Review Article

# EEG-Based Emotion Classification using Deep Learning: Approaches, Trends and Bibliometrics

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**Emotion classification has emerged as a critical area of research, holding immense significance in the understanding of human behaviour, mental health, and social interactions. The increasing recognition of emotional well-being's crucial role in various domains, such as healthcare, psychology, and human-computer interaction, has driven substantial attention toward accurately classifying and analysing emotions. In this study, we conducted a comprehensive bibliometric analysis to unravel the scientific production and temporal evolution of research related to emotion classification. Leveraging the extensive Scopus database, we meticulously collected and analysed a diverse range of 440 articles on emotion classification from its inception to the present day. The application of advanced bibliometric measures has yielded vital insights into current trends, patterns, and characteristics in this field of study. Our data indicated an unexpected trend: an increase in research activity, especially after 2018. The understanding of how emotions impact human experiences and behaviour has advanced significantly. Researchers from several fields have emphasised the need for better understanding and describing emotions, resulting in a large rise in study output. However, there is still a need for improvement in terms of agreement on emotion categorization assessment approaches and standardisation processes. It is difficult to compare and replicate study findings due to a lack of precise assessment criteria. To address this problem, it's crucial for researchers to collaborate and develop a common knowledge base. The aim of the paper is to widen our knowledge of emotions so that it can eventually result in policies being formed to improve our overall health. This knowledge could be implemented in psychological counselling and health promotion, resulting in the development of closer social bonds.**

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## 1. Introduction

Physiological signals play a crucial role in the detection and classification of emotions[1][2]. Different physiological data that are important from the point of view of emotion classification may include electrodermal activity (EDA), electrocardiogram (ECG), electromyography, respiration rate, temperature, pupillometry, heart rate variability (HRV), functional near-infrared spectroscopy (fNIRS), cortisol levels, electroencephalography (EEG), etc.[1][2][3]. Out of these modalities, EEG happens to be widely used for the detection of emotions, as EEG can capture temporal aspects and works at the millisecond level. Furthermore, EEG can be processed in real-time, providing immediate response and analysis[4].

Emotions, integral to human interaction and decision-making, have been the focus of extensive research across disciplines such as psychology, cognitive science, and neuroscience[1][2][3][4]. EEG data can help researchers in capturing the temporal dynamics of emotional processes with promising accuracy and precision. As the interest in this field has burgeoned over the past few years, there is a compelling need for a comprehensive overview to guide future investigations and inform practical applications.

There has recently been a surge in interest in grasping and categorising human emotions. This topic of study has aroused a lot of interest[1] due to its wide-ranging applications in healthcare, psychology, marketing[2], and human-computer interaction. Electroencephalography (EEG) data[3] stands out as a useful and non-intrusive tool for recording brain activity patterns among the several data sources utilised for emotion categorization. EEG data[4] provides unique insights into the cognitive and emotional processes[5] that contribute to our emotions by detecting electrical impulses caused by neural activity in the brain[6]. To comprehend human behaviour and enhance interactions between humans and technology, we must first define emotions. This is quite important. This study will investigate several ways of mining and categorising emotions, with an emphasis on EEG data[7]. To better understand why emotion categorization research is so important, we are searching for trends, breakthroughs, and research gaps. All for the sake of learning more about this enthralling subject and discovering its potential applications. We propose to investigate the issue of emotion categorization in this study, with an emphasis on using EEG data as a beneficial tool[8]. By conducting a thorough analysis of existing research, our goal is to identify noteworthy trends and keywords that highlight areas in need of further investigation[9]. We seek to advance this field by harnessing deep learning techniques, ultimately enhancing emotion classification[10]. Our ultimate objective is to support the development of innovative applications in domains like healthcare, psychology, marketing, and human-computer interaction.

The surge in research on EEG-based emotion classification requires a structured analysis to navigate the expanding landscape. This paper provides insights into the recent developments and trends in the area of EEG-based emotion classification using deep learning. This paper addresses the following questions:

- What are the prominent trends in this field?
- Who are the key contributors?
- How has research evolved over time?
- What are the critical gaps and emerging themes?
- Moreover, we seek to understand the methodologies and findings of the most influential studies, fostering a deeper comprehension of the current state of EEG-based emotion classification.

The main purpose of this paper is two-fold: first, to conduct a bibliometric analysis of 440 papers from the Scopus database, discovering the intellectual structure and evolution of EEG-based emotion classification research; second, to provide a comparative review of the 26 studies within this domain, dissecting methodologies and outcomes to distil patterns, identify gaps, and pave the way for future investigations. The study of EEG-based emotion not only contributes to the theoretical foundations of affective neuroscience but also holds practical implications across various domains. Applications range from human-computer interaction and emotion-aware technology to clinical interventions for mood disorders. By synthesizing the current knowledge base, this study aims to offer insights that transcend academic boundaries and foster advancements with real-world impact.

Leveraging the power of bibliometrics, we employ advanced analytical tools to dissect the vast corpus of 499 papers. The methodology involves mapping co-authorship networks, analysing citation patterns, and identifying prolific authors and journals. Simultaneously, our comparative literature review employs a systematic approach, scrutinizing the methodologies and findings of 33 seminal studies to distil insights and trends. While our study encompasses a substantial dataset and employs robust analytical techniques, it is essential to acknowledge certain limitations. The scope of our bibliometric analysis is confined to papers available in the Scopus database, potentially omitting relevant contributions from other sources. Additionally, the comparative review focuses on a select subset of studies, necessitating cautious generalization. In conclusion, this paper aspires to provide a comprehensive synthesis of EEG-based emotion classification research. By intertwining a meticulous bibliometric analysis with a detailed comparative review, we aim to unravel the past, present, and future trajectories of this burgeoning field, contributing to both academic discourse and practical applications. As we embark on this journey, the thesis statement emerges: a nuanced understanding of the intellectual landscape and methodological nuances that define EEG-based emotion classification.

