Universe International Journal of Interdisciplinary Research
(International Peer Reviewed Refereed Journal)
DOI No. – 08.2020-25662434

© UIJIR | ISSN (O) – 2582-6417
DEC 2023 | Vol. 4 Issue 7
www.uijir.com

TEXT-BASED EMOTION RECOGNITION:
A COMPREHENSIVE LITERATURE REVIEW

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ABSTRACT

Affective Computing as a domain has experienced rapid interest and developments with the recent advancements in machine learning and natural language processing. In the age of the internet, availability is abundant for textual data. Several studies have been conducted on emotion recognition through facial expression and speech analysis. However, emotion recognition from text is a relatively arduous task due to the lack of emotion triggers and cues. New techniques introduced in natural language processing and machine learning have made emotion recognition from text more feasible. There are four main approaches for emotion recognition from text — rule-based approach, machine learning-based approach, deep learning-based approach, and a hybrid approach. This study explores several methods and implementations of each approach and summarizes their evaluation and the preferred method.

Keywords: Affective Computing; Emotion AI; Emotion Models; Emotion Recognition; Artificial Intelligence

DOI Link :: https://doi-ds.org/doilink/12.2023-43875912/UIJIR

INTRODUCTION

Affective Computing, nestled within the expansive realm of Artificial Intelligence, unfolds as a rich tapestry of research. Within this domain, myriad human-centric pathways are explored to fathom and interpret emotions. Among these diverse routes, the predilection is often toward the recognition and understanding of emotions, employing an array of methodologies. In the multifaceted landscape of Affective Computing, predominant strategies surface, with particular emphasis on two stalwart pillars: facial expressions and speech analysis. These avenues serve as the vanguards in deciphering the nuanced language of emotions, providing a robust foundation for unraveling the intricacies of human sentiment.

However, when delving into the realm of textual data, the spotlight shifts toward the captivating arena of sentiment analysis. Here, the research converges on the written word, exploring the subtleties and nuances embedded within text to discern and illuminate the emotional undercurrents. In essence, the exploration of emotions within Affective Computing transcends conventional boundaries, weaving together a symphony of methodologies that harmonize with the intricacies of human expression.

Recognizing emotions from text poses a notably challenging endeavor when juxtaposed with facial recognition and speech analysis, primarily owing to the absence of overt cues and discernible triggers for emotion detection and comprehension. However, the landscape is evolving with the strides made in Artificial Intelligence, particularly in the realms of Deep Learning and Natural Language Processing. These advancements now render it conceivable to formulate viable solutions for emotion recognition based on text. Given the scarcity of explicit cues and triggers, our reliance shifts entirely to language processing techniques for adept feature extraction, coupled with the deployment of robust classification models to ensure a dependable and accurate output.

In light of the remarkable progress within the realms of natural language processing and machine learning, coupled with the wealth of data accessible online, research in this domain has undergone a substantial acceleration. This surge in momentum has propelled advancements by leaps and bounds, ushering in a new era characterized by the development of increasingly expansive and intricate models. These sophisticated models exhibit heightened capabilities in processing, analyzing, and comprehending language, thereby elevating the precision of their outcomes.

EMOTIONS AND EMOTION MODELS

Various researchers highlighted the inherent ambiguity surrounding the definition of "emotion"[1]. The absence of a definitive consensus on an emotion model results in researchers adopting distinct definitions and models, thereby complicating the task of emotion recognition. Emotions significantly influence our experiences and behavior, and it has been found playing a crucial role in both human experience and psychiatric illness[2].

A comprehensive definition of emotions has been offered, characterizing them as a compound phenomenon encompassing evaluative, psychological, phenomenological, expressive, behavioral, and mental concepts[3]. This multifaceted nature further contributes to the complexity of understanding and categorizing emotions. In the realm of emotion models, researchers typically adhere to one of two well-defined emotion classification frameworks[4]. The categorical framework involves the segregation of emotions into distinct categories, while the dimensional framework classifies emotions along a 2D scale, determined by the intersection of valence and arousal intensities. This diversity in approaches underscores the intricate nature of studying and comprehending the multifaceted landscape of human emotions.

