Review Article

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A Systematic Literature Review of Personality Trait Classification from Textual Content

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Abstract: The day-to-day use of digital devices with Internet access, such as tablets and smartphones, has increased exponentially in recent years and this has had a consequent effect on the usage of the Internet and social media networks. When using social networks, people share personal data that is broadcast between users, which provides useful information for organizations. This means that characterizing users through their social media activity is an emerging research area in the field of Natural Language Processing (NLP) and this paper will present a review of how personality can be detected using online content.

Approach

A systematic literature review identified 30 papers published between 2007 and 2019, while particular inclusion and exclusion criteria were used to select the most relevant articles.

Outcomes

This review describes a variety of challenges and trends, as well as providing ideas for the direction of future research. In addition, personality trait identification and techniques were classified into different types, including deep learning, machine learning (ML) and semi-supervised/hybrid.

Implications

This paper's outcomes will not only facilitate insight into the various personality types and models but will also provide knowledge about the relevant detection techniques.

Novelty

While prior studies have conducted literature reviews in the personality trait detection field, the systematic literature review in this paper provides specific answers to the proposed research questions. This is novel to this field

as this particular type of study has not been conducted before.

Keywords: Personality traits, machine learning, deep learning, personality recognition

1 Introduction

An individual's personality affects every aspect of his/her life and Majumder *et al.* [1] indicate that personality can not only predict and describe an individual behavior but also encompasses the way they think and feel, as well as influencing their motives, preferences, emotions and even health. Social networking sites including Facebook and Twitter have become an increasingly popular medium for individuals to share their ideas and emotions with each other, as well as being a forum to share opinions and sentiments about current or past news and events. The way that an individual present himself/herself online reflects their attitude, behavior and personality. Xue *et al.* [2] argue that there is a clear connection between a person's personality or temperament and the way that they behave online in the form of likes, tweets or comments.

The importance of personality recognition on social networks has been evidenced by researchers' recent attention to the development of automatic personality recognition systems. These applications have generally been based on a central philosophy of a number of well-known personality models, such as DiSC Assessment [3] the Myers-Briggs Type Indicator (MBTI) [4, 5] Big Five Factor Personality Model.

Further research is required to maximize the impact of automated personality detection, as this is still in its early stages [6]. This review will seek to provide an overview of the different types of personality models and detection techniques as well as outlining the challenges facing this field today.

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1.1 Research motivation

The motivation for this review is based on the following aspects:

- (1) Personality classification is still in the early stages of development and requires further investigation. As a challenging and complex issue, the investigation of additional directions for future research is essential in order to further enrich extant personality classification techniques.
- (2) After investigating the gradual research regarding the field of personality classification, the need of a systematic literature survey is observed. Hence, the present work is based on the systematic literature review.
- (3) This review has been motivated by the rapid advances in personality classification, so the researchers have identified, summarized and evaluated the relevant studies in this field.

1.2 The contribution of this review

This review has made three core contributions: (1) providing a discussion of personality and its associated models; (2) presenting an overview of the existing machine learning methods that are used for classifying personality traits and (3) investigating the types of deep learning techniques that can be used for personality trait classification.

1.3 Relationship to previous work

This section presents an overview of the previous relevant reviews that have been focused on the classification of personality traits.

A survey by [7] focuses on personality identification using social networks and considers recent trends. These scholars (*ibid.*) investigated the potential for using a social networking profile to predict a user's personality as such profiles provide a source of both textual and non-textual self-published information. Kaushal and Patwardhan [7] reviewed several studies that center on the topic of identifying personality types through online social networks, yet they did not systematically consider how diverse deep learning and machine learning techniques can be used for personality classification, which the present review aims to address. Furthermore, the existing survey did not conduct a quantitative comparison of different personality detection approaches. Lastly, Kaushal and Patwardhan's [7]

work did not perform a systematic literature review according to Keele [8] guidelines.

However, Vinciarelli and Mohammadi's paper [9] does survey these technologies and not only aims to provide robust knowledge about cutting edge techniques but also provides a theoretical model that underlies the three critical problems addressed by the literature. These problems are: automatic personality recognition, which infers the true personality of an individual from behavioral evidence; automatic personality perception, which is the inference of personality that other people attribute to an individual based on the person's observable behavior; and automatic personality synthesis, which generates artificial personalities from embodied agents. Moreover, this article considers potential areas for application, as well as emphasizing certain issues in the field that are yet to be resolved. However, Vinciarelli and Mohammadi's [9] paper could be considered outdated as new trends have since emerged in relation to deep learning and machine learning for automatic personality identification, which the current paper aims to address.

2 Review methodology

This review follows the methodology detailed below:

2.1 Survey protocol

This paper used a number of different electronic repositories to search related articles before applying relevant inclusion and exclusion criteria to filter the number of articles. The relevant works were then selected based on this study's research questions before an analysis was performed and reported.

2.2 Research Questions

This review addressed the following research questions:

RQ1: What is Personality Trait Classification and what are the Different Personality Models?

RQ2: What are the Different Studies Pertaining to Machine Learning Approaches for Personality Recognition?

RQ3: What are the Different Studies Pertaining to Deep Learning Approaches for Personality Recognition?

