for creating engaging stories.

LITERATURE SURVEY:

In the dynamic landscape of narrative technologies, recent studies have focused on enriching storytelling encounters through the amalgamation of emotion recognition and interactive features. A significant contribution in this domain is exemplified by the paper titled "Smart Storytelling Model with Emotion-Based Enunciation and an Interactive Query Resolver," penned by Arushi Bohra, Laksh Sethi, Karthik Nag, and Preet Kanwal in the year 2022.

Bohra and colleagues introduce an inclusive approach to smart storytelling, amalgamating emotion-based enunciation and an interactive query resolver. Their methodology integrates techniques of emotion and text recognition, harnessing computational modelling to facilitate a dynamic storytelling milieu.

In conclusion, this literature survey provides a comprehensive overview of existing research on various water quality assessment methods using based on the enunciation laying the groundwork for the current study. Moving forward, these insights will guide the implementation and analysis of our project.

METHODOLOGY:

The methodology outlined in the paper involves several key components:

Emotion Recognition: The study delves into the domain of emotion recognition, employing sophisticated techniques to discern audience emotional states. By scrutinizing facial expressions and other physiological indicators, the system adjusts storytelling narratives to align with user emotions.
Text Recognition: In tandem with emotion recognition, the manuscript underscores the significance of text recognition in smart storytelling. By parsing textual inputs and grasping semantic content, the system crafts narratives that are emotionally resonant and contextually pertinent to user inquiries and interactions.
Design Methodology: Bohra et al. adopt a design methodology emphasizing user engagement and interaction. Through iterative design iterations and user input, they endeavor to fashion a storytelling model that is intuitive, immersive, and seamlessly integrated into the user experience.

Computational Modeling: Central to the proposed approach is the utilization of computational modeling techniques. Leveraging machine learning algorithms and artificial intelligence, the system dynamically tailors storytelling output based on real-time data inputs, thereby crafting a personalized and captivating narrative experience for users.
Contribution and Implications: The paper significantly contributes to the smart storytelling domain by proffering a comprehensive approach integrating emotion recognition, text comprehension, and interactive facets. Through this amalgamation, the authors illustrate the potential for engendering immersive storytelling experiences resonating with users on a profound emotional level.
Moreover, the methodology outlined holds broad implications across diverse domains, encompassing entertainment, education, and therapy. By customizing narratives to individual emotional states and preferences, smart storytelling models stand poised to augment learning outcomes, nurture emotional well-being, and introduce innovative entertainment modalities.
DATASET:
The Datasets currently used for the task of emotion recognition. Samples were extracted directly from the dataset, except for (f), which was extracted from their arXiv manuscript with a CC-BY-SA license since the download link for the dataset is currently offline. Although some datasets explicitly show faces, such as (a,c), others, such as (b,d) have samples with severe occlusion, given their focus on other nonverbal cues.
The Acted Facial Expressions in the Wild (AfeW) dataset was proposed to tackle the limitation imposed by the lack of data from real-world scenarios. At the time of publication, datasets for this task were mainly composed of images recorded in laboratory scenarios with posed expressions. The authors argue that, ideally a dataset for this task would be recorded with spontaneous expressions and in real-world environments, which continues to be difficult today. Therefore, they propose using scenes extracted from movies, that contain environments close to the real world. We show samples of this dataset in Figure
The FER2013 dataset stands as a pivotal resource in the realm of facial expression recognition, offering a rich repository of facial images annotated with corresponding emotion labels. With its wide adoption and extensive use in research and industry, understanding the intricacies of this dataset is essential for advancing the field of computer vision and emotion analysis.
Originating from the Facial Expression Recognition 2013 Challenge (FER2013), this dataset comprises over 35,000 grayscale images of faces, each measuring 48x48 pixels. These images encompass a diverse array of expressions, including happiness, sadness, anger, surprise, fear, disgust, and neutrality. The dataset's annotations categorize each image into one of these seven emotion classes, providing a valuable resource for training and evaluating facial expression recognition models.
The FER2013 dataset is divided into three subsets: training, validation, and testing. The training set consists of approximately 28,000 images, the validation set contains around 3,500 images, and the testing

set includes roughly 3,500 images as well. This distribution ensures that models can be trained, validated, and tested on distinct subsets of data, facilitating robust evaluation and benchmarking of performance.

MODELS USED/ALGORITHMS:

Emotional Analysis Module: Employing advanced deep learning methodologies, particularly Convolutional Neural Networks (CNN), our system delves into the realm of emotion detection. It scrutinizes facial cues with precision, discerning a spectrum of seven distinct emotional states: Anger, Disgust, Fear, Joy, Sorrow, Surprise, and Equanimity. Through this module, our project pioneers an innovative approach to narrative delivery, integrating nuanced emotional nuances for a richer storytelling experience.