The Basic Emotion Theory (BET), formulated by Paul Ekman, stands as a prominent framework in the study of emotions. Ekman posits that there exists a concise set of fundamental emotions, including happiness, anger, fear, sadness, and surprise. Further, a study adeptly elucidated how BET encapsulates the essence of these emotions, providing a comprehensive understanding[5]. In addition to BET, a work underscored the diversity in emotion models, highlighting the utilization of variations of Russel's circumplex model[6]. This model ingeniously represents basic emotions in a two-dimensional space, employing valence and arousal as the defining dimensions. This approach enhances the richness of emotional exploration, contributing to a nuanced comprehension of affective states. Furthermore, Plutchik's wheel of emotions, emerges as another widely embraced emotion model[7]. This intricate wheel categorizes emotions into eight distinct categories, ingeniously pairing positive and negative emotions in opposition. Delving deeper, these emotions are meticulously classified into secondary and tertiary categories, employing the wheel as a visual representation of its intricate mechanism.

In summary, the landscape of emotion research is enriched by diverse models such as BET, Russel's circumplex model, and Plutchik's wheel of emotions. Each model brings its unique perspective, contributing to a comprehensive tapestry of knowledge surrounding human emotions.

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DEC 2023 | Vol. 4 Issue 7
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SURVEYS AND REVIEWS

Amidst the burgeoning research and exploration of emotion recognition from textual data, there has been a notable upswing in the volume of scholarly investigations dedicated to this field. This surge not only signifies a heightened scholarly interest but also heralds a wave of innovative methodologies and advancements in the meticulous curation of datasets.

A cutting-edge framework for emotion detection has been unveiled, showcasing an innovative approach to feature selection[8]. This framework identifies moderately frequent terms by assessing their relevance scores, grounded in the notion that such terms may encapsulate valuable information. Remarkably, the proposed framework consistently outperforms traditional filter-based feature selection measures, such as chi-square and gini-text.

A surge in studies within the field of emotion recognition, attributing it to the abundant availability of data and the consequential benefits derived from emotion analysis was suggested in a study[9]. A survey was conducted that not only delineates the primary approaches employed but also delves into some state-of-the-art methods. Additionally, the authors address pertinent issues and elucidate research opportunities in the domain of text-based emotion recognition.

In a parallel investigation, an insightful overview of sentiment analysis and emotion detection domains was furnished[10]. The authors navigated through diverse emotion models employed in studies and expound upon various approaches applied in emotion detection. This comprehensive examination sheds light on the evolving landscape of sentiment analysis and emotion detection.

APPROACHES FOR EMOTION RECOGNITION FROM TEXT

There are two distinct types of emotion recognition tasks in the realm of text analysis — explicit and implicit emotion recognition[11]. Explicit emotion recognition involves the identification of emotions that are overtly expressed through specific keywords, making them relatively straightforward to discern. On the other hand, implicit emotion recognition deals with emotions that are not immediately evident and are often embedded within the contextual nuances of the text.

In the comprehensive survey, the authors placed a particular emphasis on implicit emotion recognition, exploring four predominant approaches that have gained prominence in the field. These approaches encompass the rule-based approach, which relies on predefined rules to infer emotions; the classical learning-based approach, which involves traditional machine learning techniques; the deep learning approach, leveraging advanced neural network

DOI Link :: https://doi-ds.org/doilink/12.2023-43875912/UIJIR

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© UIJIR | ISSN (O) – 2582-6417
DEC 2023 | Vol. 4 Issue 7
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architectures; and, lastly, the hybrid approach, which integrates elements from multiple methodologies to enhance the robustness of emotion recognition systems.

RULE-BASED APPROACH

Rule-based approaches typically leverage predefined rules and guidelines grounded in grammar, lexical, syntactic, and semantic information. These methods commonly employ keyword identification and lexical analysis to discern emotions within a given text.

A collection of existing studies was contended relying on Ekman's emotion model, utilizing both supervised and unsupervised learning techniques for emotion-based sentiment analysis, are constrained by a limited scope of emotion words[12]. Furthermore, a deficiency in accounting for polarity shifters, negations, and an absence of support for emoticons and slangs were also noted. To overcome these limitations, the authors proposed a rule-based framework for emotion-based sentiment classification at the sentence level. This innovative framework integrates cognition-based emotion theory with sentiment analysis-based computational techniques. The primary objective was to enhance performance by incorporating additional cues, such as emotion words, emoticons, slang, polarity shifters, and negations. The results of the proposed framework demonstrated superior performance compared to previous works. Specifically, the framework achieved an average F-measure score of 60.5% using only emotional words. When including emoticons and slang, the performance significantly improved, yielding an impressive score of 75.7% on the News dataset—a key evaluation dataset utilized in the study.

