A Comprehensive Review of Machine and Deep Learning for Personality Detection

Maryam Nadhim Rasoul
Faculty of Computer Science and Mathematics
University of Kufa
Najaf, Iraq
maryamn.alzubaydi@student.uokufa.edu.iq
Orcid.org/0009-0008-7129-4911

Salam Al-augby
Faculty of Computer Science and Mathematics
University of Kufa
Najaf, Iraq
salam.alaugby@uokufa.edu.iq

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Abstract: *Over the years, with the help of technology, it has become much easier to analyze data in general and, more specifically, personality. Behavioral analysis is a new trend, and discovering what people think and feel, among other things, helps boost many things, including recommendation systems, e-commerce, fraud detection, etc. This paper focuses on personality analysis using machine and deep learning with different datasets, focusing on computational approaches and setting aside psychological studies.*

Keywords: MBTI, machine learning, deep learning, Big-five, personality analysis

I. Introduction

Automated personality analysis has been a new interest for researchers in the last couple of years, especially for personality detection. Personality traits are a crucial part of determining our behavior, patterns, interactions with others, likes, dislikes, etc.[1]. Automatic personality prediction from data has many benefits: more empathic artificial intelligence (AI) assistants, job screening, and targeted marketing[2].

This paper reviews the latest trends and techniques in this emerging field. It focuses on deep learning models across the key modalities of text. The paper summarizes common approaches, architectures, and datasets and highlights benchmark results and state-of-the-art methods. A major topic that has emerged these days is the transition from machine learning to deep learning for personality analysis. The challenges in this field remain, despite the progress. Labeled training data is still limited, especially for personality types beyond the predominant Big Five model. The reliability of personality label assignments also remains an issue. The paper emphasizes the need for larger, more diverse datasets. It also discusses important considerations around ethics and fairness as personality detection is applied more broadly. Overall, this review provides a high-level overview of the field, synthesizing recent work and emerging trends. It serves as a useful reference for researchers looking to catch up on the state-of-the-art in deep learning-based personality detection. The paper highlights open challenges and promising directions to guide future work.

I. Litterature Review

This review paper provides an overview of recent advances in automatic personality detection using machine learning techniques, with a focus on deep learning models. The applications of personality detection are diverse, spanning personalized assistants, healthcare, job screening, and more. Researchers have explored detecting personality from text, audio, visual, and multimodal data. For text, linguistic features and word embeddings fed into neural networks work well. Multimodal approaches fusing audio, visual, and text achieve the best performance by complementing each modality. Deep learning has become the dominant technique, pushing benchmarks higher. However, more diverse labeled datasets are needed for models to generalize beyond common personality measures like the Big Five. Future work may focus on efficient multimodal fusion and improving model interpretability.[3]

The paper discusses the prediction of personality traits based on social media text. Various techniques such as questionnaires, semantic similarity, machine learning, and deep learning have been employed for this purpose. Studies have focused on predicting personality traits from social media data in different languages and regions, using methods like author profiling and semantic analysis. Machine learning algorithms and models like the Big Five have been utilized to predict personality traits accurately. The future trends in this field include implementing deeper convolutional neural network (CNN) machine learning models and improving algorithm accuracy. Overall, the research aims to enhance the understanding of user behavior through social media text analysis for personalized services and recommendations.[4]

II. BACKGROUND AND MOTIVATION

Personality analysis has become an important research area in recent years, with applications across many domains, including psychology, marketing, education, workforce management, and healthcare. Traditional methods rely on self-report questionnaires and expert interviews to assess personality traits and types. Even so, these techniques could show subjectivity, potential bias, and challenges in application on a large scale. The expanding use of big data and the constant advancement of machine learning techniques have significant importance in the design of data-driven computational models for purposes of automating personality assessment[5].

Recent studies have shown promise in using machine learning to predict personality from various digital footprints of behavior[6]. In particular, deep learning techniques have enabled high-dimensional modeling of language, audio, and visual cues for personality analysis. Some motivations and applications include:

- Recommender systems: Predicting the Big Five traits improve recommendation accuracy for movies, music, products, etc. [7].
- Healthcare: Deep learning models can link linguistic signals with depression symptoms and therapeutic outcomes [8].
- Human resources: Personality modeling helps optimize hiring selections, team composition, and turnover prediction [9].
- Marketing: Targeted ads and content based on computational personality analysis can improve user engagement [10].
- Conversational agents: Generative personality models allow more natural dialogue and empathy [11].

Overall, automated personality assessment through machine and deep learning has promising potential for many real-world applications. But it also raises important ethical considerations regarding transparency, privacy, and consent.

III. PERSONALITY REPRESENTATION

A key research challenge is computationally representing human personality traits and types. Most prior works are based on existing psychometric models

- Big Five: The five-factor model is widely used with dimensions of openness, conscientiousness, extraversion, agreeableness, and neuroticism. It provides a broad representation but lacks granularity [12].