Narrative Display Module: The Depicts the storyline on the display screen according to the emotional cues identified in children. Harnessing the capabilities of Python libraries, our system vocalizes the narrative, enhancing engagement and immersion for the audience. Through this innovative mechanism, our project aims to personalize storytelling experiences, catering to the emotional needs of its young audience while fostering a deeper connection with the narrative content.

Voice Delivery : Within our system, we leverage Python libraries to orchestrate the delivery of voices, thereby crafting a holistic solution that seamlessly integrates emotion detection and storytelling capabilities. This multifaceted approach not only enhances the overall user experience but also underscores the versatility and efficacy of our model in catering to the nuances of emotional expression within narratives.

CV2: An Utilizing the functionalities offered by the computer vision library, CV2, our endeavor titled "Enhanced Emotional Storytelling Model" seeks to redefine the way narratives are delivered. Through adept utilization of CV2, we augment the emotional facets inherent in storytelling, thereby facilitating a more engaging and immersive encounter for the audience. This amalgamation of technology and narrative artistry not only reflects our unwavering pursuit of innovation but also epitomizes our steadfast dedication to sculpting narratives that evoke profound emotional resonance.

Keras: The Utilizing the Keras framework within our project titled "An Emotion-Driven Narrative Enunciation System," we endeavor to pioneer a novel approach to storytelling. By harnessing the capabilities of Keras, our model is designed to imbue narratives with a heightened emotional resonance. This integration underscores our commitment to advancing the field of narrative technology, aiming to create immersive storytelling experiences that resonate deeply with audiences.

***Tensor Flow**:* The Employing the TensorFlow infrastructure in our endeavor, "A Storytelling Model Enhanced with Emotion-Based Enunciation," we aspire to present an innovative narrative technique. Through the utilization of TensorFlow's functionalities, our model is meticulously crafted to enhance stories with intricate emotional nuances. This amalgamation emphasizes our dedication to propelling the narrative technology landscape forward, with a specific emphasis on crafting immersive storytelling encounters that deeply engage audiences.

Sentiment	# Sentences Train/Val/Test	Emotion	# Sentences Train/Val/Test	Classes Used in Reference [35]
positive	5985/807/826	happiness	2391/310/328	excited/joyful/grateful/content
		confidence	1705/237/222	confident/prepared/hopeful
		other positive	1889/260/276	proud/trusting/caring/faithful
negative	8314/1133/1080	sadness	2267/322/289	sad/lonely/disappointed/devastated
		anger	1804/243/226	angry/annoyed/furious
		fear	1565/212/207	afraid/terrified/apprehensive
		guilt	1576/215/199	embarrassed/ashamed/guilty
		other negative	1102/141/159	jealous/disgusted
neutral	7149/970/953	neutral	1787/242/238	no emotion
total	21,448/2910/2859	**total**	16,086/2182/2144	

GTTS: Implementing the GTTS (Google Text-to-Speech) tool within our project, "Emotion-Enriched Narrative Delivery System," we aim to introduce an innovative narrative methodology. By leveraging the capabilities of GTTS, our model is meticulously designed to infuse stories with a spectrum of emotions. This integration underscores our commitment to advancing the narrative technology landscape, with a focus on creating immersive storytelling experiences that resonate deeply with audiences.

Gray Scalling:

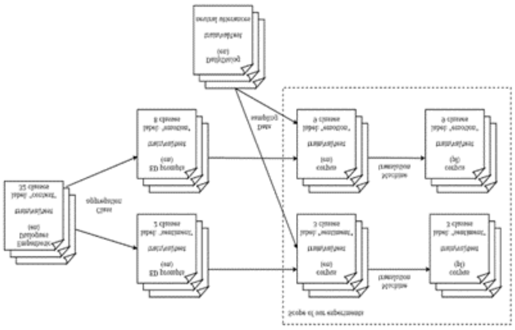
Employing gray scaling techniques within our project, "Enhancing Storytelling with Emotion-Driven Enunciation," we endeavor to introduce a novel narrative strategy. By implementing gray scaling, our model is intricately engineered to integrate emotional cues into storytelling. This incorporation underscores our dedication to advancing narrative technology, with a particular focus on crafting immersive storytelling experiences that deeply engage audiences.

RESULT:

Experiments

The corpus created as a combination of Empathetic Dialogues and Daily Dialog utterances contained 32 classes of emotions plus the neutral class. This number seemed unnecessarily high considering the context of a therapeutic chatbot. For the purpose of developing emotion classification models, we introduced new levels of class aggregation. First, we excluded some of the original emotion labels (anxious, surprised, impressed, nostalgic, sentimental, anticipating), which proved to be difficult to assign, as the utterances represented a given emotion both in positive and negative situations. Such ambiguous emotions might introduce noise to the training process. Next, we grouped similar emotion classes, taking into account the original papers that were the inspiration for emotion inventory used in Reference.

