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A Review of Approaches for Identification of Apparent Personality Using Machine or Deep Learning Models

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Abstract: The automatic identification of personality has drawn a lot of interest recently and has been the subject of numerous studies using a variety of approaches, modalities, and strategies. A person's personality can be inferred from their facial expressions, voice samples, comments, and status on social media platforms, questionnaire based interviews, body language, or any other medical approach that can detect the pattern of feelings and behavior of an individual. In general, actual personality detection is a very broad and diverse theme. With the growth in user specific data and AI techniques, while working with various datasets for regression or classification, a variety of machine learning and deep learning techniques have become more common. Also, numerous writers have demonstrated through their experimental setups that non-linguistic clues like body posture and facial expressions, as well as language cues like speech and social media data may be used to study an individual's personality with a decent amount of accuracy. The primary focus of this study is on computational approaches based on machine learning and deep learning for the given job.

Keywords: *Apparent Personality Detection, Deep Learning, Machine Learning, Neural Networks.*

1. Introduction

The personality of an individual consists of one's behaviour, emotions, motivation, and characteristics of their thought patterns. Our personalities affect choices, desires, preferences, and decisions in our lives. The ability to automatically detect personality is an interesting and challenging task. It has many important practical applications too, like personal assistants, recommendation systems, specialized health care and counseling, forensics, job screening, political forecasting, and so on. Here we have surveyed recent work and datasets for the task of apparent personality detection and found that what people express on social media in the form of text, audio, or likes plays a significant role for the task and datasets are available based on social media data. Apart from that facial expressions during communication say a lot about the personality of an individual.

2. Review of Literature

In the field of psychology numerous personality traits were introduces but the most popular measure used in the literature on machine learning based automated personality detection [1] is Big-Five personality traits also called OCEAN. These Big-Five are as follows on which major classification is based on: Openness(O) refers to a sense of curiosity about others and the world. High score shows that the person is creative, imaginative and ready to try new things in life. Conscientiousness(C) describes a careful, detail-oriented nature. High score depict that the person is well organized in life. Extraversion (E) is a score of energy in social interactions. Person scoring Low here is reserved in nature. Agreeableness(A) describes Is the person helping, caring, trustworthy versus self centric and stubborn. Neuroticism(N) is a negative trait. Scoring high means the person is sensitive, insecure and nervous.

In his paper[2] Fabio Celli presented a system for personality recognition that exploits linguistic cues that does not need supervision for evaluation. He used Italian FriendsFeed dataset (sampled from a Social Network: FriendFeed) and adopted "Big Five" as personality traits. Fabio Valente et al. in the paper[3] introduces personality traits annotations on the AMI meeting corpus. The corpus comes from the large amounts of conversational data and the transcriptions that have been done over years with annotations that can allow general studies based on linguistic or paralinguistic information. Mean best accuracy around 64 was reported.

The apparent personality analysis again came into light when ChaLearn competition 2016[4] was announced with first impression dataset providing 10,000 labeled short videos to perform automatic apparent personality analysis. In the same year a residual learning framework Resnet[5] was introduced to ease the training of networks that are substantially deeper than those used previously. These residual networks are easier to optimize, and can gain accuracy from considerably increased depth. Cre- ation of customized neural network froms graph theory is inspired by the success of Resnet[5] that won computer vision competition based on image classification. Like we know a random graph contains node and links so here [6]

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customized neurons and ran- dom links were created using stochastic network generator. These specialized neural networks are the future of applications such as computer vision, natural language processing, recommender systems and variety of other applications. Comparative analysis of artificial neural network and XGBoost algorithm for image classification [7] shown the power of XGBoost that is also a member of the gradient boosting algorithm family along with random forest. XGBoost works as distributed algorithm and perform parallel computation to construct decision tree (weak learners) using all the cpu's during training that makes it fast and popular.

Table 1. Modalities and Architectures

Ref.	Modality	Architecture
[2]	Text	Natural Language Processing(NLP)
[3]	Audio, Video	Boosting Classifier
[4]	Image, Audio	Deep Bi-model Regression using CNN
[5]	Image	Deep Residual Network(Resnet)
[6]	Image	Randomly wired Neural Networks
[7]	Image	Neural Networks and XGBoost
[8]	Image	Convolutional Neural Networks
[9]	Image	Convolutional Neural Networks
[10]	Image	Convolutional Neural Networks
[11]	Image	Weakly Supervised Dual CNN
[12]	Image	Convolutional + Prototype Layer
[23]	Audio	CNN with the Gram matrix
[24]	Image	Resnet Transfer Learning
[13]	EEG signals	Support Vector Machine
[25]	Text	Customized Deep Neural Network
[14]	EEG signals	Convolutional Neural Networks
[15]	Image,Text	Fusion of CNN and PCA
[16]	Image	CNN with VGG19 Transfer Learning
[17]	Audio,Video	Fusion of CNN with VGG Transfer Learning
[18]	Image	Convolutional Neural Networks
[19]	Text	Deep Neural Networks for Regression
[20]	Text	CNN+LSTM
[21]	Text	Multi Task CNN model
[22]	Image	CNN + VGG Transfer Learning
[26]	Image	Convolutional Neural Networks
[27]	Text	Fuzzy and Deep Neural Network
[28]	Text	Naive bayes, SVM and XG boost
[29]	Text	NLP with Transfer learning
[30]	Image, Audio	CNN with Resnet Transfer Learning
[31]	Image	CNN with Transfer Learning
[32]	Image	CNN with Resnet Transfer Learning
[33]	Image	CNN with Transfer Learning
[34]	Image	CNN with Transfer Learning