Table 1: Keywords for searching relevant papers

Machine Learning+ personality	Machine Learning+ personality traits	Machine learning+ personality models	Deep learning+ personality in text	Deep Learning+ per- sonality traits	Deep learning+ personality models
personality detection	online personality detection	personality identification	personality in social networks	Detection of personality traits	Online misinformation

2.3 Data Sources

Different digital libraries were used to identify pertinent research articles, including ACM Digital Library (www.acm.org/dl), Google Scholar (scholar.google.com.pk), IEEE Xplore (ieeexplore.ieee.org), Science Direct (www.sciencedirect.com) and Springer Link (link.springer.com). The next step involved the application of inclusion and exclusion criteria in order to select the articles that were most relevant to this paper.

2.4 The Inclusion and Exclusion principle

A systematic keyword-based search was conducted by posing different search queries in order to retrieve the most relevant research articles (see Table 1).

The inclusion and exclusion principle enabled the researchers to determine whether or not a study should be included. The inclusion principle (IP) regarding individual article is implemented in a sequence [8], described as follows:

- IP-1: Include the articles, if there is an association between the title of the article and few or entire keywords developed within this document.
- IP-2: Include the articles, whose abstract contain explanations or suggested reading related to personality classification in social media.
- IP-3: Include the articles, whose keywords are a member of the keywords created within this document.
- IP-4: Include the articles that proposed new methods regarding personality classification in social media.

The Exclusion principle (EP) is presented as follows:

- EP-1: Exclude each article that do not follow the inclusion criteria, implemented in a sequence.

The participation of authors regarding all the steps of the inclusion-exclusion process is that the first and second author creates the principles of inclusion and exclusion,

Figure 1: Relevant Research Articles Flowchart

while all the authors performed the execution of these principles to complete the process of including and excluding the papers. The relevant research articles flowchart is illustrated in Figure 1.

Firstly, to conduct a systematic literature review a number of data sources is identified, afterwards search string is created which is presented in the Table 1. The number of articles discovered in each data source is shown in Table 2. After reading and implementing the inclusion and exclusion principle on the discovered articles the relevant research article is selected that is depicted in Table 2.

Figure 2: Classification of related literature

Table 2: Data Sources with number of articles discovered and selected

Data Sources	Number of articles discovered	Number of articles selected	Number of articles rejected
ACM	30	8	22
Google Scholar	15	5	10
IEEE Xplore	90	16	74
Science Direct	20	5	15
Springer Link	25	6	19
Total	180	40	140

3 Survey Classification

In this section, a detailed summary is presented regarding the survey that was conducted on personality classification and associated techniques. This will help to identify the research gaps, as well as determining solutions for

personality classification. As illustrated in Figure 2, this review was conducted in the direction of personality-based sentiment classification and different personality models, including different types of deep learning and machine learning techniques.

3.1 RQ1: What is Personality Trait Classification and what are the Different Personality Models?

Based on a user's profile content, personality-based sentiment classification is a critical and difficult task as a result of the highly complex nature of stylistic characteristics, including likes, dislikes, comments and profile pictures. Various models for personality trait classification have been proposed previously, but here this review will present an overview of the related models. Mairesse *et al.* [10] indicate that psychologists employ several definitions of an individual's personality, with Robbins and Judge [11] considering that personality describes the behavior of humans in re-

sponse to different environmental factors, including feelings, thoughts and emotions. A summary of the various personality models is detailed below:

Allport's Trait model: Gordon Allport [12] set out one of the earliest personality models, which groups personality traits into three categories, cardinal traits, which shape the person, his/her attitudes and his/her behaviors; central traits, which are the factors that determine most of an individual behavior; and secondary traits, which may only be revealed in certain situations.

Cattell's 16 personality factor model: Cattell's [13] model includes 16 essential personality factors, which are listed under five major categories. This model had a profound influence on the development of the later Big Five model.

Eysenck's Giant Three model: This model was originally known as the PEN model [14] before psychoticism was added to his original two traits of extraversion and neuroticism to form the Giant Three.

Basic Human Values: Shalom Schwartz [15], considers the human basic values that is recognized in each society. In the proposed theory, 10 important different values are detected and the disagreement dynamics as well as agreement between these values is also mentioned. The dynamics provide an association structure between values that are frequent to various cultures groups, and thus proposing a global system regarding individual incentives. The 10 basic human values are: Security, Conformity, Tradition, benevolence, Universalism, Self-Direction, Stimulation, Hedonism, Achievement, and Power.

The Myers-Briggs Type Indicator (MBTI) model: This model [4] covers four personality dimensions: (1) Extroversion (E) vs Introversion (I); (2) Sensing (S) vs Intuition (N); (3) Thinking (T) vs. Feeling (F); and (4) Judging (J) vs. Perceiving (P)

Big Five model: According to Nettle and Robins [16] this model was proposed by Cattell and covers five dimensions of personality, which can be seen in Table 3. This also includes the sub-traits of each personality factor. A user's personality can be compared against standard personality tests in what is known as the automated classification of personality. Probably the most standardized and important personality test, the Big Five uses five factors, to describe personality and human psychology. For example, users who are high in conscientiousness usually prefer to plan things and are generally more orderly, which is represented on social media by conventional images such as a front-facing photograph. Meanwhile, extroverts are seen as energetic and enjoy interacting with others, often showing high group visibility that is evidenced on social media both by their positive emotions and through the

use of group pictures. Users who are high in Openness are likely to use unusual poses or unconventional images, as they value novelty and incline toward the arts. Conversely, users who are high in neuroticism may choose profile images that reflect the negative emotions that are associated with this trait [16].