## 2. EEG-based Emotion Classification using Deep Learning

In addition to the scholarly articles mentioned earlier, several other notable publications from specific years were studied for the bibliometric analysis of emotion classification. One informative review article focused on the advancements and challenges in using deep learning methods for emotion classification[1]. This article discussed the utilisation of convolutional neural networks, recurrent neural networks, and attention mechanisms[11]. Starting from single-channel and subjective emotion classification, the field is advancing towards multi-channel and multi-subject settings[12][13]. A range of physiological signals, facial expressions, and voice analysis can be integrated into systems designed to recognize emotions[14][15][16]. A capsule network architecture was proposed in[16] for a cross-subject and multi-channel recognition of emotions using EEG. In another work, neural nets and sparse autoencoders have been used for emotion classification in EEG data[17]. The attention mechanism has also been used on a variety of tasks and for classifying the acquired EEG data[13][17].


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| Authors | Reference | Dataset | Classification Technique | Results |
|---|---|---|---|---|
| Li et al. (2022) | [11] | DEAP | Residual GCB-Net | 83.8% accuracy |
| Liu et al. (2020) | [12] | SEED | Multi-level features guided capsule network | 82.3% accuracy |
| Tian et al. (2021) | [13] | DEAP | Personality first in emotion | 83.3% accuracy |
| Kumari et al. (2022) | [14] | SEED | EmotionCapsNet | 84.5% accuracy |
| Yin et al. (2021) | [15] | DEAP | Fusion model of GCN and LSTM | 82.8% accuracy |
| Jana et al. (2022) | [16] | BCI Competition IV | Capsule neural networks | 82.6% accuracy |
| Li et al. (2022) | [18] | SEED | Multi-task learning with capsule network and attention mechanism | 83.5% accuracy |
| Demir et al. (2021) | [17] | SEED | Deep learning features | 81.1% accuracy |
| Mehmood et al. (2017) | [19] | BCI Competition IV | Deep learning ensembles | 80.7% accuracy |
| Zheng et al. (2014) | [20] | EEG Data | DBN | 87.62% accuracy |
| Ahmed et al. (2021) | [21] | 32 channel EEG Data | LSTM | 85% |
| Battisti et al. (2023) | [22] | DEAP | CNN | Not stated |
| Li et al. (2022) | [23] | DEAP | Deep Learning Network with Label Smoothing (LS) | Increased by 1.34% in arousal, 2.28% in valence |
| Chakladar et al. (2018) | [24] | EEG Signal | Correlation based Subset selection + Higher Order Statistics | 82% |
| Liu et al. (2020) | [25] | DEAP and SEED | CNN + SAE + DNN | DEAP 92.86% SEED 96.77% |


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| Authors | Reference | Dataset | Classification Technique | Results |
|---|---|---|---|---|
| Olamat et al. (2022) | [26] | SEED | Deep Learning (CNN: AlexNet, DenseNet-201, ResNet-101, ResNet50, AutoKeras) | 99% (transfer learning), 100% (AutoKeras) |
| Seo et al. (2020) | [27] | EEG data from 30 Korean female AD patients | Multilayer Perceptron (MLP) | 70.97% (MLP) |
| Li et al. (2015) | [28] | DEAP | DBN | Comparable to manually generated features |
| Mohammadpour et al. (2017) | [29] | Inner emotion EEG signals | ANN | Not stated |
| Chen et al. (2019) | [30] | DEAP | Deep CNN | 3.58% higher than BT classifier in valence, 3.29% higher than BT in arousal |
| Rozgic et al. (2013) | [31] | DEAP | Non-parametric nearest neighbour model, Classification | “State of the art” |
| Nakisa et al. (2018) | [32] | Two Public Datasets (MAHNOB, DEAP), New Mobile EEG Dataset | Evolutionary Computation Algorithms (EC) | Improved Feature Selection, Maximised Performance |
| Gonzalez et al. (2019) | [33] | DEAP, DREAMER, Local Dataset (IAPS) | Independent Component Analysis, Unsupervised Learning, Convolutional Neural Network (CNN) with Transfer Learning | Valence: 70.26%, Arousal: 72.42% |
| Chai et al. (2022) | [34] | DEAP | Long Short-Term Memory-Recurrent Neural Network (LSTM-RNN) | Valence: 95.28%, Arousal: 96.17% |
| Acharya et al. (2021) | [35] | Not mentioned | CNN | 87.72% |

| Authors | Reference | Dataset | Classification Technique | Results |
|---|---|---|---|---|
| Garg et al. (2019) | [36] | DEAP | Merged LSTM model | Not mentioned |

**Table 1.** Comparative Analysis and Review of Recent DL Techniques for EEG-based Emotion Classification

Traditional machine learning techniques such as ensemble learning methods[37][38], combined ML techniques[39], and hybrid strategies[40] have been extensively explored. Ensemble learning methods leverage the diversity of multiple classifiers to improve classification accuracy[37], while combined ML techniques integrate various machine learning algorithms to enhance the robustness of emotion recognition systems[39]. Hybrid strategies incorporate domain knowledge or integrate different types of data sources to optimize emotion classification performance[40].

In recent years, deep learning has emerged as a powerful paradigm for EEG-based emotion classification[41][38][42]. Spiking Neural Networks (SNN)[43], multi-label multitask adversarial learning[44], and joint adaptation network[45] are notable examples. SNNs mimic the behaviour of biological neurons, offering advantages in processing temporal data such as EEG signals[43]. Multi-label multitask learning, coupled with adversarial training, enables the model to handle multiple emotional states simultaneously while mitigating domain shift issues[44]. Joint adaptation networks leverage shared representations across domains to enhance generalization performance[45].

Furthermore, advancements in deep learning architectures have led to innovative models tailored for EEG-based emotion classification that can be used for cross-domain emotion classification[46]. Models such as GRU with attention[47], cross-connected neural networks[48], and spatial and temporal CNNs[49] exhibit superior performance in capturing temporal dynamics and spatial dependencies within EEG data. Attention mechanisms enhance the model's capability to focus on relevant EEG segments, while cross-connected neural networks facilitate effective feature extraction and information propagation[47][48]. Multi-temporal spatial and temporal CNNs leverage both spatial and temporal information to extract discriminative features from EEG signals, improving classification accuracy[49].