There is a limitation to handmade neural network as we know there could be no Universal neural network for all kind of applications. Since design of neural network is problem specific and with evolution of problem area there arises the need of auto- matically evolution of neural network based on components and hyper parameters. Improvement possibilities of convolutional neural network has shown success in psychotic personality analysis[16], recognizing handwritten scratches including signatures for identification of personality features[8] and also fingerprint pattern identification[9] that seems to be a complex task.

H.y.suen et al. have introduces a Tensorflow based setup[10] for automatic personality recognition from asynchronous video interviews. They have focused on nonverbal features of such video interview clips of limited applicants and shown that semi supervised techniques can do fairly well when big data is not available for training . This setup gave them above 90 percent accuracy with limited data set applied for this experiment. Combination of two convolutional neural networks one for classification, other for regression may also be used to solve the problem of weakly-supervised data set [11]. Another Idea of prototypical part network [12] works on dissecting the image into several sub images and classify each sub image to make prediction and combining these set of prediction gives final classification. Experimentally prototype layer is introduced between convolutional and fully connected layer to achieve such human way of classification.

S.Vijaykumar et al. in their papers[13] studied machine learning techniques for emotion recognition from peripheral physiological signals. These EEG signals received from DEAP database were used for classification of emotions with the help of various machine learning techniques. Among all the techniques used the authors were satisfied with support vector machine even the classification accuracy varied between 10 to 87.5 percent. This yields an area of scope in order to achieve stable accuracy by other advanced deep learning techniques.

O.Sanyal et al. [14] has also worked on multi model approaches with temporal and spatial convolution for classification of personality on big five personality traits, from random EEG signals. Papers [15-18] suggested creating a framework having multi-model for the detection of personality as it is evident in the form of facial expression, gestures, signature, hand writing, reaction to interview questions, tweet-like-comments on social media and even speech signal analysis.

Sun, Jianshan, et al.[19] has introduced convolutional neural network based model for creation of digital twin based on individuals text and behavioral data recorded via social media this model has been deployed in manufacturing business to make it smart this work we comments text factor from user documents and neural network for equation for better semantic information for further analysis.

Salminen, Joni, et al.[20] presented data-driven generation of persona containing text description ,demographics, topical interest sports viewed content follower size etc. They created neural network with two Major Sub architectures, First the Single dimensional convolutional neural network for spatial structure of input text and second, LSTM network temporal correlation between words of input text. Li, Yang, et al.[21] suggested that every personality trait is associated with positive or negative emotion. Here task of detecting personality trait and emotion detection is performed using convolutional neural network and both tasks were coordinating and cooperating each other with the help of information flow links between two different models. Gupta, Shalini, et al.[22] created six layers deep convolutional neural network for classification of images into seven emotions based on facial expression however medium accuracy has motivated them to adopt pretrained model like VGG.

Similar work[35, 26, 27] has emphasized on the use of multimodal deep learning approaches on either a single or different modalities like text audio or images to achieve better accuracy or and further enhancement of the precision. [28] have analyzed sentiments using Twitter comments with the help of three different approaches of machine learning , naive bayes, support vector machine and xg boost with 78,80 and 85 percent accuracy respectively. They have used MBTI personality traits for the task instead of big5.

[29] have made classification of personality based on text using two datasets i.e. Facebook posts and ESSAY with approximately 72 and 60 percent accuracy. They have used Natural language processing with transfer learning for the task. [30] presented a multiple modality based model where face images and audio were extracted from videos and they have trained this bi-model with transfer learning and achieved 91.43 percent accuracy.

[31] have used facial action units like raising eyebrows or lips movement and established a link between these facial action units and emotions which leads to personality assessment. They have used three transfer learning models VGG16, Resnet and AlexNet from which Resnet gave maximum accuracy i.e. above 90 percent. Similar work was done by [32] using facial images of

Table 2. Comparison of dataset, accuracy and Keypoints

Ref.	Dataset	Accuracy	Key-Points
[1]	Celebrity images generated from FaceGen software	90	Holistic facial representation
[2]	FriendFeed Social media Network	63.1	Correlation between linguistic fac- tors
[3]	AMI Meeting Corpus	0.64 mean Accuracy	Multiclass boosting algorithm
[5]	ImageNet 2012,CIFAR-10	Error 3.57	Resnet Architecture
[6]	ImageNet 2012	94.8	Random Wired Neural Network