Table 3: Personality Traits in Big Five Model

Extraversion vs. Introversion	Sociable, assertive, playful vs. aloof, reserved, shy
Emotional stability vs. Neuroticism	calm, unemotional vs. insecure, anxious
Agreeableness vs. Disagreeable	Friendly, cooperative vs. antagonistic, fault finding
Conscientiousness vs. Unconscientious	Self-disciplined, organized vs. inefficient, careless
Openness to experience	Intellectual, insightful vs. shallow, unimaginative

3.2 RQ2: What are the Different Studies Pertaining to Machine Learning Approaches for Personality Recognition?

3.2.1 Supervised machine learning for personality recognition

The corpus-based approach (CBA) is also known as the supervised approach and requires an annotated corpus for classifier tests and training, which Shivakummar and Vijaya [17] advise represents the key disadvantage of these techniques. The performance of a number of ML classifiers, including SVM, Logistic Regression (LR), Random Forest and Naïve Bayes were evaluated in a study by [18], who used an MBTI model to predict individual's personalities from online text. LR resulted 66.5 percent accuracy for all MBTI types and parameter tuning improved this figure. As the winner of Kaggle and other data science competitions, the XGBoost algorithm can be used to improve these results still further.

A new MBTI dataset for personality prediction was derived from the Reddit social media network and introduced by [19]. The classification in this model is performed using Logistic Regression and SVM and extracts a rich set of features, as well as evaluating benchmark models for personality prediction. Using a combination of all the linguistic features enabled the classifier to outperform others across all of the MBTI dimensions. The principal limitation of this model is that Reddit posts tend to contain a large number

of words, which can sometimes inhibit the accuracy of personality prediction due to presence of noisy strings, so additional experiments should be performed on more models in order to achieve more robust results.

The over and under-sampling techniques for an imbalanced dataset were compared in a study by [20], which found that classification did not perform well when applied to imbalanced dataset classes. This class imbalance issue is generally solved by implementing three approaches, algorithmic level, data level and hybrid. This study also experimented with data level method and found that the under-sampling technique (RUS) performed less well than the SMOTE over-sampling method. Future studies should provide additional investigation and evaluation of re-sampling techniques.

[21] proposed a multilingual predictive model, which used tweets to identify a user's age, gender and personality traits. Personality prediction uses the ERCC regressor model and age, and gender classification is carried out using the SGD classifier with n-gram features. User attributes were recognized in four different languages with an average accuracy of 68.5 percent, while performing experiments in different languages enhances author profiling.

The status texts of Facebook users were used by [22] to automatically detect personality traits, based on the Big Five model and using a number of different machine learning classification techniques. The proposed system was evaluated through weighted average accuracy (WA), unweighted average accuracy (UA) and macro-averaged precision, recall and F1.

An interesting study by [23] designed a system to identify personality traits through graphology and handwriting analysis. Artificial Neural Network (ANN) was used to identify personality traits through handwriting analysis, delivering an impressive 90 percent accuracy rate. The drawback of this approach is that a user's handwriting may vary depending on their mental state and age.

Ilmini and Fernande's [24] personality recognition system was developed using machine learning techniques, which identified personality types based on face recognition. This study manually collected facial features, which were then input to SVM and ANN for analysis and recognition, with the results revealing that SVM performed less well than ANN. It is suggested that considering psychological factors with enhanced feature selection would achieve more accurate results.

Twitter profile images based on a range of features, including facial presentation, aesthetics, emotions and colours were used by [25] to develop a personality identification system, using a correlation-based analysis to evaluate the model. In regard to this study, a more in-depth anal-

ysis of users' profile images on social media would require additional research and experimentation.

Sagadevan *et al.*'s [26] study suggests that publicly-expressed sentiments on Facebook can be used to identify the personality traits of users of this social network. This research used a Factor Personality (PEN) Model and extracted words from Facebook messages to recognize the psychoticism trait, based on a specifically designed questionnaire.

The Big Five personality model was used to identify user's personalities from tweets in both Indonesian and English in a study by [27]. The My Personality dataset was used as a basis and different classifiers were applied to it, including KNN, which had an accuracy level of 58 percent and SVM, which had 59 percent accuracy. However, the best-performing classifier was Naïve Bayes (NB), with 60 percent accuracy; while this study achieved its goal of using Twitter messages to predict personality, it did not improve on the accuracy of previous research, which had demonstrated a 61 percent accuracy. These results could be improved if a semantic approach was implemented, together with an extended dataset.

Ong *et al.*'s [28] work presents an explanation and discussion of previous research on personality classification from text. These prior studies had been conducted on a range of social media networks, including YouTube, Blogger, Facebook and Twitter, and Ong *et al.* evaluated the features, tools and methods, as well as the results. Several issues were identified, including the fact that certain languages make it difficult to identify features, while other problems such as the unavailability of datasets and challenges with ascertaining the necessary pre-processing methods are also considered. Developing additional methods for non-English languages could help to ameliorate these issues, together with the introduction of more personality models, including extra feature selection for data pre-processing and introducing more accurate machine learning algorithms.