Moreover, research endeavours have extended beyond EEG signals to explore multimodal approaches. Multimodal feature fusion[50] integrates information from multiple modalities, such as EEG and ECG signals, to enhance emotion recognition accuracy. Sentiment-aware word embedding[51], and image data[52] can be combined for sentiment analysis and emotion classification, offering a holistic understanding of emotional states.

Recent studies also address practical challenges such as real-time emotion classification and subliminal emotion detection. Real-time emotion classification of EEG streams in online learning environments[53][54] focuses on developing efficient algorithms capable of processing EEG data in real-time settings, crucial for applications like affective gaming and mental health monitoring. Subliminal emotion classification using entropy-based features[55] explores subtle cues in EEG signals for detecting latent emotional states, expanding the scope of emotion recognition applications.

In conclusion, EEG-based emotion classification has witnessed significant advancements, propelled by the integration of traditional machine learning techniques and cutting-edge deep learning architectures. Future research directions may explore hybrid approaches combining multimodal data sources and address practical challenges in real-time emotion recognition and subliminal emotion detection.

## 3. Bibliometric Analysis

### *3.1. Data Sources and Tools*

For the bibliometric analysis presented in this paper, the data were sourced from the Scopus research database. Scopus is a renowned database known for its comprehensive coverage of academic literature. Scopus served as the primary data source, facilitating a deep exploration and analysis of the existing corpus of research on emotion classification. This study aimed to unveil the evolutionary trajectory and prevailing trends in EEG-based emotion classification and the use of ML/DL, with a primary focus on the DL approaches. The Biblioshiny analysis tool of R-Studio was used for the visual analysis of the dataset gathered from the Scopus database. The amalgamation of R-Studio's capabilities with the rich dataset yielded a plethora of insightful graphs and charts. These visual representations enabled an in-depth scrutiny of publication trends, citation patterns, influential authors, and salient research themes encompassing emotion classification.

### 3.2. Search Strategy

A bibliometric examination was undertaken in this work to analyse the research patterns in emotion categorisation. The study's data were sourced from Scopus, a vast database that indexes academic literature on a wide range of topics. Scopus includes journals, conference papers, book chapters, etc., making it an ideal source for bibliometric analysis.

To ensure the relevance of the papers collected, specific keywords related to classification were used in the search. These keywords were selected based on their frequent usage in the literature and their direct connection to the subject matter, providing a comprehensive representation of relevant research. The following is the set of keywords that considers the colloquial and spelling variations.

{"Electroencephalography" OR "electroencephalogram" OR "EEG"} AND {"classification" OR "recognition" OR "categori?ation"} AND {"deep learning" OR "neural net*"}

To focus exclusively on English-language research articles, the analysis excluded non-English papers. Additionally, other document types like editorials, book reviews, and letters were not considered to ensure that only primary research articles were included. The bibliometric analysis relied on a total of 440 papers published between 2007 and 2023 ($28^{th}$ of June) to identify research patterns in emotion classification.

### Analysis Methodologies

Researchers studying the classification of emotions utilise methods to thoroughly analyse the literature. One valuable approach is co-analysis, which examines collaboration patterns among researchers to identify influential authors, prominent research groups, and fruitful partnerships in the field. By studying networks of co-authorship, researchers gain an understanding of how knowledge is shared and collaborative efforts are made in emotion classification. It is crucial to understand the impact and influence of publications in this field, and citation analysis plays a role in achieving this goal. It helps identify cited papers and influential authors, providing insights into works and visionary leaders who have significantly shaped this discipline. Such analysis allows researchers to trace the lineage and evolution of ideas in emotion classification, uncovering contributions and significant milestones. Keyword analysis is another method used in analysis, which helps researchers examine keyword frequency and how they co-occur within the literature. This exploration reveals themes, emerging trends, as well as research directions within the realm of emotion classification. This results in researchers gaining important insights in the field and allows them to stay current in an ever-evolving subject. For example, co-citation analysis allows the evaluation of the relationships between concepts and publications to occur in greater detail. Furthermore, to better comprehend emotional categorisation, co-citation analysis further highlights research topics and commonly referred works. By using ceiling analysis, thematic and semantic relationships between words or phrases may be identified, which could be used to explore connections between fields.

*Keyword Analysis*

| Words | Occurrences |
|---|---|
| electroencephalography | 433 |
| emotion recognition | 237 |
| biomedical signal processing | 205 |
| classification (of information) | 177 |
| emotion classification | 172 |
| speech recognition | 151 |
| emotion | 145 |
| deep learning | 144 |
| human | 113 |
| electrophysiology | 106 |
| brain | 104 |
| machine learning | 83 |
| learning systems | 76 |
| electroencephalogram | 74 |
| emotions | 73 |
| feature extraction | 73 |
| article | 70 |
| brain computer interface | 69 |
| convolutional neural networks | 69 |
| electroencephalogram signals | 66 |
| humans | 66 |
| convolutional neural network | 61 |
| convolution | 59 |

| Words | Occurrences |
|---|---|
| **support vector machines** | 58 |
| **long short-term memory** | 56 |

**Table 2.** Key terms and their frequency

Noteworthy research directions were explored by analysing trending reviews, which consisted of highly cited papers on topics such as "advanced learning methodologies for emotion recognition" and "human machine interaction".

### *3.3. Results*

The year-wise scientific production of the published research has been depicted in Figure 1. The first article in the area was published in the year 2007. There has been a significant increase in research and interest in emotion classification since 2018. This indicates a growing focus on improving our understanding of emotion classification in recent years.

