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Emotion and personality analysis and detection using natural language processing, advances, challenges and future scope

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Abstract

Emotion detection from text is a relatively new sub-field of artificial intelligence closely related to Sentiment Analysis (SA). SA detects positive, neutral, or negative emotions in text. In contrast, emotion analysis detects and distinguishes certain types of emotions expressed in textbooks, such as disgust, fear, anger, happiness, surprise and sadness. Meanwhile, personality is a critical psychological concept that accounts for unique characteristics. Identifying and validating an individual's personality efficiently and reliably is an admirable goal. This article aims to present a simultaneous review of Emotion and Personality detection from texts and elaborates upon approaches in developing text-based Emotion and Personality detection systems. The studies' essential contributions, methodologies, datasets, conclusions drawn, strengths, and limitations are also explored. Additionally, this article discusses some of the field's state-of-the-art ideas. In conclusion, the study delves into specific challenges and possible future research directions for detecting emotions and personalities from the text.

Keywords Emotion analysis · Personality detection · Natural language processing · Deep learning · Computational linguistics · Survey

1 Introduction

Personality has an impact on job performance, satisfaction, and tenure intention. Personality assessments can benefit recruiters, hiring managers, and candidates in the recruitment process (Tadesse et al. 2018). Certain mental health illnesses are associated with specific personality traits. On the other hand, people use text-based input to express their opinions and emotions about products or services on social media shopping platforms. However, humans can make mistakes when reading emotions conveyed through writing (Nasir et al. 2020). Recognizing emotions from text has become a crucial task in recent years, as emotions play a vital role in expressing meaning in dialogue (Chowanda et al. 2021).

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Researchers explore using NLP to classify personality and emotions, but more methods for detecting these are needed. This systematic review simultaneously addresses personality and emotion classification, aiming to lay the groundwork for future research in Human-Robot Interaction. Emotions play a crucial role in personality, and their integration into personality psychology has grown since the 1980s (Shand 1920; Murray and Clinic 1938; Corr and Matthews 2009). The emotion system monitors event relevance to motives and desires, significantly impacting how individuals think and act, thereby defining personality (Frijda 1986; Reisenzein 2009). NLP, Machine Learning, and Computational Linguistics are increasingly used to extract text emotion relevance. Both personality and emotion detection follow similar processes, and some studies explore multitask research for both (Acheampong et al. 2021).

Compared to previous surveys, this paper brings forth several important and novel aspects, which are briefly outlined below:

(a) This paper simultaneously explores the intricate relationship between personality and emotion and its impact on text mining. It also assesses the mediating role of NLP between personality and emotion models and text analysis.
(b) It investigates the performance of Machine Learning (ML), Deep Learning (DL), and Hybrid approaches in a well-organized manner.
(c) This paper covers recent cutting-edge advances in NLP, personality and emotion detection, including transformers, ChatGPT, personalized chatbots, emotional chatbots, Sentic emotion detection, and multitasking approaches for personality and emotion detection.
(d) It offers a concise glossary of datasets, personality, and emotion models, along with their comparisons and limitations.
(e) This paper uniquely advances the practical development of personality and emotion detection by summarizing the limitations of state-of-the-art methods and identifying promising directions for future research.

The rest of this article is presented as follows: Sect. 2 explains the organization of the current review paper. Sect. 3 offers an introduction to NLP. Next, Sect. 4 digs deep into text-based emotion detection, presents emotional models, and explains relevant state-of-the-art approaches. Section 5 considers text-based personality detection and models; it also explains personality detection approaches and the related work. Afterward, in Sect.6, open issues and significant limitations are discussed, and recommendations for future research are offered. Eventually, Sect. 7 concludes the paper.

2 Review methodology

This paper searched several electronic archives for related articles, including the ACM Digital Library (https://dl.acm.org/), Google Scholar (https://scholar.google.com/), IEEE Xplore (https://ieeexplore.ieee.org/), Semantic Scholar (https://www.semanticscholar.org), Science Direct (https://www.sciencedirect.com/) and Springer Link (https://link.springer.com/). A series of keywords in Table 1 has been searched. The collection of articles with the most relevant content to the research topic has been selected based on different criteria, including the relatedness of the article's title to the keywords and the discussion of the NLP in the paper's abstract for emotion or personality detection.

Table 1 Keywords for finding relevant studies

Machine Learning + Personality Traits	Personality Detection + Text
Deep Learning + Personality Detection + Text	Emotion Detection + Text
Emotion Detection + Text	Emotion+Machine Learning
Deep Learning + Emotion Detection	Text Mining + Emotion Detection
Natural Language Processing + Personality Models	Text Mining + Personality Detection
Text-based + Emotion Detection	Machine Learning + Emotion Detection

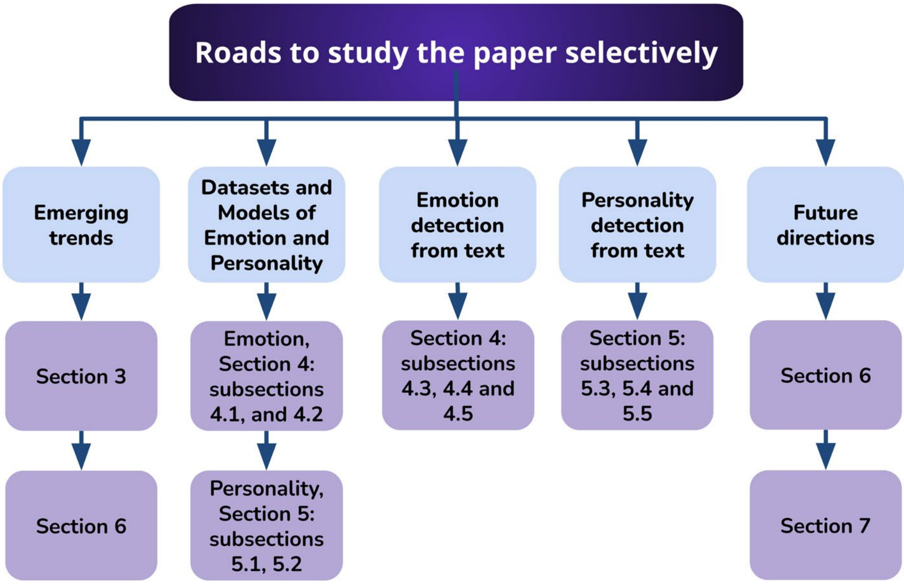

Fig. 1 A guide for readers who want to read the paper in a selective manner

Some readers may read this paper selectively if they already possess some fundamental knowledge or wish to learn more about a particular subject. Figure 1 illustrates the paper's contents categorized into five groups. Besides, Fig. 2 organizes the reviewed studies into different thematic groups. This way, similar articles within each subject category are easily found for an in-depth investigation.