Table no. 1 (experiment)



Discussion

The envisioned study objectives have been met: we have created and tested a sentiment (3-class) and emotion (9-class) text-based classification engine for a therapeutic dialogue system, working in Polish. To achieve this, we had to create our own emotion labeled corpus, which we generated using a neural MT system and two source English corpora. For sentiment and emotion recognition, we employed the state-of-the-art deep learning classifier based on the BERT model, which outperformed the classic models, such as Naïve Bayes or Support Vector Machines. We analyzed the misclassifications made by the best model (BERT) in more detail by looking at the examples related to the highest values from the confusion matrix, especially the cases when a positive emotion label was confused with a negative emotion prediction and vice versa. The most problematic class was other positive, as it was quite frequently predicted for sentences labelled with negative emotions, such as anger, sadness, and other negative. The models for both languages did well in distinguishing between neutral and emotional texts; we obtained high F1-scores for the neutral class: 97.6%forEnglish.

Emotion	Happin.	Conf.	o_pos	Anger	Fear	Sadness	Guilt	o_neg	neutral	F1-Score [%]
happiness	**247**	15	27	4	5	10	8	5	7	75.08% ± 1.53
confidence	24	**158**	15	2	7	7	3	2	4	74.70% ± 1.54
other_pos	39	16	**180**	5	6	8	10	10	2	67.04% ± 1.67
anger	3	0	7	**159**	12	13	10	18	4	70.04% ± 1.62
fear	0	4	4	8	**171**	10	7	3	0	80.28% ± 1.41
sadness	10	0	8	17	9	**215**	11	14	5	75.84% ± 1.52
guilt	0	3	7	15	2	10	**148**	13	1	73.45% ± 1.56
other_neg	3	1	11	18	3	5	7	**111**	0	66.07% ± 1.68
neutral	4	4	2	0	4	0	0	1	**223**	92.15% ± 0.95

Table no. 2 (discussion)

Output:

We evaluated four different models for sentiment and emotion recognition, for each of the languages, using the developed CORTEX dataset. The numbers of sentences in individual subsets (train/val/test) are displayed. In each experiment, we measured the values of accuracy and support-weighted F1-score. We conducted statistical analyses using the Wilson score interval, for the confidence level set to 90%. We assessed the confidence intervals for F1-score based on the confidence intervals for precision and recall. We also generated confusion matrices, allowing for a more detailed analysis of the results, including the models' mistakes.

Experiment	Metric	Language	Classifier			
			NB	SVM	FT	BERT
Sentiment (3-class)	Accuracy	en	85.41 ± 1.08	86.99 ± 1.03	88.07 ± 0.99	93.74 ± 0.74
		pl	83.00 ± 1.15	84.89 ± 1.10	85.59 ± 1.08	92.24 ± 0.82
	F1-score	en	85.44 ± 1.05	86.89 ± 1.02	88.00 ± 0.97	93.75 ± 0.71
		pl	83.08 ± 1.12	84.75 ± 1.08	85.43 ± 1.06	92.26 ± 0.79
Emotion (9-class)	Accuracy	en	63.29 ± 1.71	65.11 ± 1.69	68.42 ± 1.65	78.96 ± 1.44
		pl	62.27 ± 1.72	63.43 ± 1.71	65.25 ± 1.69	75.19 ± 1.53
	F1-score	en	63.06 ± 1.70	64.86 ± 1.67	68.33 ± 1.63	79.08 ± 1.40
		pl	62.06 ± 1.71	63.11 ± 1.70	65.01 ± 1.67	75.15 ± 1.49

Table no. 3 (output)

CONCLUSION:

In this paper, we introduce a concept termed Emotional Storytelling, which serves as an extension to current Interactive Storytelling practices, applicable to both virtual reality (VR) experiences and traditional settings. The aim is to establish structures that foster more engaging user experiences. We assert that creating such immersive experiences is crucial for the advancement of VR, especially in its utilization across various fields. Emotional Storytelling augments Interactive Storytelling systems by providing a framework to manage user emotional experiences explicitly. We advocate for the integration of explicit parameterization of the user's emotional responses into Interactive Storytelling systems, which we believe is essential. Our proposal outlines the extension of a generic Interactive Storytelling system to incorporate these parameters, applicable to both VR and conventional storytelling systems.

Our proposal delineates several key components of this extension, including the Emotional Tracking Engine, parameter extensions to story segments, and the Emotional Path Graph. Together, these components furnish authors and systems with a mechanism to guide users' emotional journeys by specifying anticipated emotions such as tension, anger, or excitement across different story segments and their evolution throughout the narrative. Furthermore, we provide a concrete example illustrating how this integration could be beneficial, leveraging Mateas' Facade.

Finally, we reflect on additional considerations that merit attention, such as timing constraints, the interface's impact on user emotional states, and the inclusion of an emotion recognition system. These aspects contribute to a comprehensive understanding of Emotional Storytelling's implementation and its potential implications.

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