In a notable study, a groundbreaking framework named RBEM-Emo emerged as an extension of the Rule-Based Emission Model (RBEM)[13]. This innovative framework is designed to discern emotions, building upon sentiment analysis rooted in Plutchik's comprehensive wheel of emotions. The evaluation of this framework, alongside other methodologies, took place on a diverse Twitter dataset featuring three languages. Impressively, the RBEM-Emo framework showcased superior performance, achieving an accuracy of 88.4%. Notably, even in the absence of neutral samples, it maintained a commendable accuracy rate of 67.1%. This study marked a significant stride forward in the realm of emotion detection and sentiment analysis.

A comprehensive examination of emotion classification within Indonesian Twitter data which utilized a corpus comprising 7622 tweets, categorizing them into six distinct emotions—anger, disgust, fear, joy, sadness, and surprise—while also including a label for neutral emotions[14]. The categorization was performed by five native speakers of the language. The

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researchers compared the efficacy of two different methods: a rule-based approach and a statistical-based approach. In the rule-based method, an existing Synesketch algorithm was implemented, incorporating two emotion word lists. Conversely, the statistical-based method utilized an SVM algorithm with unigram features, complemented by feature-selection algorithms such as gain and minimum frequency. Upon evaluation and comparison, the statistical method exhibited superior performance, achieving an accuracy of 71.74%. The rule-based method closely followed with an accuracy of 63.17%.

To address data imbalances, SMOTE (Synthetic Minority Over-sampling Technique) was employed, resulting in an impressive F-measure score of 83.20%. Moreover, the researchers explored a hybrid approach by combining elements of both methods, yielding an overall F-measure score of 81.59%. This nuanced study not only shed light on effective emotion classification methodologies but also demonstrated the adaptability of combining rule-based and statistical approaches for enhanced results.

Table 1. Summary of Rule-based Approaches

Method	Evaluation Measure	Score
Cognition-based emotion theory[12]	F-measure	75.7%
RBEM-Emo[13]	Accuracy	88.4%
Synesketch + SVM[14]	F-measure	81.59%

CLASSICAL LEARNING-BASED APPROACH

In the realm of machine learning, the discernment of emotions typically involves the classification of features into distinct categories, facilitated by both supervised and unsupervised machine learning algorithms. This methodology stands out as one of the extensively explored and frequently employed techniques for emotion recognition, placing a primary emphasis on the process of classification.

For example, a toolkit named EmoTxt, employed a sophisticated approach to emotion detection[15]. This toolkit utilizes a TF-IDF weighting schema along with uni-gram and bi-gram

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models to harness a comprehensive set of lexical features for identifying cues that convey emotions. To achieve this, EmoTxt integrates external libraries such as the Stanford NLP Library and WordNet Affect. These libraries aid in tokenizing the text and detecting emotion lexicons, establishing associations between words and emotion categories. The study focused on six basic emotions: love, joy, anger, sadness, fear, and surprise. To address each emotion individually, the researchers deployed a suite of six binary Support Vector Machines. Each machine was tasked with detecting the presence of a specific emotion. Training and evaluation of these models were conducted on a custom dataset comprising 4,800 posts from StackOverflow, supplemented by a second dataset from another source. The performance metrics chosen for evaluation were Precision, Recall, and F1 Score. The proposed EmoTxt toolkit demonstrated notable effectiveness, achieving an average F-measure score of 0.79. Notably, when examining the emotion with the lowest F-measure score (surprise), considered an outlier, there was a noteworthy increase in the F-measure score to 0.84.

A comprehensive framework for emotion recognition in English sentences was introduced by constructing the emotional data representation of a given input sentence, drawing upon its semantic and syntactic structure[16]. This representation undergoes generalization through the integration of ontologies such as WordNet and ConceptNet, culminating in the formation of an emotion seed termed the emotion recognition rule (ERR). Subsequently, a suite of K-nearest neighbors (KNN) classifiers was employed to categorize the ERR based on its similarity to a predefined set of other ERRs from the training dataset. The chosen similarity measures for the KNN classifiers included Point Mutual Information (PMI) and PMI with Information Retrieval (PMI-IR). Remarkably, the proposed framework exhibited superior performance compared to existing state-of-the-art machine learning and rule-based classifiers, achieving an impressive average F-score of 84%.