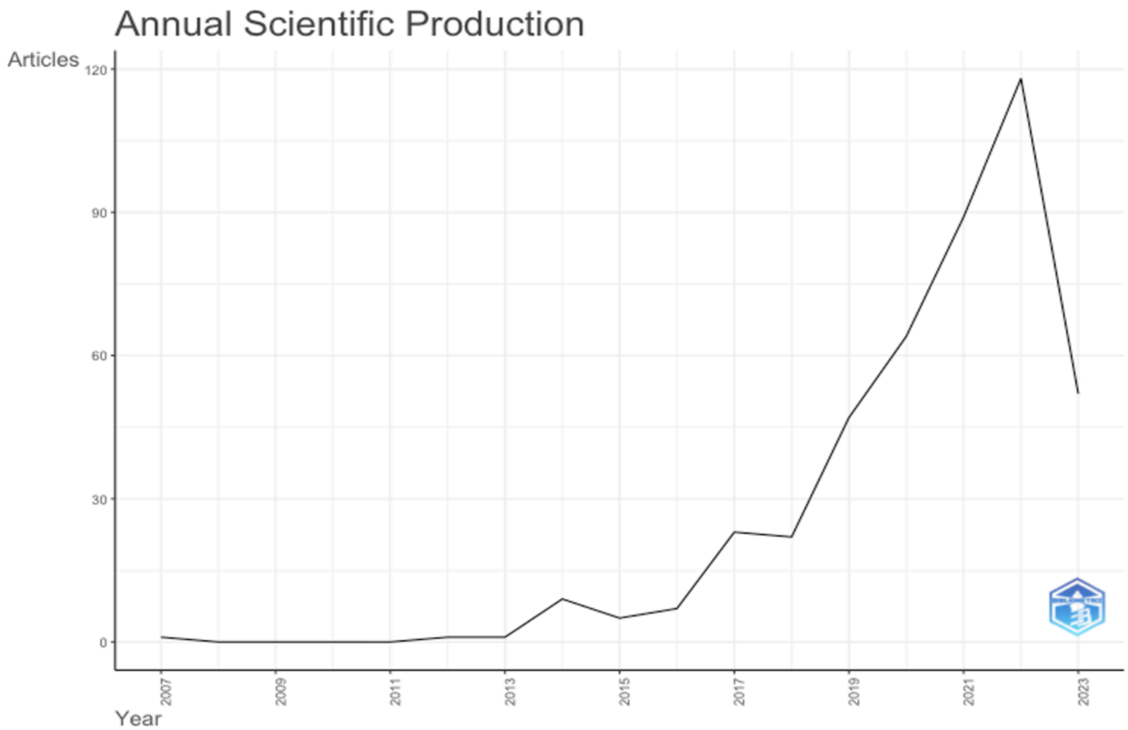


**Figure 1.** Annual scientific production of the published research.


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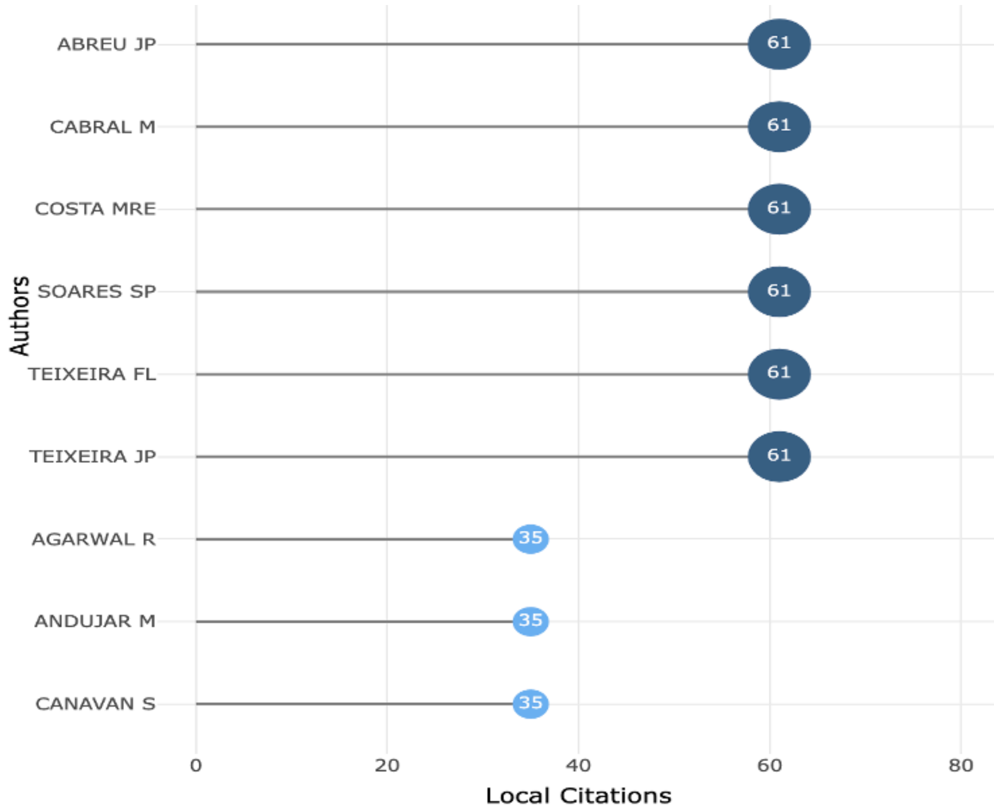


**Figure 2.** Top cited authors in the field.

As seen in Figure 2, Arbeu JP is also considered the author with the greatest number of local citations, emphasising his contributions to the scientific community. Teo J is another author who has proven proficiency and involvement in emotion classification. Both have gained great acclaim for their contributions to the discipline of emotion classification.