3 Natural language processing

NLP, also known as computational linguistics (CL), engineers computational models and processes for solving problems and using the solutions to build helpful software which can understand human language. NLP has two broad subfields, including core concepts and applications. Core concepts include language modeling, which emphasizes quantifying connections between words in texts. Processing morphology involves segmenting meaningful words into their constituent parts of speech and identifying what they are. The linguistic process of parsing, or syntactic processing, is an early stage in semantic processing

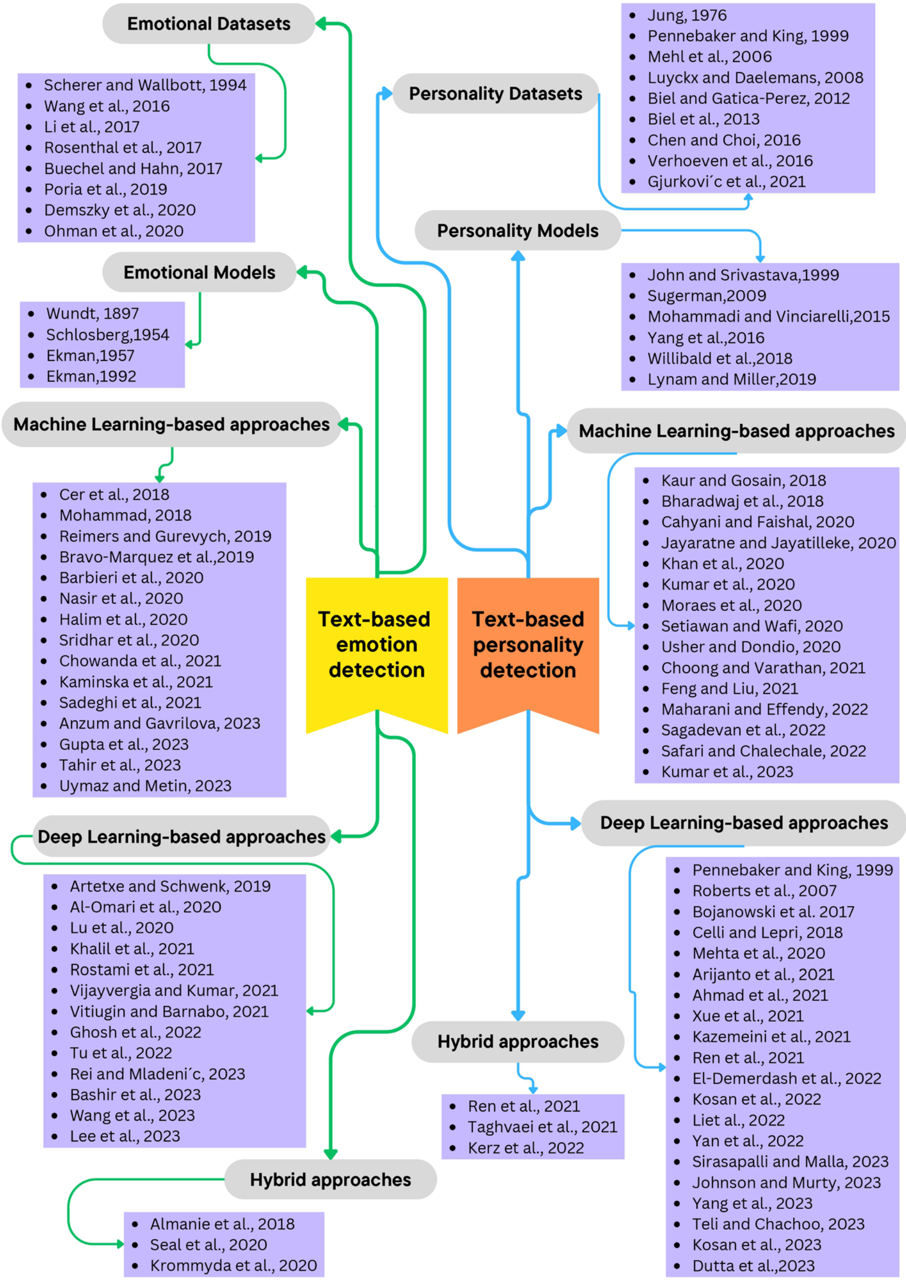

Fig. 2 Taxonomy of relevant studies for emotion and personality analysis and detection

by constructing sentence diagrams. Words, phrases, and components are analyzed to determine their semantic meaning (Chowdhary 2020). Some applications of NLP include machine translation, information extraction, question-answering systems, automated text summarization, and text classification.

4 Emotion detection

Text-based emotion detection is a crucial task in natural language processing. Several approaches have been proposed to address this challenge. One approach is using pre-trained word embeddings from GloVe to identify emotions in text (Alla et al. 2022). Another approach is using deep learning models, such as the LSTM network model, which leverage recurrent neural networks like Long-Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) to improve emotion detection performance (Zhang 2022).

Additionally, open-source frameworks like Emotion-Core provide tools for training, evaluating, and showcasing emotion detection models, making it easier for researchers to develop and extend existing solutions (Alvarez-Gonzalez et al. 2021a). Furthermore, benchmarking studies have been conducted using large-scale datasets like GoEmotions and Vent, developing novel models that outperform previous baselines (Alvarez-Gonzalez et al. 2021b). Finally, transformer-based models with the fusion of adapter layers have shown promising results in emotion detection tasks, even when using only textual data (Nguyen-The et al. 2022).