In an exploration of sentiment analysis, a noteworthy shift from traditional rule-based techniques, backed by lexical resources, was observed[17]. The primary drawback of these conventional approaches lied in the constrained capacity to capture a comprehensive range of emotional cues, ultimately resulting in suboptimal performance. To overcome these limitations, the study introduced a novel approach centered around a supervised learning-based Logistic Regression classifier. This method not only circumvented the pitfalls associated with prior techniques but also exhibited a substantial enhancement in performance. The evaluation of the proposed model utilized the ISEAR dataset, encompassing five distinct emotions—joy, fear, sadness, shame, and guilt. Comparative analysis with other supervised learning classifiers,

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DOI No. – 08.2020-25662434

DEC 2023 | Vol. 4 Issue 7
www.uijir.com

including SVC, KNN, and XG-Boost, showcased the superiority of the Logistic Regression classifier, achieving an impressive F-measure score of 0.85.

An exploration of emotion detection spanned several languages, but an oversight remained for the Urdu language, primarily owing to the absence of a standardized benchmark corpus[18]. To address this gap, the researchers proactively constructed a novel corpus comprising 18,000 samples sourced from diverse domains, each annotated with six distinct emotion labels. The researchers employed various baseline machine learning classifiers, including KNN, Decision Tree, SVM, and Random Forest. Notably, the Support Vector Machine (SVM) classifier emerged as the frontrunner during the evaluation phase, exhibiting superior performance with a notably elevated F-measure score of 0.69.

In the realm of machine learning methodologies, the Support Vector Machine (SVM) emerges as a preeminent and highly efficacious classifier algorithm. Widely acclaimed for its superior performance, this algorithm stands out prominently among the diverse array of machine learning approaches.

Table 2. Summary of Classical Learning-based Approaches

Method	Evaluation	Score
Emo-Txt[15]	F-measure	79.0%
ERR + KNN[16]	F-measure	84.0%
Logistic Regression[17]	F-measure	85.0%
SVM[18]	F-measure	69.0%

DEEP LEARNING-BASED APPROACH

Deep learning stands as a sophisticated realm within machine learning, characterized by intricate and profound architectures. These structures empower algorithms with heightened resilience and a heightened capacity to adeptly navigate ambiguous tasks.

The significance of incorporating both semantic/syntactic word embeddings and emotional word embeddings for effective and resilient emotion detection was explored[19]. The scrutiny revealed that numerous preceding studies relied on word embeddings to capture rich

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semantic and syntactic information but faltered in discerning emotional relationships between words. Conversely, some recent studies introduced emotional word embeddings, yet necessitated semantic and syntactic information. Addressing this observed limitation, a groundbreaking neural network architecture was proposed named the Semantic-Emotion Neural Network (SENN) to rectify the deficiencies of previous approaches. SENN integrates two sub-networks: a bidirectional Long-Short Term Memory (BiLSTM) model for semantic representation and a Convolutional Neural Network (CNN) to handle emotional embedding and extract emotional features. Through an extensive performance assessment against traditional and deep learning models, coupled with various embedding techniques, using the F-measure score as the benchmark, SENN consistently outperformed many state-of-the-art baseline models across multiple datasets. Notably, in the case of the DailyDialogs dataset, SENN exhibited an impressive F-measure score of 84.8%.

An innovative approach was employed to delve into the analysis of emotions within textual narratives[20]. A meticulously curated dataset, comprising 144,701 tweets adorned with emotion-specific hashtags for classification, was amassed to facilitate the training of their model. The classification task was undertaken through the adept utilization of a Convolutional Neural Network (CNN). The synergy of the word embedding layer and the classifier was aptly coined as the ‘Emotion Embedding Model’. The prowess of this model was then harnessed to discern and categorize emotions within narrative texts. The classification encompassed eight distinct emotion classes, yielding a commendable average accuracy rate of 51.25%. This implies a noteworthy degree of success in the model's ability to decipher and interpret the nuanced emotional content embedded within the story text.

A significant trend in previous research was highlighted, where the emphasis was predominantly on employing a uni-model approach for emotion recognition[21]. In response to this trend, the researchers introduced an innovative multi-model framework termed an "attention network." This framework comprises three distinct convolutional neural networks, each assigned to a specific task. The first network focuses on extracting features from speech spectrograms, the second on processing word embedding sequences, and the third serves as a classifier responsible for categorizing emotions based on the feature outputs from the preceding two models. The training of this model took place on a subset of the CMU-MOSEI dataset, with the implemented model adopting a binary network structure. To comprehensively evaluate its performance, experiments were carried out for each of the six primary emotions: sadness, happiness, anger, disgust, surprise, and fear. Impressively, the model demonstrated noteworthy

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DEC 2023 | Vol. 4 Issue 7
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success by achieving a class accuracy (non-weighted) of approximately 77.23% and an overall accuracy (weighted) of around 83.11%. This outcome underscores the effectiveness of the proposed multi-model "attention network" in enhancing emotion recognition across diverse emotional states.