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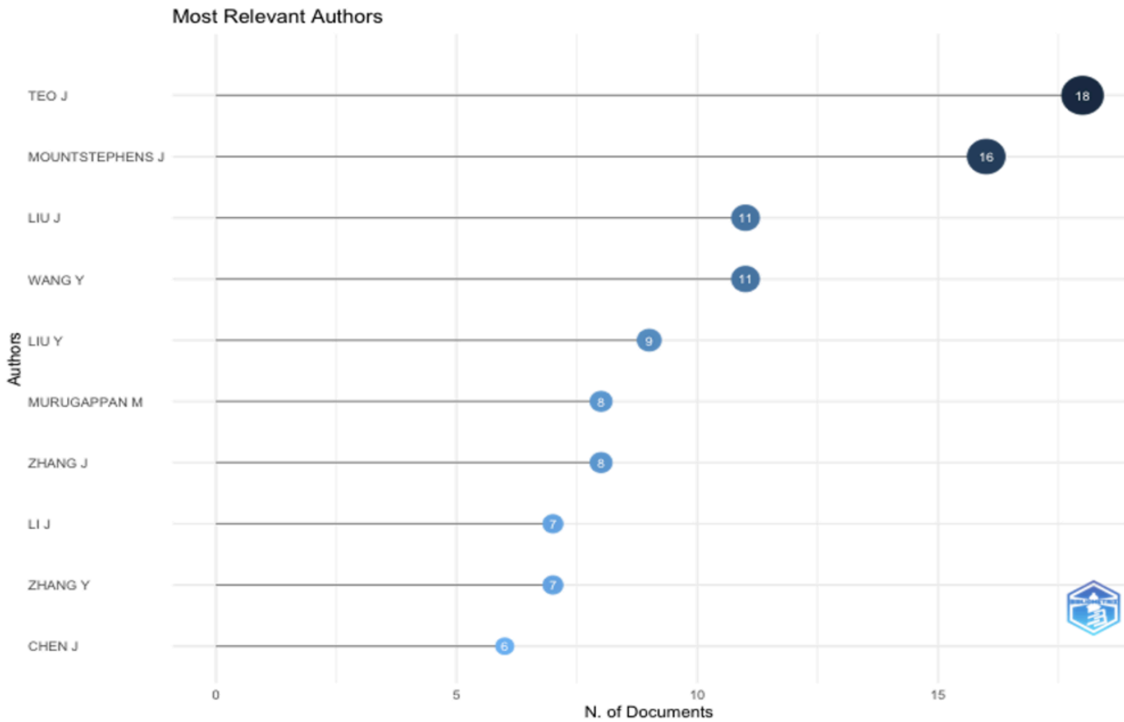


**Figure 3.** Most relevant (productive) authors in the field.

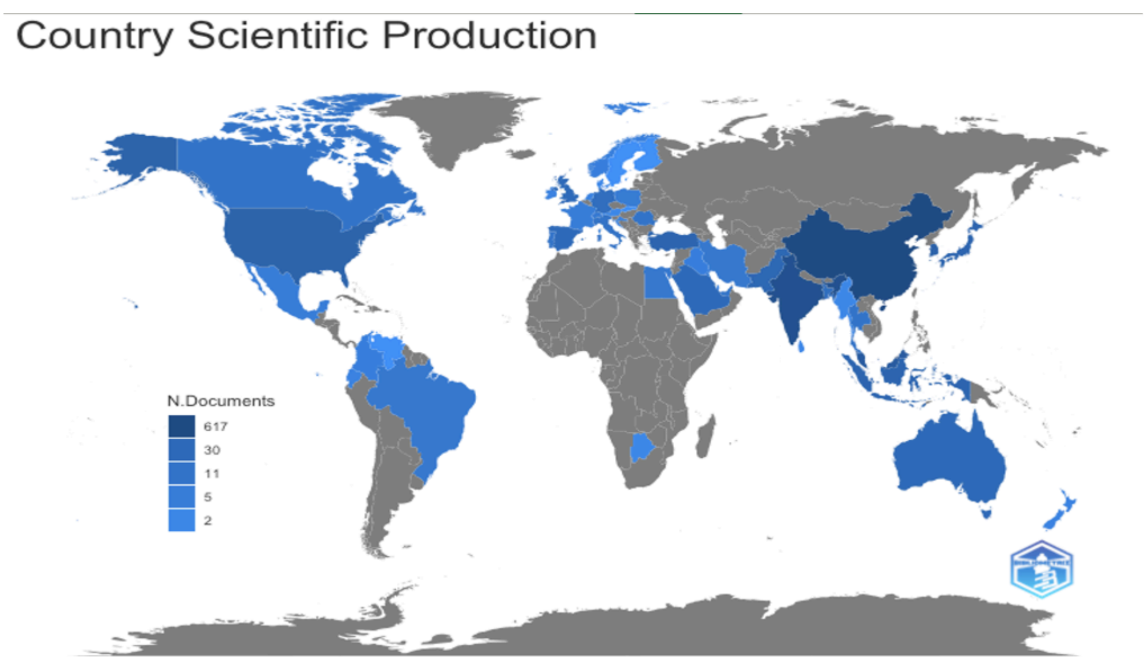


**Figure 4.** Country-specific scientific production.


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Figure 4 depicts that in the realm of emotion classification research, China is the major contributor. This discovery magnifies the prominent role and formidable contribution of China in shaping the landscape of this dynamic field. With an abundance of papers hailing from this progressive nation, it becomes evident that China exhibits an unwavering dedication and passionate involvement in the pursuit of knowledge and enlightenment within the area of emotion classification.

The analysis of scholarly articles on the categorization of emotions worldwide revealed a significant increase in annual production. Figure 5 shows the country-specific research output in the field. The top countries contributing to the field are namely China, India, Korea, Malaysia, and the USA.