Meanwhile, a study by Buraya *et al.* [29] used various social networks such as Instagram, Twitter and Foursquare to complete personality profiling. The NUS-MSS multisource large dataset was used in this study for three geographical regions, using machine learning classifiers to evaluate date for average accuracy. This research advises that the classification performance could be improved by more than 17 percent when different data sources were concatenated in one feature vector. The performance could be improved by enriching the available dataset with multi (SNS) by cross-posting from users.

The Extraversion trait of the Big Five was considered in relation to students' personalities by [30], who analyzed

Table 4: Selected Studies for Personality Trait Classification Using Supervised Machine Learning techniques

Std. no	Study	Aims and objectives	Techniques	Results	Limitation and Future Work
1	Arsa and Shubhangi, (2015) [33]	Developed handwriting-based personality and behaviour identification system.	Supervised. • SVM. • ANN.	98.5% (Accuracy)	<ul style="list-style-type: none"> prone to error and time consuming. In future, analysis will be performed for multiple lines
2	Kedar <i>et al.</i> (2015) [23]	Developed system for personality identification through Handwriting analysis and Graphology study.	Supervised. o ANN. o Zernike and Pseudo-Zernike methods.	90% (Accuracy)	<ul style="list-style-type: none"> handwriting constantly keeps changing based on the person's age and current mental state the system can be used in personal recruitment, in marketing, medicine and counselling etc.
3	Ilmini and Fernando, (2016) [24]	Identifying the personality traits from face image. Identification of criminal behaviour in criminology etc.	Supervised • SVM • ANN	98.5% (Accuracy)	<ul style="list-style-type: none"> large dataset can improve the accuracy of the classification. More study on psychology and improve feature extraction phase may improve final results.
4	Liu <i>et al.</i> (2016) [25]	To analyse a broad range of interpretable image for personality features from Twitter profile pictures.	Supervised o Linear regression. o Root Mean Squared Error.	89% (Accuracy)	<ul style="list-style-type: none"> Further experiments needed on a data set orders of magnitude larger than previous To analyse more diverse set of psychological traits based on set of photos that user post on social media.
5	Sagadevan <i>et al.</i> (2015) [26]	recognizing the personality of Facebook users from messages based on Three Factor Personality (PEN) model.	1: Supervised 2: Stemming • 3: Part of Speech Tagging (POST)	95% (Accuracy)	<ul style="list-style-type: none"> In future, use of the higher negative words as cues to detect the psychoticism trait among Facebook users will be implemented.
6	Alam <i>et al.</i> (2013) [22]	Automatic personality detection based Big Five Factor Personality Model w.r.t individual status text from Facebook	Supervised • Multinomial NB, • Logistic Regression (LR) and • SMO for SVM	78% (Accuracy)	Incorporating feature selection and more classifiers, may enhance the performance.
7	Chaudhary <i>et al.</i> (2018) [18]	performance evaluation of different classifiers using MBTI model to predict user's personality from the online text	Supervised • Naïve Bayes, • SVM, • LR • Random Forest	65% (Accuracy)	Results may further be improved by using XGBoost algorithm, which remained winner of most Kaggle and other data science competitions.
8	Bharadwaj <i>et al.</i> (2018) [6]	analysing social media posts/ tweets of a person and produce personality profile accordingly	Supervised • Neural Net, • Naïve Bayes • SVM	SVM achieved highest accuracy	Further enhancement can be made by incorporating more state of the art techniques.
9	Gjurković and Šnajder (2018) [19]	a new MBTI dataset is proposed for personality prediction, which is derived from Reddit social media network	<ul style="list-style-type: none"> Supervised Machine Learning Algorithms SVM, Logistic Regression 	78% (Accuracy)	number of words in the posts are very large, which sometimes don't predict the personality accurately.
10	Ong <i>et al.</i> (2017a) [28]	classification of personality from text, carried out on various of social networking sites	<ul style="list-style-type: none"> Supervised Machine Learning Algorithms 	83% (Accuracy)	developing methods for non-English language, introducing more accurate machine learning algorithms, implementing other personality models,
11	Sewwandi <i>et al.</i> (2017) [31]	Personality recognition using ontology based text classification	<ul style="list-style-type: none"> supervised machine learning questionnaire based personality recognition 	91% (Accuracy)	to improve personality recognition by the combinations of text and social behavioural aspects of user on multiple social media.

different machine learning classifiers' performance in this regard. A variety of ML algorithms were applied to the WEKA platform, including Random Forest, Random Tree, AdaBoostM1, OneR, ZeroR, Naïve Bayes, SMO, JRip and

Simple logistic. Time taken, F-Measures and correctly classified instances were all used to evaluate the classifiers' efficiency and the best performing classifier was found to be OneR, which demonstrated the best performance, with 84

percent accuracy. Additional insight could be achieved in future by considering the remaining dimensions of the Big Five.

Sewwandi *et al.* [31] developed a technique that has an accuracy of 91 percent, which compares favorably to real-world personality recognition questionnaires. The model combines ontology-based text classification and a linguistic feature-vector matrix based on the PEN model, which uses questionnaire-based personality recognition and supervised machine learning algorithms. Despite its success-

ful accuracy rate, personality recognition could be improved by merging the social behavioral and text aspects of the user on multiple social media platforms.