The intricacies and uncertainties inherent in languages pose substantial hurdles in emotion recognition was emphasized[22]. The researchers advocated for performance enhancement, highlighting the potential for improvement. However, they acknowledged that addressing the unique demands of the task necessitates the customization of a recurrent neural network (RNN). This tailored RNN incorporates bidirectional processing, dropout layers for regularization, and weighted loss functions. In addition to this, the authors introduced an alternative method called sent2affect. This approach is characterized by a specialized form of transfer learning, wherein the network undergoes training for sentiment analysis. Notably, the output layer undergoes fine-tuning specifically for emotion recognition. To evaluate the efficacy of both approaches, the researchers conducted assessments across six different datasets. The results revealed a significant outperformance compared to traditional machine learning approaches across all evaluated criteria.

An EmoContext, an innovative framework for contextual emotion detection in text was introduced in a study[23]. In this study, the authors addressed the challenge of implicit emotions concealed within the context, which may not be immediately evident through keywords, thereby introducing ambiguity. The study focused on four primary emotion classes—happy, sad, angry, and others. To facilitate model training, a dataset comprising 30,160 samples was meticulously curated. Additionally, two test sets, one with 2,755 samples and another with 5,509 samples, were employed to assess the model's performance. The findings revealed that bidirectional Long Short-Term Memory (LSTM) emerged as the predominant choice among the various architectures explored. Interestingly, the sad emotion class exhibited superior performance compared to the other classes, while the happy emotion class demonstrated the least favorable results. Among the diverse architectures implemented, the highest observed F-measure score stood at an impressive 0.7957, underscoring the efficacy of the proposed EmoContext framework in capturing and discerning contextual emotions within text.

The evolving nature of user profiling, underscoring the increasing importance of a comprehensive approach was emphasized[24]. The study particularly highlighted emotion recognition from text as a pivotal aspect in profiling, shedding light on psychological traits. The study delves into an exploration of three distinct deep-learning methodologies: Deep Neural

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DEC 2023 | Vol. 4 Issue 7
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Networks, Bi-LSTM, and CNN. Additionally, the researchers leverage three pre-trained word embeddings for encoding purposes. Among the array of models scrutinized, FastTextEmb emerges as the frontrunner, showcasing superior performance. Notably, it attained an impressive F-measure score of 0.703 on both the SemEval 2019 task 3 dataset and the SemEval 2018 task 1 dataset. This robust performance positions FastTextEmb as a standout choice in the realm of user profiling, further affirming its efficacy in capturing and interpreting emotional nuances from textual data.

Among the myriad of deep learning algorithms, Bidirectional Long Short-Term Memory (Bi-LSTM) and Convolutional Neural Networks (CNN) stand out as the top-performing choices.

Table 3. Summary of Deep Learning-based Approaches

Method	Evaluation	Scores
SENN[20]	F-measure	84.8%
CNN[21]	Accuracy	51.25%
CNN[22]	F-measure	83.11%
RNN[23]	F-measure	69.0%
EmoContext + DL[24]	F-measure	79.59%
FastTextEmb[25]	F-measure (70.30%)	

HYBRID APPROACH

In this innovative strategy, the robust rule-based models seamlessly converge with the advanced machine learning and deep learning models, giving rise to a harmonized model that harnesses the distinctive advantages of each methodology.

An innovative approach was presented, employing a hybrid of cascaded Gaussian Mixture Model and Deep Neural Network (GMM-DNN)[25]. The investigation leverages the 'Emirati Speech Database (Arabic United Arab Emirates Database)' encompassing six distinct emotions: neutral, happy, fearful, sad, disgusted, and angry for the model's assessment.

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DEC 2023 | Vol. 4 Issue 7
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Comparative performance analysis against an SVM and an MLP classifier, two widely utilized machine-learning methods for emotion classification, reveals the model's superiority. It achieved an accuracy of 83.97%, surpassing the 80.33% and 69.78% accuracy rates of the SVM and MLP classifier, respectively.