This section introduces publicly available datasets tailored for emotion detection from textual content, emotion models, and the latest state-of-the-art techniques laying the foundation for understanding the cutting-edge methods employed in text emotion detection.

4.1 Datasets

This subsection describes datasets for text-based emotion detection, which are as follows:

- **ISEAR**[1]: in total, 7665 sentences have been labelled with joy, sadness, fear, anger, guilt, disgust, and shame (Scherer and Wallbott 1994).
- **DailyDialogue**[2]: here are 13118 sentences in total with discrete emotion labels for neutral, anger, disgust, fear, happiness, sadness, and surprise (Li et al. 2017).
- **GoEmotions**[3]: with 27 emotion categories, this corpus contains 58k carefully curated comments from Reddit (Demszky et al. 2020).
- **MELD**[4]: over 1400 dialogues and 13000 utterances from the Friends tv show, were categorized as disgust, anger, fear, sadness, surprise, joy, and neutral (Poria et al. 2019).
- *ArmanEmo*: this dataset comprises nearly 7000 Persian sentences, labeled for anger, fear, happiness, hatred, sadness, wonder, and "Other" emotions not covered by Ekman's model. The sentences are sourced from various platforms like Twitter, Instagram, and Digikala[5].
- *SemEval*[6]: the SemEval dataset contains Arabic and English news headlines from sources like BBC Online, CNN, and Google News. It consists of 1250 records with extensive emotional content for emotions like joy, sadness, fear, surprise, anger, and disgust, categorized based on Ekman's emotional categories (Rosenthal et al. 2017).

1 https://www.kaggle.com/shrivastava/isears-dataset.

2 https://www.aclweb.org/anthology/I17-1099/..

3 https://metatext.io/datasets/goemotions.

4 https://github.com/SenticNet/MELD.

5 https://www.digikala.com/.

6 http://alt.qcri.org/semeval2017/task4.

- *XED*[7]: the XED dataset offers fine-grained multilingual emotion records with 25k Finnish and 30k English sentences, annotated for various emotions in multiple languages, including Plutchik's core emotions and a "Neutral" label (Öhman et al. 2020).
- *EMOBANK*[8]: EMOBANK contains over 10,000 sentences annotated using the VAD (Valence-Arousal-Dominance) model and Ekman's basic emotion model. It includes data from sources like news headlines, blogs, essays, newspapers, letters, fiction, and travel guides, suitable for dual representational analysis (Buechel and Hahn 2017).
- *Smile*[9]: the Smile dataset comprises 3085 tweets annotated with discrete emotion labels of sadness, happiness, disgust, surprise, and anger, collected from the British Museum Twitter account (Wang et al. 2016).

4.2 Emotion models

This subsection explains popular emotion models in detail.

Basic emotional models: An organism evolved basic emotions to assist with basic life tasks; for example, fear and anger help an organism flee for safety or defend itself. It is possible to combine basic emotions to form complex emotions (Ekman 1992). Many psychologists agree that basic emotions exist, but there is no consensus regarding the precise number of emotions. Anger, fear, sadness, disgust, surprise, anticipation, and joy are the eight primary emotions identified by Plutchik. The seven basic emotions of Ekman were fear, anger, joy, sadness, contempt, disgust and surprise. In his later work, he changed this to six basic emotions, which are as follows: fear, anger, joy, sadness, disgust and surprise.

Dimensionality models: An initial proposal for multiple dimensions of emotions was made by Wundt (1897) followed by Schlosberg (1954), who proposed three independent dimensions of emotions: pleasant-unpleasant, tension-relaxation, and excitation-calming. A later study by Ekman (1957) found overlap between these dimensions and suggested an active-passive scale to capture the differences between emotions and a pleasant-unpleasant scale.

4.3 Machine learning-based approaches

An interesting study by Nasir et al. (2020) suggested an ML-based emotion prediction system. Researchers found that Term Frequency-Inverse Document Frequency (TF-IDF) with a 3-gram size was preferred for data preprocessing methods, such as tokenization on the ISEAR as a benchmark used for the system's assessment. The study by Halim et al. (2020) identified emotions in emails using supervised ML. In this research, three feature selection approaches include Principal Component Analysis (PCA), Information Gain (IG), and Mutual Information (MI). Artificial Neural Networks (ANNs), Random Forest (RF), and Support Vector Machine (SVM) classifiers were also used. Meanwhile, in a study by Sridhar et al. (2020), researchers used Word2Vec based on skip-gram architecture for feature extraction and K-earest eighbor (KNN), Extra Trees Classifier (ETC), and Multi-Layer Perceptron (MLP) architectures for classification. Chowanda et al. (2021)'s work identified emotions from the social media conversation through Naïve Bayes (NB), Generalized

[7] https://metatext.io/datasets/xed.

[8] https://github.com/JULIELab/EmoBank.

[9] https://figshare.com/articles/smile_annotations_final_csv/3187909.

Linear Model (GLM), Fast-Large Margin (FLM), Decision Tree (DT), SVM, RF, and ANNs on AffectiveTweets Dataset (Bravo-Marquez et al. 2019). N-grams, SentiStrength (Bravo-Marquez et al. 2019) were used as features.

The emotion detection by Kaminska et al. (2021) followed the SemEval-2018 project (Mohammad 2018). Each raw tweet was represented by embeddings: DeepMoji[10], Word-2Vec[11], the Universal Sentence Encoder (USE) (Cer et al. 2018), BERT, Sentence-BERT (SBERT) (Reimers and Gurevych 2019), and finally the Twitter-roBERTa-base (Barbieri et al. 2020). These vectors were fed into weighted KNN as a standalone or ensemble model for classification. Sadeghi et al. (2021) worked on the corpus's syntactic, semantic, and pragmatic aspects as well as the cognitive and linguistic features. The Word2Vec algorithm and so-called features were used for classification through NB, DT, and SVM, aiming to retain the semantic relations in the text.