A novel approach to personality recognition was proposed in Poria *et al.*'s [32] study, which incorporated the affective, sentiment and common-sense knowledge aspects of text. Poria *et al.*'s approach uses psycholinguistic and frequency-based features in combination with common sense knowledge features, which are then used by five SMO (Sequential Mining Optimization) algorithms, based on a supervised classifier for five personality traits. The previous framework used frequency-based analysis and psycholinguistic features at a lexical level, which this approach improves on, delivering more accurate results.

Table 4 represents the summary of selected studies for personality trait classification using Supervised Machine Learning techniques.

Algorithm 1 shows Pseudocode steps of supervised machine learning classifiers for classifying personality traits from text.

Algorithm 1 Pseudocode steps of the Supervised Machine Learning Steps for Personality Recognition

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Result: Classified Tweets w.r.t Personality
Personality Traits: ["Neuroticism", "Extraversion",
"Openness", "Agreeableness", "Consciousness"]
Classifiers: ["SVM", "NB", "KNN", "Decision Tree",
"Random Forest", "Logistic Regression", "XGBOOST"]
Begin
//Scanning the Text
SET Text = Scan Tweets

#Preprocessing
#Tokenization
    SET Tokens = Tokenizer (Text)
#Remove Stop Words
    SET PlainText = RemoveAllStopWords (Tokens)
#Punctuations
# Split all the Dataset items into Test/ Train
SET totalTestSize = 20%
ATrain, BTrain, ATest, BTest = Split (PlainText, total-
TestSize)
#Term Frequency and Inverse Document Frequency
#Apply Classifiers
SET ClassifierModel = classifiers ( )
SET ClassificationModel = Model: fit(ATrain, BTrain)
#Predictions
SET PredictionModel = Classification: predictions
(YText)
#Accuracy
SET AccuracyModel = Accuracy (PredictionModel,
XText)
#Confusion Matrix
Set ConfusionMatrix = confusionMatrix (BTest, Predic-
tionModel)
#Performance
Measure (PrecisionModel, FMeasure)
SET Result = classificationReport (BTest, Prediction-
Model, PersonalityClass)
Return (Result)

```

3.2.2 Unsupervised machine learning for personality recognition

The following sections present an overview of the selected studies that relate to machine learning approaches.

An unsupervised approach was suggested by [34], who created a personality recognition system using the Big Five personality traits. Taking information from social media sites such as Friend Feed, the system classified and extracted user's personality traits and built a personality model using different linguistic features that relate to personality. The system obtained acceptable results when computing personality scores from text but did not consider features relating to interaction between users.

Celli and Rossi [35] also created an unsupervised personality recognition system that was designed to tackle how personality types interact on Twitter. Celli and Rossi's system exploits statistical and linguistic features, testing the system on a dataset, which was annotated with human judgment-based personality models. The study found that secure users posted less than those who were neurotic, with the latter also tending to construct longer chains of users who interacted with the posts.

In another study, Celli [36] annotated the data of 12 distinct linguistic features from Twitter and identified a correlation between the writing style used and the personality. The data was taken from different devices and cross-regional users, and users with more than one tweet were also evaluated. The researcher observed that compared to

Table 5: Selected Studies for Personality Trait Classification Using Unsupervised Machine Learning techniques.

Std. no	Study	Aims and objectives	Techniques	Results	Limitation and Future Work
1	Celli (2012) [34]	personality recognition system with linguistic features using Big Five Model	Unsupervised Score-based	81.43% (Accuracy)	System didn't address features related to inter user interaction.
2	Celli and Rossi, (2012) [35]	personality recognition system with linguistic features	Unsupervised Score-based	78.29% (Accuracy)	Hybrid set of features needed
3	Celli (2011) [36]	user's personality recognition from writing style	Unsupervised Score-based	84.24% (Accuracy)	More Twitter data for classification may enhance the efficiency of personality identification model.
4	Kafeza <i>et al.</i> (2014) [37]	modularity based community detection algorithm pre-processing step removes graph edges based on users' personality	Graph-based	86.74% (Accuracy)	scalability problems need to be addressed while considering large graph.
5	Sun <i>et al.</i> (2019) [38]	group-level personality recognition	Unsupervised Adawalk	97.74% (Macro-F1)	TF-IDF approach is used, exploit the small dataset comprehensively, made the proposed system more robust.
6	Chishti <i>et al.</i> (2015) [39]	detecting the personality regarding website	Unsupervised K-Mean	K=10 is a correct value	to add further element during experiments, adding further websites within verification, the software upgradation will be conducted.

users who posted from the Blackberry, iPhone, Facebook and UberSocial platforms, Twitter users are unbiased, introverted and secure. However, this personality identification model could be enhanced by additional Twitter data for classification.

A Twitter personality-based Influential Community Extraction (T-PICE) system was proposed by [37]. The system generates a network graph of the most influential communities, identifying personality traits by extending extant approaches through the aggregation of data that exhibits further aspects of user behavior based on machine learning techniques. To do this, a pre-processing step was added to an existing modularity-based community detection algorithm to remove graph edges according to users' personalities. In regard to this study, the scalability issues of the large graph should be addressed.

The aim of the work conducted by [38], is to investigate the group-level personality recognition by exploiting unsupervised feature learning technique. For this purpose, adawalk algorithm is used. The results depict that in case of Micro-F1, the performance of adawalk is better with at least 7% for Wiki, 3% for Cora, and 8% for BlogCatalog. Furthermore, in case of SoCE personality dataset, the proposed approach attained 97.74% Macro-F1. The limitation of the study is that it is based on TF-IDF approach, also the developed text networks are not an imitation of real social networks like retweeting networks, and following net-