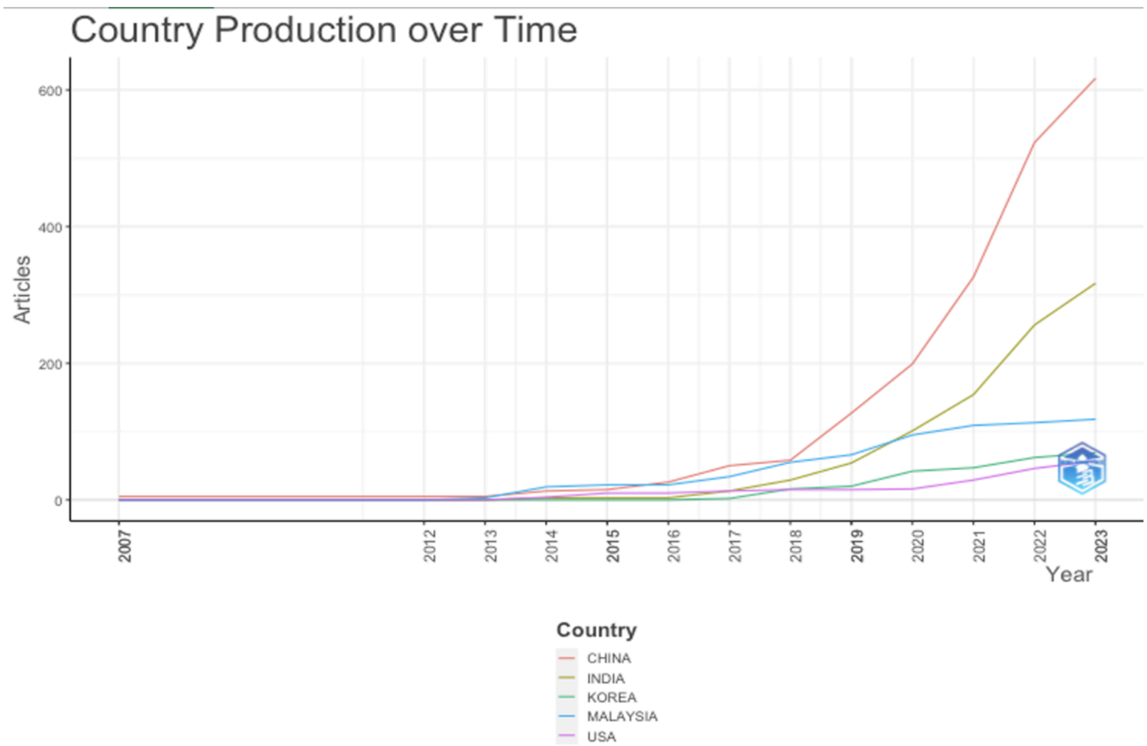


**Figure 5.** Country-specific research output over time in the field.

Figure 6 reveals that two sources, SENSORS and IEEE ACCESS, have emerged as highly relevant and influential in the field of emotion classification. Together, these sources have contributed 15 papers, highlighting their significant presence and impact in research. The substantial number of publications from IEEE ACCESS and SENSORS underscores their esteemed position as platforms for sharing research specifically focused on emotion classification. Researchers recognize these sources as invaluable channels for disseminating findings and advancing knowledge, demonstrated by their consistent


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expansion in publication output over the years. This continuous growth reflects their dedication to broadening the scope of emotion classification research and solidifies their reputation as leading outlets in the field. Figure 7 further shows the time-specific production of the top sources in the field.