Anzum and Gavrilova (2023) captured users' emotional states using an advanced Genetic Algorithm (GA) technique to construct the input representation. This representation includes stylistic, sentiment, and linguistic features extracted from tweets. The researchers introduced a voting ensemble classifier with weights optimized by the GA to enhance detection accuracy. The research by Gupta et al. (2023) detected mood disorders like depression using tweets and emoticons. The SentiEmoDD dataset was introduced as a benchmark for depression detection, encompassing both text and emoji modalities.

Researchers (Tahir et al. 2023) investigated detecting emotions in translated text data across multiple languages. The study demonstrates that emotions remain preserved to some extent after translation, with the highest accuracy achieved when translating from English to French. The framework utilizes TF-IDF features and employs PCA and Discriminant Analysis for effective emotion detection in translated text data. The study (Uymaz and Metin 2023) applies three emotion enrichment models to a Turkish dataset using two semantic embeddings (Word2Vec and GloVe) and a contextual embedding (BERT). The experiments involve in-category/opposite-category cosine similarity based on eight emotion categories and classification with sequential minimal optimization, Logistic Regression (LR), and MLP. Table 2 covers previous research using ML to detect emotions from the text.

4.4 Deep learning-based approaches

The study by Al-Omari et al. (2020) employed a fully connected neural network architecture and a Bidirectional-LSTM (BiLSTM) neural network to produce much superior performance. Lu et al. (2020) exerted BiGRU followed by a Softmax layer for emotion classification. An iteration mechanism utilized the loss to improve the prediction of emotions iteratively. Khalil et al. (2021) developed a DL-based emotion classification system for Arabic tweets. The Aravec word embeddings' model (Rostami et al. 2021) generated word vectors for each word in the dataset.

In another interesting study, Vijayvergia and Kumar (2021) exploited the strengths of shallow models while ignoring their weaknesses to detect emotions on Twitter data, using two models of LSTM with varying layers. These models were constructed independently to identify emotions. Later, Vitiugin and Barnabo (2021) used DistilBert and

[10] https://deepmoji.mit.edu/

[11] https://radimrehurek.com/gensim/models/word2vec.html.

Table 2 Relevant studies for emotion detection using machine learning

Study	Dataset(s)	Techniques	Results	Limitations and future works
Singh et al. (2019)	ISEAR	SVM	The SVM with two-stage technique improved the rate of emotion recognition by 34.45%	Developing a knowledge base with regards to the relationships between the features.
Nasir et al. (2020)	ISEAR	Multinomial Naive Bayes (MNB), SVM, KNN, DT	(Average ROC score) 87.83%	Adding various features or rule-based approaches to the model.
Halim et al. (2020)	Enron8715, Emotion616, Emotion135106	ANN, RF, SVM	67% average accuracy on three datasets	Using this functionality to interpret the genuine emotion of their clients' questions when answering via email.
Sridhar et al. (2020)	Twitter	KNN, ETC, MLP	(Accuracy) ETC 95%	To include other language models to represent text data.
Chowanda et al. (2021)	AffectiveTweets (Bravo-Marquez et al. 2019)	NB, GLM, FLM, DT, SVM, RF, ANN	GLM Achieved highest accuracy, 90.2%	A local language may be gathered and used to train algorithms discussed in the research. DL algorithms such as LSTM and Convolutional Neural Network (CNN) to be investigated further.
Kaminska et al. (2021)	Twitter	wKNN	0.635 Pearson Correlation Coefficient (PCC)	Including exclamation marks and lemmatization of words, and adding to the weight of hashtags and emojies.
Sadeghi et al. (2021)	Bijan Khan's Corpus	NB, DT and SVM	(Accuracy) SVM 97%	Consideration of statistics and cognitive features and expansion of textual material in Persian.
Anzum and Gavrilova (2023)	Twitter	Random Forest, XGBoost, and SVM	TF-IDF + Stylistic + Sentiment features: (Accuracy) Random Forest 90%, XGBoost 90% and SVM 89%	Expolation of categorical and multi-dimensional emotion models.
Gupta et al. (2023)	SentiEmoDD	CNN, RNN, and GRU	(Accuracy) SentiEmoDD1 87.69%, SentiEmoDD2 86.99%	Including more complex sentence structures, detection of different levels of depression.

Table 2 (continued)

Study	Dataset(s)	Techniques	Results	Limitations and future works
Tahir et al. (2023)	Manually created dataset	SVM and PCA	(Accuracy) on English 92.75%	Applying deep learning and extracting distinct features influencing emotion detection in translated texts.
Uymaz and Metin (2023)	TEI, TEC and TREMO	Linear Logistic Regression, Sequential Minimal Optimization Algorithm and MLP	(Highest accuracy) MLP + BERT 64.14%	Designation of multi-modal architectures, using BERT variants, and applying enrichment to different levels of text units.

Language-Agnostic Sentence Representations (LASER) (Artetxe and Schwenk 2019) for feature extraction independently. Furthermore, the temporal orientation and sentiment classification were investigated by Ghosh et al. (2022) by analyzing the victims' emotional states. In this study, features from multiple tasks are shared through a multi-layer cascaded attentive network to maximize the effectiveness of multi-task learning. Tu et al. (2022) introduced an exploration and exploitation mechanism through a Multi-task Graph Neural Network (MGNN). A weighting scheme balanced exploration and exploitation by filtering out the main contextual features in different tasks.

Rei and Mladenić (2023) employed a semi-supervised technique that utilizes textual entailment classification for emotion-specific weak labeling. Additionally, the researchers evaluated the model's performance in zero- and few-shot transfer scenarios using benchmark datasets. Another research by Bashir et al. (2023) focuses on emotion detection in a low-resource language, Urdu, by introducing the publicly available UNED corpus. Furthermore, Wang et al. (2023) introduced DeepEmotionNet, a deep learning-based emotion detector that combines various features and linguistic knowledge to improve emotion detection performance. The research by Lee et al. (2023) combined the detection of self-reported emotions with synchronization to social emotions identified by human annotators, and the proposed model achieved robust performance across different contexts. Table 3 summarizes previous DL research for text-based emotion detection.