works. In future, they will exploit the additional datasets in a more comprehensive way, and made the proposed system more robust.

In their work on detecting the personality regarding website visitors, Chishti *et al.* [39] used an unsupervised learning method based on quantitative elements of website. The unsupervised clustering algorithm, namely K-Mean is proposed. The experimental results show that the proposed approach can be used perform the website personality prediction more efficiently. The future aim is to add further elements during experiments as well as verification of further websites will be added by upgrading the software.

The summary of selected studies for personality trait classification using unsupervised machine learning techniques is presented in Table 5.

3.2.3 Semi-supervised and hybrid approaches for personality recognition

Features of the lexicon-based and supervised techniques including annotated datasets, supervised learning-based classifiers and lexicons are incorporated into both the semi-supervised and hybrid approaches. The studies detailed below have each used hybrid approaches.

Table 6: Selected Studies for Personality Trait Classification Using Semi-Supervised and Hybrid Machine Learning techniques

Std. no	Study	Aims and objectives	Techniques	Results	Limitation and Future Work
1	Kramer <i>et al.</i> (2011) [40]	To develop personality comparison between human and chimpanzees.	Hybrid	78% (Accuracy)	<ul style="list-style-type: none"> • To investigate more features common between human and • Individual differences in AQ measures need to be correlated identify traits in chimpanzee's faces.
2	Lukito <i>et al.</i> (2016) [41]	to detect MBTI type personality traits from social media (Twitter) in Bahasa Indonesian language.	<ul style="list-style-type: none"> ◦ Machine Learning ◦ Lexicon-based, ◦ linguistic Rules driven. 	83% (Accuracy)	<ul style="list-style-type: none"> • Lower accuracy is due to limited corpus in Bhasha Indonesia. • by increasing the training data set, accuracy may get improved.
3	Bai <i>et al.</i> (2012) [43]	automatic and objective personality prediction system based on user's behaviours on Social Network Sites (SNSs) using Big Five model.	Feature-based	81.53% (Accuracy)	To incorporate additional features for performance improvement

A personality comparison system between humans and chimpanzees was developed by Kramer *et al.* [40], who used still images with neutral expressions for their investigation. The study found that humans are able to identify characteristics more accurately than chimpanzees, but it is suggested that additional research is carried out to further investigate different features among humans and chimpanzees.

Lukito *et al.*'s [41] study focused on identifying MBTI-type personality traits from Twitter in the Bahasa Indonesian language. The study selected 97 users from 142 respondents, the former averaging 2500 tweets each. The training and classification set was build using WEKA and the training set used three approaches for prediction (1) linguistic rules-driven, (2) machine learning and (3) lexicon-based. Naïve Bayes performed the best of all the methods, with 80 percent accuracy for I/E and 60 percent for the remaining traits (S/N, J/P and T/F). The limited corpus in Bahasa Indonesian means that there was reduced accuracy on the lexicon-based and linguistic rule-driven approaches, which could be improved by increasing the training dataset.

Alsadhan and Skillicorn [42] devised a personality prediction technique based on word count from social media-based text, which works in eight different languages, for the Big Five and MBTI personality models. For both these

models, four types of labelled corpus were used to conduct the experiments, using one thousand frequently used words. The prediction accuracy for the S/N dimension of the MBDT was higher than that of the other dichotomies, while the Openness trait of the Big Five was also higher across all corpus. The major drawback of this model is the fact that it focuses solely on word count, which could be improved by introducing ML algorithms and choosing additional features.

Self and observer ratings of personality were used by [10] for their study that extended the field of automatic recognition of pragmatic variation from text for sentiment and opinion based on the personality traits of the Big Five model. Mairesse *et al.*'s work investigates several methods to help understand the association between language and personality, but the study has limitations in terms of the unsatisfactory performance of utterance-type features.

Finally, Bai *et al.*'s [43] study bases its objective and automatic personality prediction system on the behavior of users on social network sites (SNS), using the Big Five model. This system has similar results to conventional inventory-based psychological analysis, which used experiments to prove that online behaviors can be predictors of user personality types.

Table 6 shows a summary of selected studies for personality trait classification using semi-supervised and hybrid machine learning techniques

3.3 RQ3: What are the Different Studies Pertaining to Deep Learning Approaches for Personality Recognition?

3.3.1 Deep Learning

A deep learning is a sub-field of machine learning and is also known as hierarchical learning, deep machine learning and deep structured learning. In its simplest form, one set of neurons receives an input signal and the other set sends an output signal. Models based on deep learning can facilitate tasks including computer vision, speech recognition, automatic handwriting generation and natural language processing [44].

The complex and dynamic nature of social media scenarios means that a deep neural network is an effective method as it is able to extract local and global significant features automatically and identify misinformation [44]. As a result of his/her learning capacity, deep learning-based neural network models are particularly effective for detecting personality traits [45].

3.3.2 Classification of online content into Personality Traits using deep learning

Several deep learning techniques, such as LSTM, CNN and RNN, can be used to classify personality traits from online content [45] and this section presents an overview of how the CNN deep learning technique can be used for this purpose. CNN operates in two phases, the first of which is *feature representations*, which encodes the target information into feature representation vectors [44].