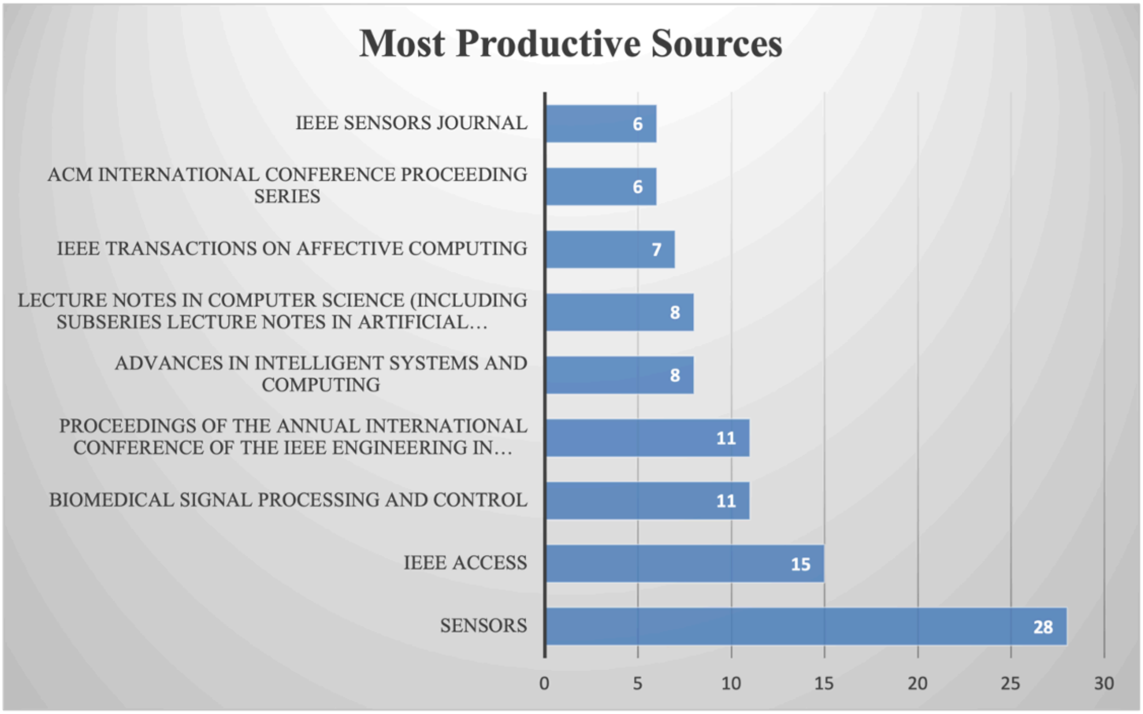


**Figure 6.** Most productive sources.

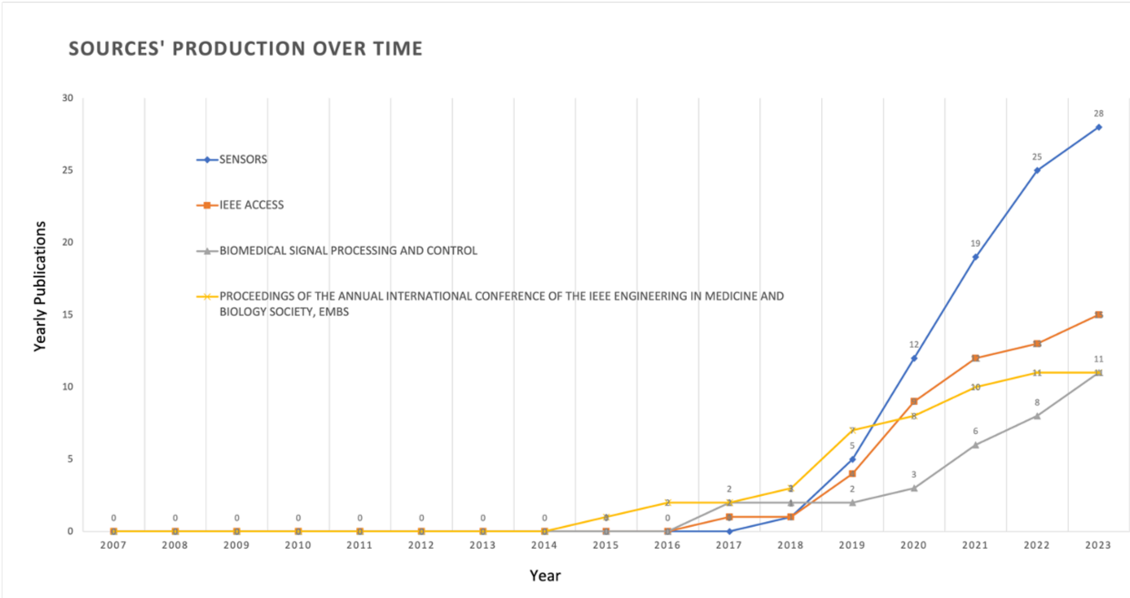


**Figure 7.** Sources' publication output over time.

Using Lotka's Law, also known as the Inverse Square Law, we examined how authors contribute to the field of emotion classification by analysing the number of articles they published (Figure 8). The results confirmed Lotka's Law and revealed a concentration of highly productive authors alongside a long tail of less prolific ones. The data strongly support this law, showing that there is an exponential decrease in author frequency as the number of articles published increases. Interestingly, authors who only published one article made up around 80% of the total authors. On the other hand, as the number of articles per author increased, their frequency sharply declined, with only a small group contributing multiple articles. The distribution of author productivity within the field of emotion classification supports the applicability of Lotka's Law.

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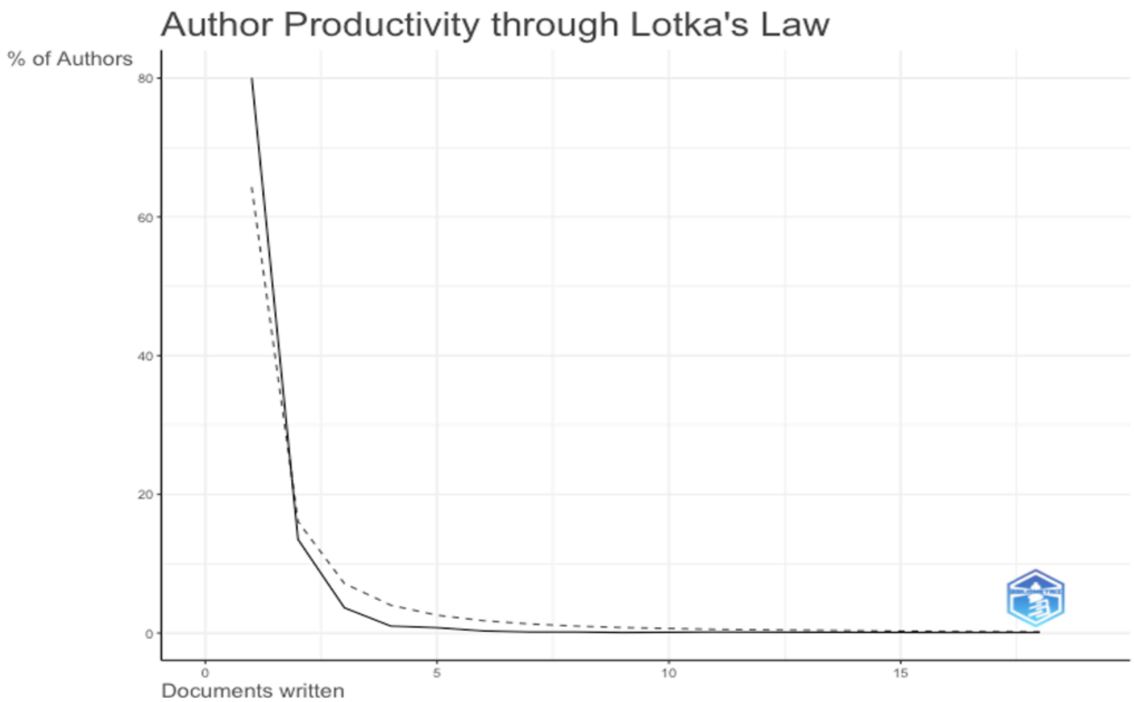


**Figure 8.** Assessment of authors' productivity using Lotka's law.

As seen in Figure 9, the term "electroencephalography" was observed to appear 433 times in the scrutinised papers on emotion classification. This demonstrates the frequent application of electroencephalography as a method or technique in examining and analysing emotions. Electroencephalography, which measures brain activity through electrodes positioned on the scalp, has emerged as a valuable instrument in comprehending the neural underpinnings of emotions. The substantial recurrence of its usage underscores the importance of electroencephalography in the domain of emotion classification and its pertinence in exploring the physiological facets of emotions.