4.5 Hybrid approaches

Almanie et al. (2018) presented a real-time picture of people's emotions in several Saudi cities via a website by text mining and emojis of tweets. A dataset of over 4000 emotional terms was created to classify tweets (happy, sad, angry, scared, surprised). Additionally, the website displayed the trending hashtags linked with each city and other mood information. A technique suggested by Seal et al. (2020) detects emotions by searching emotional terms in a database of emotional keywords. In this work, researchers recognized emotions from phrases containing emotional words. Krommyda et al. (2020) has addressed two main issues with annotated datasets and the multidimensional concept of emotions. After preprocessing tweets, the annotation of the dataset was examined against the emojis; if they were present in the model categories, the tweet was classified accordingly; otherwise, emojis were replaced by the word explaining it.

5 Personality detection

Personality is a collection of cognitions, behaviors, and emotions formed over time by environmental and biological factors[12] (Corr and Matthews 2009). While no generally accepted personality definition exists, most theories shifted their focus on motivation and psychological interactions with the environment (Sadock et al. 2017). Behavioral approaches define personality in terms of habits and learning. Most theories believe that personalities are relatively stable (Corr and Matthews 2009). Psychology of personality, or personality psychology, tries to elaborate on the differences in behavior by understanding the tendencies that

[12] https://www.theatlantic.com/magazine/archive/2022/03/how-to-change-your-personality-happiness/621306/.

Table 3 Relevant studies for emotion detection using deep learning

Study	Dataset(s)	Techniques	Results	Limitations and future works
Al-Omari et al. (2020)	Task 3: EmoContext of Semeval-2019	BiLSTM	F1-Score 0.74 (F1-Score)	To use other DL architectures.
Lu et al. (2020)	IEMOCAP and MELD	Iterative network, CNN, cLSTM, cLSTM+CRF, DialogueRNN and DialogueGCN	(Weighted F1-Score) MELD: 62.28, IEMOCAP: 66.75	Evaluating other models of language for context representation.
Khalil et al. (2021)	Twitter	BiLSTM, SVM, RF, fully connected deep NN	(Accuracy) BiLSTM 49.8%	Reducing ambiguity caused by stemming nouns and pluralizing words.
Vijayvergia and Kumar (2021)	Twitter	LSTM	(Accuracy) 86.16%	Applying the model in online web and mobile applications.
Vitiugin and Barnabo (2021)	EmoEvalEs @IberLEF2021	Combo LASER	(Accuracy) 67.54%	Over-representation of specific classes in train and test.
Rei and Mladenić (2023)	Tales, GoEmotions, ISEAR and EmoINT	Language models (RoBERTa)	(Macro F1-Score): Zero shot transsfer: Tales 0.83, ISEAR 0.76, EmoINT 0.82. Few shot transfer: Tales 0.82, ISEAR 0.62, EmoINT 0.72	Removing noisy samples and robust model training from noisy data.
Bashir et al. (2023)	Urdu Nastalique Emotion Dataset (UNED)	MLP, LSTM and BiLSTM	(Accuracy) Word2Vec and Sentence-based dataset: MLP 81%, LSTM 85%, BiLSTM 85.3%. Word2Vec + Paragraph-based dataset: MLP 12%, LSTM 50%, BiLSTM 50%	Using semi-supervised approaches.
Wang et al. (2023)	DailyDialogue, EmotionLine and IEMOCAP	DeepEmotionNet incorporating CNN	(Accuracy) DailyDialogue 79.9%, EmotionLine 78.5%	Using multimodal datasets and extending the proposed model to downstream tasks.
Lee et al. (2023)	Affective Text, Emotion Cause, Emotion Intensities 2017 in Tweets, GoEmotions and seven other datasets	RoBERTa Transfer learning and finetunning	(Weighted F1-Score) highest 0.98 on Emotion Cause	Limited generalizability of the model, using other social media datsets, and ensemble learning.

underlie them. The study of personality has been approached from many angles, including biological, learning cognitive, and trait-based theories, along with psycho-dynamic and humanistic approaches.

5.1 Datasets

The datasets used in text-based personality detection are presented in this subsection as follows:

- **essays**: 2468 anonymous essays in English annotated in Big Five scales (Pennebaker and King 1999).
- **myPersonality**[13]: 250 anonymous Facebook profiles scored in the Big Five by asking users to answer questions. The dataset approximately has 9900 records.
- **Pandora**: it consists of 17 million comments, personality, and demographic labels for over 10K Reddit users, including 16K with Big Five labels. It is the first Reddit dataset to include Big 5 traits, as well as other personality models such as MBTI (Gjurković et al. 2021).
- **Kaggle**[14]: consists of 8675 rows, each representing one person. This dataset is created using cognitive functions from Carl Jung and finally, MBTI personality tags derived from Jungian Typology (Jung 1976).
- **Youtube**: the dataset consists of personality scores for 404 YouTube vloggers. Amazon Mechanical Turk and the Ten-Item Personality Inventory (TIPI) were used to annotate recordings of people talking on webcams about various topics. Youtube datasets include video, speech, and transcripts to text (Biel and Gatica-Perez 2012; Biel et al. 2013).
- **FriendPersona**[15]: it is developed using Friends TV Show Dataset[16] (Chen and Choi 2016) and 711 conversations extracted from it.
- **Conversation Dataset**: the dataset contains extracts of daily-life conversations gathered from 96 subjects wearing an Electronically Activated Recorder (EAR). A total of 118, 259 words and 15, 269 conversation utterances are included (Mehl et al. 2006).
- **TWISTY**: it contains 18,168 authors, annotated with MBTI personality labels and gender for six languages (Dutch, German, French, Italian, Portuguese, and Spanish) (Verhoeven et al. 2016).
- **Personae**: it comprises 145 BA-level students' essays, each about 1400 words long, on a documentary about Artificial Life (Luyckx and Daelemans 2008).