[7]	Polsar(geospatial data)	92.08 max Accuracy	ANN and XGBOOST comparison on land classification images
[8]	Custom handwriting image dataset	98.03	Graphology
[9]	NIST Fingerprint dataset	92.9	Fingerprint pattern classification
[10]	Custom dataset of interview processing andself reported personality	above 90	Semi supervised deep learning model
[11]	Psycho flickr dataset	above 90	Map user liked images into personality traits
[12]	CUB-200-2011 birds dataset,Stanford cars dataset	above 84	Prototyping on image segments
[24]	Flickr 30 and COCO	above 80	Image personality captioning
[13]	DEAP(emotion analysis using physiological signals)	64.45	Peripheral physiological feature extraction
[25]	Twitter and Facebook using tweepy library	85	Manual annotations
[14]	Random EEG dataset	86.49	Independent component analysis
[15]	Imagenet	64.5	Locally pooled textual features within images
[16]	The salsa dataset, Personality in a non social context dataset	Max F1 Score 75.6	Motion features
[19]	Mypersonality dataset of Facebook users	Mean abs error 0.5-0.63	Aggregation of text and likes in input layer of DNN
[20]	Youtube analytics data, ESSAYs and Mypersonality	F1 Score 60	Text vector with persona info
[21]	ISEAR,TEC and personality	Max Avg 71.98	Information sharing between two DNN
[22]	Kaggle facial expression recognition challenge(FER 2013)	57	Modified CNN
[26]	Chicago face database	80	Multiple feature spaces
[27]	Personality dataset(Facebook)	78.62	Fusion of fuzzy and DNN
[28]	Kaggle(Twitter comments dataset annotated on MBTI traits)	Max 85	Naive baise,svm,xgboost
[29]	Facebook post, ESSAY	Max 72	NLP+transfer learning
[31]	MMA facial expression, extended cohn-kanade database	Max 90	Facial actions correlation with emotions
[34]	MyPersonality dataset	92	Transfer learning experiment

Chalearn first impression dataset with transfer learning and reported 81 percent accuracy after feature extraction. [33] has established correlation between facial key points and personality attributes and gave comparisons using four state of the art models including FaceNet and Resnet.[34] have emphasized on detecting leadership quality in a human by considering a particular personality trait named as conscientiousness. They have used Facebook images as temporal sequences and achieve 92 percent accuracy in a transfer learning based deep network.[36] have shown benchmarking of models on audio, video and audio-visual modalities using two datasets , CVPR and UDIVA and used big5 traits for assessment.

Table 3. Work on Chalearn First Impression dataset 2016 & 2017

Ref.	Accuracy	Key-Points
[4]	91.3 mean Accuracy	Bi-model(images and audio features)
[23]	90.61	Gram matrix of convoluted acoustic features
[17]	90.9	Multi-model fusion with transfer learning
[18]	65.86	Tailor made regression and classification network
[30]	91.43	Multiple modality with transfer learning
[32]	81	Transfer learning
[33]	92	Correlation between facial key points and personality attributes

Summary of studied approaches is given in Table 1 and Table 2. Table 1 gives an idea about various work done recently on various modalities based personality assessment architectures where as Table 2 depicts datasets and key-points for the task along with scores for relative comparisons.

Normalization and validation of dataset is important to avoid saturation and over fitting and various python/R libraries are available to ease the task. From the dataset social media statements, Audio, Facial cue's, scene or gesture streams may be extracted and handled separately for further training of separate deep neural networks.

3. Discussion

Datasets are available for automatic detection of personality in the form of images, audio, video, and text. These datasets were extracted from social media, streaming websites, and data challenges like Chalearn for which a separate Table 3 is shown. We cannot directly use them as they are not readily available in the form of the input layer requirements of a network. Also, not all are annotated on personality traits; some of them are labeled with human emotions like happiness, sadness, excitement etc. that surely have a correlation with personality traits. Many authors have used multiple datasets and architectures in their work to support each other in the form of boosting confidence in the task of classification, Authors have also found transfer learning very useful as they are able to predict primary features very efficiently with partially or fully pre trained models. As we know, that detection of personality is a complex task and people have tried it with what you say, how you say, face expressions, body gestures, brain signals, even handwriting and fingerprint data. Accuracy has been evaluated on diverse metrics, including mean accuracy and F1 score and many work have shown above 90 percent accuracy that may not be directly comparable. Overall, in the field of psychology the involvement of deep learning significantly plays its role in the judgment of apparent personality.

4. Conclusion

After the review of related literature and work, it is clear that the personality of a person can be analyzed using multiple modalities and their combination to create a multi-model framework. The area of machine and deep learning has been expanding rapidly and providing techniques suitable for such kind of problem. Recent work has shown that customized deep neural networks, state of the art networks with or without transfer learning may serve the ultimate goal of achieving accuracy and complexity demands. Various data challenges focused on machine and deep learning techniques have been providing not only the labeled dataset but also the state-of-the art networks that can be used to create a customized deep neural network for a specific application or problem.

Author contributions

Amit Garg: Conceptualization, Study of Methodology and Preparation of Paper. **Rakesh Rathi:** Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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