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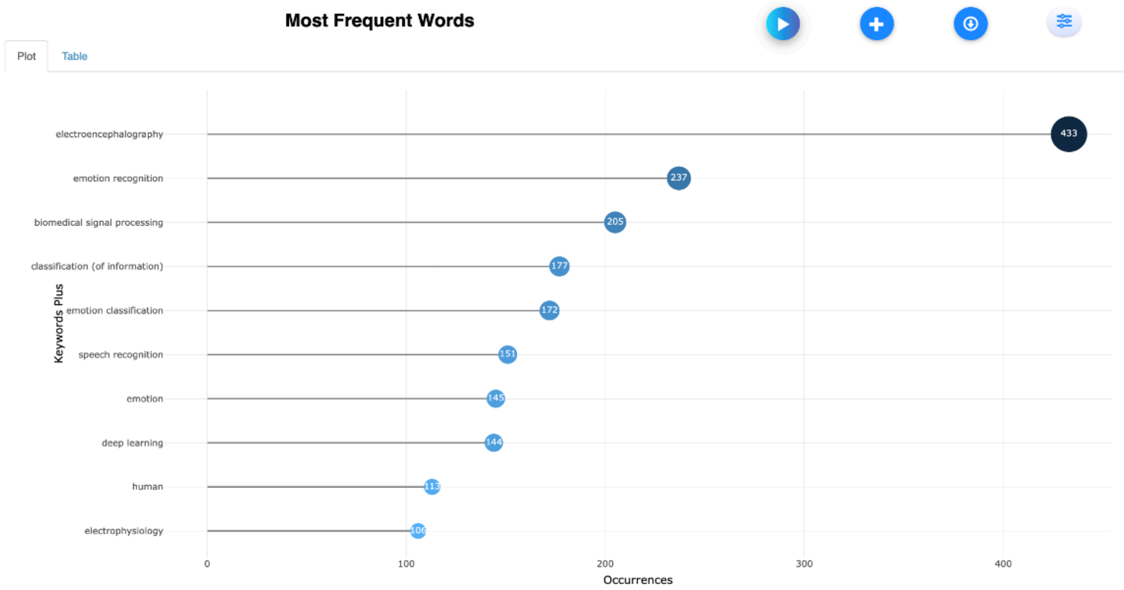


**Figure 9.** Most frequent words.

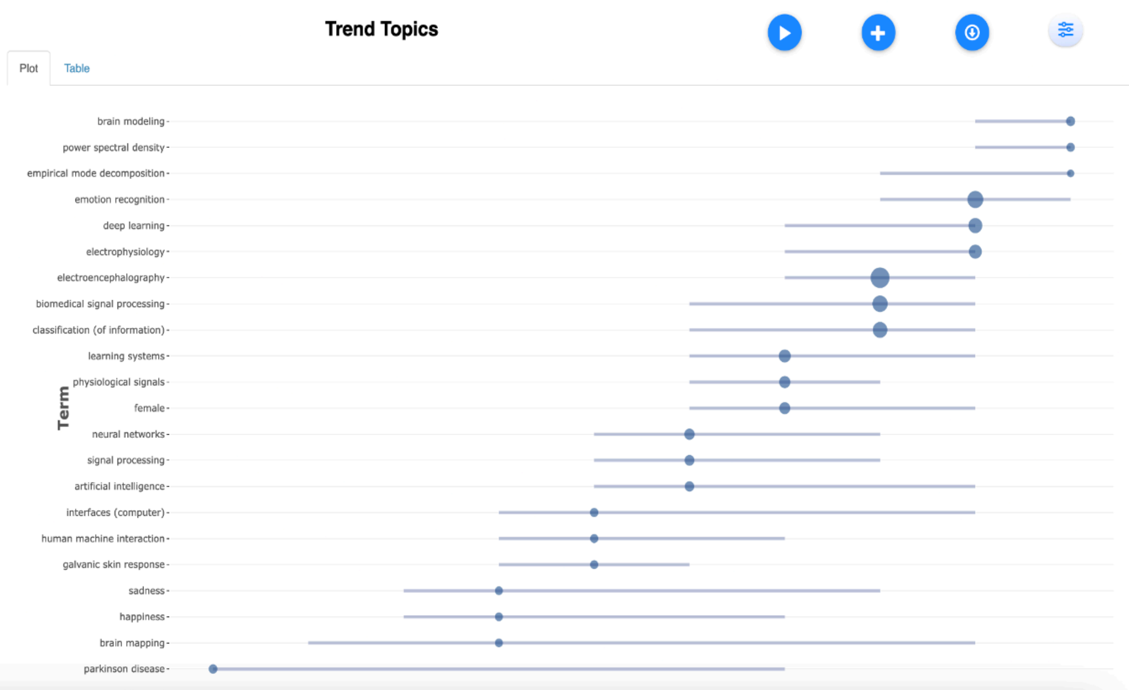


**Figure 10.** Trend topics in the field.


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By meticulously examining keywords and themes embedded within the collected papers, the most profound and impactful topics in emotion classification were unveiled (Figure 10). This approach not only bestowed upon us invaluable insights but also illuminated the ever-evolving landscape of emotion classification research. With each paper, a panoramic view of the current research trends and laser-focused areas of exploration vividly materialised, painting a comprehensive tapestry of comprehension and understanding.

## 4. Discussion

In this elaborate and exhaustive analysis, we delved deep into emotion classification papers sourced from diverse online databases. This allowed us to examine the current trends and advancements in this captivating field. As we meticulously combed through the literature, certain keywords kept popping up like "emotion recognition," "machine learning," "affective computing," and "natural language processing." These little powerhouses underpin the very foundation of emotion classification research. Our investigation unveiled a prevailing movement towards embracing cutting-edge deep learning methodologies and the fusion of multimodal data techniques. Our analysis zoomed in on specific domains where emotion classification is making waves, particularly in the realms of healthcare and human-computer interaction. The remarkable significance and incredible impact of emotion classification emerge from these distinct and unwavering patterns. Our findings seamlessly coincide with prevailing research themes, affirming the vibrant and rapid evolution that defines this captivating field. The practical implications and far-reaching potential it holds are impossible to ignore.

## 5. Conclusion

In conclusion, the analysis of emotion classification research through bibliometrics provides valuable insights into the field. The findings show a surge in research activity starting from 2018, indicating a growing interest in this topic. Notably, Arbeu Jp is the most cited author, and China has made significant contributions with the highest number of papers. The influential sources identified are IEEE Access and Sensors. By applying Lotka's Law, it's evident that there is a concentration of prolific authors in this field. The frequent mention of "electroencephalography" highlights its relevance in understanding emotions. The keyword analysis sheds light on the prevailing research topics in emotion classification. These findings collectively showcase a vibrant and dynamic research landscape within emotion classification. Researchers, policymakers, and practitioners can utilise this information to gain a comprehensive understanding of the field, identify influential authors and sources, recognize emerging research themes, and ultimately contribute to the progress of emotion classification research.

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