5.2 Personality models

Some popular personality models are explained in this subsection along with their key features.

13 https://sites.google.com/michalkosinski.com/mypersonality.
14 https://www.kaggle.com/datasnaek/mbti-type/.
15 https://github.com/emorynlp/personality-detection.
16 https://github.com/emorynlp/character-mining.

Big Five: Also known as the Big Five, define this paradigm: Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism, referred to as OCEAN (John and Srivastava 1999).

DISC (Sugerman 2009): DISC is another simple yet powerful model that is available and describes four dimensions of personality which are, Dominance, Influence, Steadiness, and Consciousness, respectively. Each individual can reflect a combination of mentioned dimensions. Neither of the dimensions is superior to the others.

Mayer Briggs Type Indicator (MBTI) (Yang et al. 2016): The MBTI's purpose is to help people better understand and investigate their personality, including their interests, capabilities, weaknesses, potential job choices, and compatibility with others. As a result of the MBTI, respondents' preferences are divided into four opposite pairs, also called Dichotomies. Dichotomies demonstrate two mutually exclusive groups, typically denoted with abbreviations: Extraversion (E) vs. Introversion (I), Sensing (S) vs. Intuition (N), Thinking (T) vs. Feeling (F), and Judging (J) vs. Perceiving (P). These patterns of preferences categorize a person into 16 personality types, with a combination of the four dichotomies, e.g., ISFJ.

PEN model: By linking criminal behaviors with socialization processes (Ruch et al. 2018), the PEN model has been widely used in criminological research. The model includes three broad personality factors: Extraversion, Neuroticism, and Psychoticism (Mohammadi and Vinciarelli 2015). An extravert's arousal reflects their interest in social situations and interactions. Neuroticism is thought to reflect emotional stability and is influenced by the sympathetic nervous system. In contrast, psychoticism strongly correlates with psychotic episodes and represents aggression, interpersonal hostility, or individuality (Lynam and Miller 2019).

5.3 Machine learning-based approaches

In a study by Cahyani and Faishal (2020), SVM and Multinominal Naive Bayes (MNB) were used to analyze Twitter to classify Big Five traits for various data splits. Jayaratne and Jayatilleke (2020) developed a regression model to infer the values of HEXACO traits from the text. Khan et al. (2020) exerted a re-sampling technique (Kaur and Gosain 2018) to deal with the skewness of Kaggle dataset (Bharadwaj et al. 2018). Afterward, Kumar et al. (2020) extracted Social Network Analysis (SNA) and Linguistic Inquiry and Word Count (LIWC) features using the NLTK library for personality prediction using a manually created dataset from Twitter.

The study by Moraes et al. (2020) produced word vectors using the TF-IDF weighting approach. Setiawan and Wafi (2020) used the NB classifier approach to identify Twitter users' personality types. Another study by Usher and Dondio (2020) used spaCy[17] embeddings to train a supervised learner classifier. Regarding MBTI, Choong and Varathan (2021) approached the Judging-Perceiving dichotomous using char-level TF-IDF, word-level TF-IDF, and LIWC features.

In a later study, Feng and Liu (2021) detected personality on Weibo users' data using language lexicon. Recently, Maharani and Effendy (2022) classified the personality of Twitter users who filled the questionnaire of the Big Five using three sets of features of emotion, sentiment, and social. Sagadevan et al. (2022) developed Seed-guided Latent

[17] https://spacy.io/.

Dirichlet Allocation (SLDA). They incorporated a small set of seed words into the unsupervised SLDA to produce topics associated with PEN model traits. Safari and Chalechale (2022) used pre-trained language models for feature extraction and a multipartite graph for key phrase extraction from the dataset.

Most recently, Kumar et al. (2023) introduced the Kernel-Based Soft-Voting Ensemble Model. The researchers first evaluated different SVM kernels, including radial basis function (RBF), linear, sigmoidal, and polynomial kernels, to determine the most suitable seed for personality detection. Next, they combined the predictions of multiple SVM kernels to improve the accuracy of personality detection. Table 4 summarizes the above-mentioned ML-based personality detection approaches.

5.4 Deep learning-based approaches

Mehta et al. (2020) incorporated BERT, Albert, and Roberta for personality prediction and traditional psycholinguistic features. They used essays (Pennebaker and King 1999) and Kaggle dataset (Roberts et al. 2007). For the classification, they utilized SVM, LR, and an MLP. A recent study by Arijanto et al. (2021) extracted features from the multilingual dataset (Celli and Lepri 2018), including LIWC, N-gram, word embeddings, and Analysis of Variance (ANOVA) along with data augmentation approaches. Ahmad et al. (2021) proposed a hybrid model of CNN and LSTM for MBTI personality detection.

Furthermore, El-Demerdash et al. (2022) used fusion at the data and classifier levels. The researchers employed Universal Language Model Fine-Tuning (ULMFIT), Embeddings from Language Model (ELMo), and BERT. In an interesting study, Xue et al. (2021) used a word-level semantic presentation as vectors fed into a fully connected layer to extract higher-order features. In newer studies, Kazemeini et al. (2021) provided rich semantic embeddings for psychological statements. Bi-LSTM with max-pooling outperforms CLS and average BERT methods. In the same year, Ren et al. (2021) applied the BERT model to extract sentence-level semantics from texts.

Kosan et al. (2022) proposed a personality detection system composed of word pool and FastText vectorization methods by Bojanowski et al. (2017). Li et al. (2022) proposed a new framework for multi-task learning using sigmoid weighted linear gates between personality and emotion detection. Later, Yan et al. (2022) investigated the problem of joint cascade prediction and personality recognition utilizing a multi-task GNN framework. The research by Sirasapalli and Malla (2023) proposed a new personality prediction model that utilizes data source mapping and fusion techniques. The proposed methodology achieves superior results by combining data from multiple sources, including mapping the MBTI personality model to the Big Five traits and the fusion of essays and myPersonality datasets. In another study, Johnson and Murty (2023) leveraged an aspect-aware enhanced psycholinguistic knowledge graph.