The Big Five model represents personality along five dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism. There has been growing interest in leveraging machine learning to automatically predict these traits from digital records of human behavior. Earlier work focused on predicting personality from profile information and controlled linguistic inputs like essays [13]. With social media proliferation, recent research extracts features from large-scale unstructured digital footprints including tweets, posts, images, and metadata [14]. Prediction models have evolved from linear regressions to neural networks [15][16].

Prediction performance varies across traits and datasets. Extraversion exhibits the strongest signals in online behavior while openness and neuroticism remain challenging[17] [18]. Typical accuracies range from 60-80%, with ensemble and deep learning methods outperforming simpler approaches [19][20]. Feature engineering and selection are crucial for interpretability and generalization[16].

Key challenges include label quality issues in self-reported data, difficulty modeling contextual variations, and privacy concerns over extracting unfettered social media patterns [14]. Future work should explore explanatory models incorporating psychological theory to complement data-driven methods [15].

In summary, digital footprints present new opportunities for personality sensing alongside ethical risks. Holistic frameworks integrating psychological validity and rigorous computational methods will be critical for further progress. This review highlights promising directions and open issues as machine learning enters personality research.

- Myers-Briggs Type Indicator (MBTI): categorizes people into 16 distinct personality types based on four dichotomies. It has been criticized for poor scientific validity but remains popular in practice [21].

There has been a surge of research interest in automating MBTI prediction from various behavioral signals using machine learning and deep learning models.

Earlier works relied heavily on conventional machine learning models like support vector machine (SVM), random forests, and ensemble methods with handcrafted features. Performance was modest with accuracies around 60-70%. Recent focus has shifted to deep learning models like CNN, recurrent neural network (RNN), and Transformer networks which can implicitly learn robust feature representations[22]. State-of-the-art studies now report accuracies of 70-90% using neural approaches.

The Myers-Briggs Type Indicator (MBTI) approach has been widely used for personality classification in natural language processing research. Cerkez et al. (2021) proposed a novel loss function for multiclass MBTI classification which improved accuracy over baseline models. They used context-sensitive BERT embeddings [23]. Santos et al. (2021) also found that pre-trained transformers like BERT outperformed traditional word embedding methods for MBTI prediction [24].

Ontoum & Chan (2022) incorporated the Cross Industry Standard Process for Data Mining (CRISP-DM) methodology to guide the MBTI learning process but had limited success, with accuracies below 50% [25]. Ryan et al. (2023) handled class imbalance with Synthetic

Minority Over-sampling TEchnique (SMOTE) oversampling before applying machine learn algorithms, improving results [26].

Several papers compared machine learning algorithms. Pansare et al. (2022) found that extreme gradient boost (XGBoost) with count vectorization performed best [27]. Nisha et al. (2021) also saw XGBoost outperform other algorithms in tweets, using count vectorization [28].

Sang et al. (2022) predicted fictional character personalities using movie dialogues and a multi-view BERT model, avoiding privacy issues [29]. Mushtaq et al. (2020) combined questionnaires and forum data, finding that predicted MBTI types were often accurate except for the J/P dimension due to class imbalance [30]. Amir Hosseini & Kazemian (2020) used correlation and TF-IDF before optimizing an XGBoost classifier, improving some binary classification accuracies [31].

Finally, Abidin et al. (2020) added new features to the RF classification of MBTI types. Compared to other machine learning models, RF performed best overall for predicting personality from text [32].

Most works frame MBTI prediction as a multi-class classification. However recent models explore dichotomy-specific binary prediction and joint modeling with related attributes like personality and emotion. Model interpretation methods are also emerging, to explain predictions.

In summary, deep learning now dominates for MBTI prediction, achieving high accuracy if sufficient labeled data is available. Future directions include robustness across domains, integrating psychological knowledge, and increasing trust through explainability. More diverse multimodal datasets could also boost progress.

TABLE I. COMPARISON TABLE

Name	Method	Dataset	Accuracy	Pros	Cons
Cerkez et al. (2021) [23]	Novel loss function, context-sensitive BERT embeddings	MBTI forum posts	Improved over baseline	Better accuracy than baseline models handles imbalanced classes	Requires fine-tuning, computationally expensive
Santos et al. (2021) [24]	Pre-trained BERT transformer	MBTI9k, TwiSty	Outperformed traditional methods	Captures semantic relationships, high accuracy	Requires large dataset, computationally expensive
Ontoum & Chan (2022) [25]	Naive Bayes, SVM, RNN+BI-LSTM	MBTI forum posts	49.75% (RNN)	RNN handles sequences well	Overall low accuracy
Ryan et al. (2023) [26]	Word2Vec, machine learning models (LR, LSVC, etc), SMOTE	MBTI forum posts	83.37% (LR+SMOTE)	Handles imbalanced data, with good accuracy	Many models to fine-tune
Mushtaq et al. (2020) [30]	K-nearest-neighbour (KNN), XGBoost	MBTI forum posts	86.3%	Reasonable accuracy, intuitive steps	Limited tuning, may overfit
Amirhosseini & Kazemian (2020) [31]	XGBoost	MBTI forum posts	75.43%	Can optimize well, interpretable	Prone to overfitting

- HEXACO: This six-dimensional model extends the Big Five by separating emotionality into emotional stability vs anxiety and incorporating honesty-humility [33]. It has greater cross-cultural applicability.