The second step is *classification layers*, where the representation vectors from the first stage are input into the classification part. All the deep learning models have a particular way of encoding the target information into a feature when given an input. Local dependency layers are captured using convolutional filters in the CNN layer, while the convolutional layer extracts local features and pools them into a smaller dimension, using a MAXpooling layer to prevent overfitting.

In this paper, the CNN deep learning model is used, and the embedding layer generates the word embedding representations when the input is given. The term word embedding means to perform mapping of

words/sentences mapping with respect to natural language towards vector format that could be computed with machine. Different algorithms exploit this vector format to process and accomplish different natural language processing challenges. The word vector representation scheme, namely word embedding is proposed by Hinton. The key concept of this scheme is to perform word mapping towards the lower dimensional space (real valued vector), that assists in solving the issue of vector sparseness. Additionally, within the low dimensional space, the position association among word vectors may better consider its semantic link, that is very appropriate for the extraction of abstract features at a higher level [46]. Figure 3 illustrates the structure of word embedding that is trained on a personality related textual data.

Figure 3: Word Embedding Representation Scheme

The first layer's output, embedding representation, is input to the CNN layer to create a feature vector, before the CNN layer's output is passed to the dense layer using a sigmoid activation function to label the text as personality traits (see Figure 4).

The studies detailed below have each used deep learning approaches

Hernandez and Scott [47] developed a deep learning classifier which takes text/tweet as input and predict MBTI type of the author using MBTI dataset. After applying different pre-processing techniques embedding layer is used, where all lemmatized words are mapped to form a dictionary. Different RNN layers are investigated, but LSTM performed better than GRU and simple RNN. While classifying user, its accuracy is 0.028 ($.676 \times .62 \times .778 \times .637$), which is not good. The predictive efficiency of this work may be improved by increasing the number of posts per user. As the model is tested on real life example of Donald trump's 30,000 tweets, which correctly predict his actual MBTI type personality.

Figure 4: Deep learning model for Personality Trait Classification from Text

Arnoux *et al.* [48] proposed a model that requires 8 times fewer data to predict individual's Big Five personality traits. GloVe Model is used as Word embedding to extract the words from user tweets. Firstly, the model is trained and then tested on given tweets. Further, the data is tested on three other combinations: (i) GloVe with RR, (ii) LIWC with GP, and (iii) 3-Gram with GP, and the proposed model performed better with an average correlation of 0.33 over the Big-5 traits, which is far better than the baseline method. Findings of this method are based on English Twitter data, which may be extended to other languages. Similarly, the performance of the model can be examined with small number of tweets.

Majumder *et al.* [1] proposed a deep learning model for personality trait classification based on collection of es-

say dataset. The proposed CNN model promising results, however, further improvement can be made by introducing LSTM layer with additional features.

Liu *et al.* [49] applied machine learning and deep learning techniques for identifying five personality traits in a text written in three languages, namely English, Italian, and Spanish. The experimental results show that in case of English language the attained Root Mean Square at tweet level ($RMSE_{tweet}$) of the proposed method for Extroversion(EXT) is 0.142, for Emotional Stability(STA) the $RMSE_{tweet}$ is 0.188, for Conscientiousness(CON) the $RMSE_{tweet}$ is 0.136, and for Openness(OPN) the $RMSE_{tweet}$ is 0.127. In case of Spanish language $RMSE_{tweet}$ of the proposed method for EXT is 0.158, for Agreeableness(AGR) the $RMSE_{tweet}$ is 0.153, for CON the $RMSE_{tweet}$ is 0.168, and for

Table 7: Relevant Studies for Personality Trait Classification Using Deep Learning techniques

Std. no	Study	Aims and objectives	Techniques	Results	Limitation and Future Work
1	Hernandez and Scott (2017) [47]	Identifying the personality traits from text using MBTI dataset	<ul style="list-style-type: none"> Deep Learning <ul style="list-style-type: none"> LSTM GRU RNN 	86.72%(accuracy)	<ul style="list-style-type: none"> To use BiLSTM
2	Arnoux <i>et al.</i> (2017) [48]	Identifying the personality traits from text using Big five model	<ul style="list-style-type: none"> Deep Learning Glove Model 	92% (accuracy)	<ul style="list-style-type: none"> Limited dataset Incorporation of multilingual features
3	Majumder <i>et al.</i> (2017) [1]	Identifying the personality traits from text using essay dataset	<ul style="list-style-type: none"> Deep Learning CNN model 	83.2% (accuracy)	<ul style="list-style-type: none"> Lack of rich feature set To add LSTM layer
4	Liu <i>et al.</i> (2016) [49]	Personality trait classification based MBTI dataset	<ul style="list-style-type: none"> Deep Learning RNN model 	$RMSE_{tweet}$ English(EXT=0.142, STA=0.188, CON=0.136, OPN = 0.127 Spanish(EXT=0.158, AGRO=.153, CON=0.168, OPN= 0.150. Italian(STA=0.156, CON=0.109, OPN= 0.141)	<ul style="list-style-type: none"> To extend the system upto six languages
5	Xue <i>et al.</i> (2018) [45]	Personality trait recognition from user's posts using Big Five model	<ul style="list-style-type: none"> Deep Learning AttRCNN model 	89% (accuracy)	<ul style="list-style-type: none"> To use deep semantic features as input to special-purpose regression model

OPN the $RMSE_{tweet}$ is 0.150. In case of Italian language, the obtained $RMSE_{tweet}$ of the proposed method for STA is 0.156, for CON the $RMSE_{tweet}$ is 0.109, and for OPN the $RMSE_{tweet}$ is 0.141.

Xue *et al.* [45] proposed a personality recognition system from textual content using deep learning approach. For this purpose, a hierarchical structure AttRCNN model is proposed, which is able to learn deep semantic features of user's posts. Experimental results are encouraging, showing that the proposed deep semantic features are more effective than the baseline features.