Afterward, Yang et al. (2023) introduced D-DGCN, a dynamic deep graph convolutional network, to predict personality traits from online posts. The model effectively captured the connections between posts by employing a dynamic multi-hop structure and a learn-to-connect approach, combined with a DGCN module. Teli and Chachoo (2023) employed multi-label semi-supervised learning algorithms to classify personalities in the YouTube Personality dataset. The study used several supervised algorithms, including neural networks, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), LSTM, Bi-LSTM, GRU, and Bi-GRU.

Table 4 Selected studies for personality trait classification using machine learning approach

Study	Dataset(s)	Techniques	Results	Limitations and future works
Cahyani and Faishal (2020)	Twitter	SVM, MNB	(Accuracy) 82%	Lowering the dataset's boundaries; adding student case studies.
Jayaratne and Jayatilleke (2020)	PredictiveHire FirstInterview	Random Forest	(TF-IDF and LDA) achieved the best accuracy in terms of average correlation	Only semantic characteristics were employed. Examining the algorithm's phrase and topic patterns connected with each characteristic.
Khan et al. (2020)	Kaggle	KNN, DT, RF, MLP, LR, SVM, XGBoost, MNB and SGD	(Accuracy) XGBoost on I/E-S/N 99% and on T/F-J/P 95%	Including other DL architectures and language models for feature extraction.
Kumar et al. (2020)	myPersonality	XGBoost	(Accuracy) 81.23%	Using profile statuses on Twitter and mutual connection information of users.
Moraes et al. (2020)	Kaggle and essays	SVM, DT, KNN, NB	(Average accuracy) Kaggle: SVM 81.64%, essays: DT 85.82%	Using local datasets and comprehending local languages and proposing semantic approach.
Setiawan and Wafi (2020)	Twitter	NB	(Accuracy) 76.19%	Expanding the datasets and incorporating additional preprocessing stages to improve detection accuracy.
Usher and Dondio (2020)	Twitter	NB, SVM, MLP	SVM Achieved the highest accuracy	Utilizing the Facebook myPersonality dataset to train a CNN on future user personality descriptors ratings.
Choong and Varathan (2021)	Kaggle	Logistic regression, Complement Naive Bayes (CNB), SVM, RF, LightGBM	(F1-Macro Score) 81%	Developing a validated corpus with a more accurate depiction of the MBTI distribution.
Feng and Liu (2021)	Weibo texts	SVM, RF, and NB	(Average accuracy) RF 64.1%	Consideration of emojies in text to develop lexicon for personality detection.

Table 4 (continued)

Study	Dataset(s)	Techniques	Results	Limitations and future works
Maharani and Effendy (2022)	Twitter	NB, SVM and KNN	(Accuracy) SVM with 59.45%	Including the frequency of words, their connections, and user profiles as features.
Kumar et al. (2023)	Kaggle MBTI and Manual Dataset	SVM and KBSVE	Averag accuracy on Kaggle, Soft voting: 85.48%	Multimodal personality detection & employing intrepretable deep learning.

The study (Kosan et al. 2023) found that the Bidirectional Encoder Representations from the Transformers vectorization method and the Stemming preprocessing step are highly successful for personality detection from the Turkish dataset. The proposed approach by Dutta et al. (2023) uses a Semi-Supervised Deep Embedded Clustering (Semi-supervised DEC) model to extract personality features, learn feature representations, and cluster assignments simultaneously. Table 5 summarizes a selection of studies discussed for personality classification using DL.

5.5 Hybrid approaches

Ren et al. (2021) used BERT to produce sentence-level embeddings for text semantic extraction. For text sentiment analysis, a sentiment dictionary was also used to take sentiment information into account. Finally, the researchers created an automatic personality detection model by feeding the neural network the emotional and semantic data. In a hybrid framework, Taghvaei et al. (2021) combined different Fuzzy Neural Networks (FNNs) classifiers with Deep Neural Networks (DNNs) classifiers in a proposed two-stage decision fusion scheme. FNN and DNN were trained using a unique subset of features obtained from a Feature Extractor (FE) module. Later, Kerz et al. (2022) demonstrated how pre-trained transformers could perform better when using hybrid models incorporating these features, even when the latter is based on a larger model (BERT-large). The researchers also demonstrated how various methods for using pre-trained language representations from the transformers affect the model's functionality.

6 Lessons learned

Despite the extensive research conducted in sentiment/emotion and personality analysis and recognition in text, persistent challenges warrant further investigation. This section delves into some of these issues and presents several potential solutions for future research in the field. To begin with, detecting emotions and personality traits in the text is complex due to the intricacies of human expression, metaphorical language, and context dependency. Largely annotated datasets and establishing local expression dictionaries are crucial to address this. Techniques like text data augmentation, leveraging NLPaug and Texgenie libraries, and audio transcriptions can help alleviate imbalanced datasets and enhance classification models.

On the other hand, deep learning approaches often neglect pre-trained word embeddings, but utilizing transformers like Google's BERT can improve text vectorization and contextual understanding. Moreover, employing language models at various linguistic levels can capture richer meanings, while dropouts and regularization methods prevent over-fitting or under-fitting. Summarizing text using tools like SpaCy or Sumy can extract relevant information effectively. In Sentic Computing, SenticNet presents a multidisciplinary framework to tackle ML issues, bridging the gap between statistical NLP, linguistics, affective computing, commonsense reasoning, and semiotics. Furthermore, by understanding natural language holistically, Sentic Computing addresses sub-problems in extracting meaning from text.