These psychology-grounded models enable supervised learning with labeled data. However, recent studies also explore more data-driven personality embeddings using representation learning techniques:

- Word and sentence embeddings derived from language corpora to encode personality-relevant linguistic cues [1].
- Neural network encoding of audiovisual and textual features into personality embedding spaces.
- Graph neural networks that jointly learn personality representations and social network structures.

In general, existing psychometric models provide useful prior knowledge to guide representation learning. However data-driven techniques can complement them by accommodating greater flexibility, granularity, and contextual adaptation. Evaluating the trade-offs between theory-driven and data-driven representations remains an open research challenge.

IV. PREDICTION FROM LANGUAGE AND TEXT

A major approach for computational personality analysis is predicting traits from textual data using natural language processing and text mining. Recent studies have explored various techniques:

- Topic modeling through latent Dirichlet allocation (LDA) and Non-negative matrix factorization (NMF) to extract personality-relevant semantic and linguistic dimensions from the text.[34]
- Sentiment, emotion, and style analysis for modeling affect and social dynamics.[35]
- Linguistic Inquiry and Word Count (LIWC) based feature extraction of psycholinguistic processes [36].
- Word and sentence embeddings using Transformer models like BERT fine-tuned on personality text corpora [1].
- CNNs and RNNs for neural sequence encoding of short texts into personality embeddings.[37]
- Graph neural networks to jointly model text and social connections.[38]
- Multi-task frameworks combining personality, emotion, sarcasm, and intent detection [39].

- Semi-supervised models leveraging unlabeled data through consistency training.
- Data augmentation techniques to expand labeled training data.[40]

The latest deep learning approaches particularly enhance the contextual modeling of personality-relevant semantics and styles in text. But robustness to noisy social media language and integration of psychological knowledge remain open challenges. More work is needed in explainable predictions and balancing model complexity, data requirements, and overfitting.

V. Prediction from Audio and Visual Cues

In addition to textual signals, personality traits can also be predicted from audio and visual cues using speech, facial, and multimodal analysis:

- Audio processing to extract suprasegmental features including pitch, tone, pace, rhythm as well as sentiment [41].
- Computer vision techniques like facial emotion recognition, pose analysis, and micro-expression detection [42].
- Multimodal Transformer models to jointly encode text, audio, and video features.
- CNN-RNN architectures to model spatial visual information and temporal dynamics.
- Adversarial training and domain generalization techniques to improve robustness.
- Weakly supervised learning using transcript, caption, or incomplete labels to mitigate labeling costs.
- Knowledge transfer through pretraining on large labeled datasets followed by domain-specific finetuning.

The fusion of diverse multimodal signals enhances contextual personality modeling. However, training data access and labeling remain a key bottleneck. Emerging semi-supervised and weakly supervised techniques may help alleviate this. Overall, multimodal personality analysis is still a nascent research direction with much scope for innovation.

VI. Challenges and Opportunities

Despite promising progress, computational personality analysis continues to pose several research challenges:

- Limited labeled training data that captures sufficient within-person variation across contexts. Most datasets are small-scale and demographic-specific.
- Complex modeling of contextual variations, social dynamics, and within-person inconsistencies over time. Personality is multi-faceted.
- High-dimensional multimodal feature spaces require careful feature engineering and selection [39].
- Lack of model explainability and interpretability for linking predictions to behavioral evidence [36].
- Difficulty in evaluating predictions beyond self-report questionnaires which have inherent subjectivity [1].

VII. Conclusion

In summary, personality analysis with machine and deep learning is an emerging interdisciplinary field with many open research questions deserving contributions from both computational and psychological sciences.
Addressing these open issues can enable several impactful opportunities:

- Natural human-AI interaction by generating controllable personality-adaptive dialogue and behavior [43].
- Psychologically aware educational technologies that respond to student traits and emotional states [21].
- Early screening systems combining multimodal analytics and predictive diagnostics of mental health disorders.
- Demographic-inclusive personality recognition by learning from diverse unlabeled data.
- Ethical application in assistive technologies that enhance accessibility and psychological well-being [44].

Overall there remain many open research directions before the promises of computational personality sensing can be fully realized in responsible ways.

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