The realm of transformer-based models for Natural Language Processing (NLP) tasks was complrehensively studied[26]. The investigation provided a thorough analysis of the strengths and weaknesses inherent in a spectrum of models, including Generative Pre-Training (GPT) and its derivatives, Transformer-XL, Cross-lingual Language Models (XLM), and the widely recognized Bidirectional Encoder Representations from Transformers (BERT). Recognizing the surge in BERT's popularity, the study also delved into a selection of pertinent BERT-based models. Remarkably, the researchers observed that XLNet surpassed BERT with a substantial margin in terms of performance. However, they acknowledged the computational overhead associated with XLNet, underscoring its computational expenses. The researchers further highlighted the vast availability of unlabeled data for emotion recognition in contrast to the limited availability of labeled data. In light of this, the researchers advocated for the utilization of GPT models, emphasizing their lexical robustness. Among the diverse models scrutinized in the study, SenticNet6 emerged as a consistently high-performing model across various datasets. For instance, on the SemEval-2016 dataset, SenticNet6 achieved an impressive accuracy of 82.23%.

The regional languages, specifically Punjabi, was often overlooked in studies compared to English[27]. In response, the researchers advocated for a novel hybrid approach to emotion recognition. This approach seamlessly blended a keyword-based strategy with a machine learning algorithm, resulting in the development of a robust hybrid model.

An innovative hybrid approach that combines a lexical technique with a machine-learning algorithm was introduced in a study[28]. The study emphasized the efficacy of incorporating a machine learning classifier to overcome certain limitations inherent in a purely lexical method. Specifically, this hybrid method proved advantageous in capturing the nuanced contextual information intricately linked to specific emotions embedded within sentences. Through a comprehensive evaluation comparing the lexical method, the machine-learning model, and the proposed hybrid approach, the researchers demonstrated a notable enhancement in performance. The F-measure score, a key metric in evaluating precision and recall, reached an impressive 84.6 for the proposed hybrid method. This result underscores the effectiveness and superiority of their approach in addressing the complexities associated with emotion

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DEC 2023 | Vol. 4 Issue 7
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analysis.

An innovative hybrid rule-based algorithm was designed for dataset acquisition with automated annotation in the realm of social media, leveraging Plitchik's emotional model, which encompasses 8 fundamental emotions[29]. This algorithm adeptly employed emojis, keywords, and semantic relationships to discern emotions in an impartial and objective manner. The study incorporated diverse machine learning algorithms, including Support Vector Machine (SVM) with Stochastic Gradient Descent (SGD), XGBoost, Naive Bayes, Decision Tree, Random Forest, and LSTM. Following a comprehensive evaluation on the acquired dataset, the LSTM model emerged as the top performer, exhibiting an impressive accuracy of 91.90%.

Table 4. Summary of Hybrid Approaches

Method	Evaluation	Score
GMM-DNN[26]	Accuracy	83.97%
SenticNet6[16]	Accuracy	82.23%
Lexical + ML[28]	F-measure	84.6%
Semantic+LSTM[29]	Accuracy	91.90%

CONCLUSION

Analyzing emotions from text has evolved into a more achievable endeavor, thanks to the rapid progress in machine learning and natural language processing. Processing textual data, prevalent on the internet, has proven to be notably efficient compared to other media forms like images, videos, and voice. This efficiency makes it practical to implement emotion recognition on a larger scale.

The realm of emotion recognition lacks a unified definition, leading to various proposed models and classifications. These include the basic emotion theory, Russell's circumplex model, Plutchik's wheel of emotions, and the primary color model of emotions, among others. Complementing these models are diverse approaches such as rule-based, classical machine learning, deep learning, and hybrid methods.

With the integration of advanced algorithms, models have witnessed significant enhancements in accuracy and robustness across all fronts. The advent of hybrid approaches has

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DEC 2023 | Vol. 4 Issue 7
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further increased adaptability to different niches, contributing to heightened overall robustness.

This paper delves into several implementations of each approach, providing a comparative analysis of their performance based on the F-measure score. The findings encapsulate a comprehensive summary, highlighting the most favored algorithms and approaches in the landscape of emotion recognition from text.

DOI Link :: https://doi-ds.org/doilink/12.2023-43875912/UIJIR

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Universe International Journal of Interdisciplinary Research
(International Peer Reviewed Refereed Journal)
DOI No. – 08.2020-25662434

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DEC 2023 | Vol. 4 Issue 7
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