Meanwhile, emotionally intelligent chatbots aim to create natural interactions between people and machines, enhancing services like customer support and personal assistance. Moreover, personality computing has seen significant progress, particularly in automatic

Table 5 Selected studies for personality detection using deep learning

Study	Dataset(s)	Techniques	Results	Limitations and future works
Mehta et al. (2020)	essays and Kaggle	MLP and SVM	(Highest accuracy) BERT-large + MLP: Kaggle 77.1%	Employing datasets with continuous personality trait scores.
Ahmad et al. (2021)	Kaggle	CNN and LSTM	(Accuracy) 86%	Expanding the dataset, using GloVe and Word2Vec embeddings, applying ensemble methods.
Arijanto et al. (2021)	Twitter	BERT, CNN, SVM, BERT-LR and BERT-SVM	(Accuracy) BERT-LR 60%	Expanding the dataset or employing a semi-supervised approach to collect larger dataset.
El-Demerdash et al. (2022)	essays and myPersonality	ULMFIT, ELMo, BERT	(Highest accuracy) Data Fusion myPersonality: Proposed method 73.91%	Including subjectivity and notion terms of sentiment, emotion, and opinions in the model.
Sirasapalli and Malla (2023)	Twitter MBTI, essays, and myPersonality	Feedforward neural network + data fusion	(Highest accuracy) MBTI + essays + myPersonality: 75.69%	Using other pretrained language models and addition of sentiment and emotion information into generated data.
Xue et al. (2021)	essays and Youtube	SEPRNN	(Highest accuracy) Youtube dataset 70.73%	To focus on other personality models, e.g., HEXACO and DSM-5.
Kosan et al. (2022)	Twitter	Bi-LSTM, LSTM	BiLSTM performed better	Inclusion of a hybrid model from multiple datasets and development of Turkish dataset for personality types.
Johnson and Murty (2023)	Essays and myPersonality	BERT + NLP + Hidden knowledge-based personality detection	(Highest accuracy) myPersonality 77.17%	Identification of the relationship between the five personality traits in generated context.
Yang et al. (2023)	Kaggle and Pandora	Dynamic Deep Graph Convolutional Network	(Highest Macro F1-Score) Kaggle 70.21%	Developing personality-related pre-training tasks.
Teli and Chachoo (2023)	Youtube personality dataset	CNN, RNN, LSTM, Bi-LSTM, GRU, Bi-GRU	(Highest accuracy) RNN 70.5%	Using more datasets for models' robustness, and using customized deep learning.

Table 5 (continued)

Study	Dataset(s)	Techniques	Results	Limitations and future works
Kosan et al. (2023)	Manually created Turkish dataset	RNN, GRU, LSTM, and 1D Convolutional LSTM	(Lowest RMSE) Bi-GRU 0.2237, Bi-LSTM 0.2237	Employing hybrid approaches, different data preprocessing techniques, tokenization and multimodal datasets.
Dutta et al. (2023)	Kaggle Personality dataset	Semi-supervised deep embedding clustering	(Accuracy) 95.90%	Extending the proposed model to mental health monitoring automation.

personality recognition, which integrates user personality traits into computing systems. Personality-aware recommendation systems and personalized chatbots show how this research direction has improved user experiences and engagement. At the same time, emotion models face significant limitations due to cultural variations, challenging the idea of universal emotional classifications. In other words, expressions of emotions and the norms governing their display vary across cultures.

Language disparities play a significant role in the categorization of emotions. Some languages lack specific emotional terms found in others, and certain emotions have unique names in particular languages without direct English equivalents. Additionally, in some cultures, emotions may not be distinguished as explicitly as in English, and specific languages combine terms for what are considered primary emotions in English. Interestingly, some cultures may not even have a specific word for "emotion," suggesting that the universality of this concept is subject to cultural variation and interpretation.

Furthermore, personality models such as the Big Five and MBTI come with several limitations. Despite its significance in personality psychology, the Big Five needs to include observer attributions beyond broad dimensions and would benefit from an integrated model of personality. In contrast, the MBTI faces criticism for its accuracy in assessing personality, with doubts arising from the absence of continuous scoring criteria, impacting its validity. The MBTI's stability is also questioned due to test-retest evaluations, affecting its long-term reliability. Many personality questionnaires, including the MBTI, need more psychometric status, eroding confidence in their results. Transparency issues in self-reported surveys may also introduce biases to the data. Furthermore, the DISC assessment disregards cultural differences and requires more comprehensive task analysis while evaluating problem-solving and thinking skills.

Recent developments include ChatGPT, an innovative language model OpenAI developed, representing a breakthrough in NLP and AI. Powered by GPT-3.5 architecture, it can understand and generate human-like text, making it versatile for various applications. To overcome two main issues with earlier LSTM-based language models - the inability to value certain words more than others and the individual-sequential manner of input processing due to a fixed-size window moving through the input sequence -, ChatGPT utilizes transformers with an attention mechanism. Therefore, ChatGPT processes input data simultaneously and understands the context. It also considers human feedback in training to align outputs with user input, resulting in a language model with high language comprehension and contextual understanding.

7 Conclusion

Recent years have witnessed substantial advancements in understanding the empirical structure of emotional dispositions, including measurement, regulation, coping styles, and emotion recognition. Studies have explored the relationship between these dispositions and classical personality traits, providing some causal explanations. However, further research is required to elucidate these dispositions' underlying cognitive and motivational structures and the interplay between heritable traits and learning experiences in their development. Therefore, closer collaboration between personality and emotional psychology is essential to progress in these areas.

This paper presents a comprehensive overview of personality and emotion analysis and detection, focusing on NLP and text-based approaches. It encompasses various topics, such as text-based personality and emotion detection, emotional models, and critical datasets used in research. The paper examines the advantages and disadvantages of different text-based personality and emotion detection systems, reviewing state-of-the-art work, including methodologies, datasets, key contributions, and limitations. Finally, the paper emphasizes open issues and suggests future research directions.

These limitations underscore the importance of carefully interpreting and applying personality models in various contexts, emphasizing the continuous pursuit of research to enhance their effectiveness and validity. Overall, the evolution of emotion and personality detection in the text offers promising avenues for further advancements in natural language understanding and human-machine interactions.

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