In Table 7 relevant studies for personality trait classification using deep learning techniques is summarized.

4 Results and Discussion

4.1 Answers to posed research questions

The systematic literature review analyzed 33 studies focused on the detection of personality types and traits and it was notable that all the articles that formed this review used deep learning and machine learning approaches. It was also observed that most of the data sources of the articles were either Twitter or manually acquired like MBTI for the purposes of these experiments. This paper's researchers believe that data from other social networks such as YouTube should also be used to extend the applicability of the models.

In response to RQ1, we have explored different personality models. Several researchers have conducted studies that make impressive contributions to the body of work that seeks to understand the extant correlation between

personality and social media platforms. Although the personality models have been investigated in the recent past, but its role in text analytics has been focused less. So further survey is required in order to unveil its role in text processing under social media platforms. However certain drawbacks of the prior work are: (i) The existing personality models need refinement to best fit with the language used by the social media users in the form of emojis, slang terms and informal language constructs like short poetic texts [49], (ii) Personality models dealing with dark triads of the online users are still not rich enough in terms of enhanced feature sets [50]; (iii) There is a significant increase in the outlier when the number of personality traits to be predicted become higher [18] (iv) manual annotation and categorization of personality-related reviews is a time-consuming process [51]. Following solutions are recommended for the aforementioned limitations: (i) Extended set of personality models are required to cope with social media language constructs like emojis and slang terms. (ii) More enhanced feature engineering techniques can be applied for improving the efficiency of personality models to deal with dark triads, especially psychopaths; (iii) Different outlier detection techniques, such as z-score, proximity-based models and probabilistic modeling, can applied for more efficient prediction of personality traits; (iv) Automatic annotation and categorization of personality-related reviews can be used to made it input to classifier.

Different machine learning techniques for personality detection and classification were identified in response to RQ2 and the researchers observed that existing machine learning techniques had a number of deficiencies: (1) the personality detection model uses only the text content of social media [18]; (2) improvement in performance with regard to personality identification model is essential [18]; (3) bias detection has a degraded accuracy, leading to impaired performance (Alam *et al.*, 2013); (4) improved performance with regard to classification of personality traits is limited by existing datasets [29]; (5) the credibility of the micro-blog system is affected by fake followers, so it essential that such followers are tracked [52]; and (6) the machine learning algorithm's accuracy decreases when n-gram features such as tri-gram and four-gram increase [31]. Particular solutions are proposed to overcome these deficiencies: (1) other social media content such as short videos and images could be included to further improve the personality detection model; (2) to achieve improved results, further classification methods plus an additional set of features should be explored; (3) impaired performance can be avoided by developing new and more robust features; (4) researchers should collaborate to build

a shared dataset to facilitate progression in personality detection; (5) adding new features would enable followers based on personality features to be tracked; and (6) since deep learning can extract latent features automatically, it could also be used to maintain the accuracy of the algorithm.

This paper's researchers identified different deep learning techniques and highlighted their importance for personality detection in response to RQ3. The challenges that this paper identified were: (1) there is relatively poor personality detection accuracy for the disagree label [1]; (2) only social network information is used for personality detection (Liu F *et al.*, 2016); (3) there are too few manual facts check profiles to train the deep neural network [45]; (4) in spite of some encouraging results, personality detection remains an open challenge [48]. Solutions have been devised for each of these challenges, as follows: (1) the disagree label model's accuracy could be improved by increasing the number of instances; (2) because content information is readily available, this can be combined with social network information; (3) to manually check personality in real-time, a web application should be developed; (4) the researcher will investigate a model that integrates crowdsourcing and reinforcement learning concepts in order to achieve timely and accurate predictions.

4.2 Comparison of personality detection techniques

The best performing approach should be chosen for practical applications and research work, although the presence of certain factors makes a direct comparison among systems challenging. First, the original authors' datasets are different, so it is not possible to directly compare the reported and implemented results. Moreover, the reported results cannot be reproduced as the authors describe their systems with varying accuracy; while some methods report excellent results, their actual performance is sometimes lower than what was originally reported.

The MBTI data set [49] was applied to the methods reported in the papers and the researchers of this paper aimed to follow the description in each paper as closely as possible, although this was sometimes challenging due to inadequate explanation of the method. The original authors frequently omitted to describe the tools they used, but this paper used an Anaconda-based python environment to conduct a quantitative comparison of the methods using a consistent dataset.

To conduct a quantitative comparison on the same dataset we used a consistent dataset to evaluate the per-

Table 8: Quantitative comparison of Personality detection approaches

Article	Technique	Parameter Setup	Reported accuracy (%)	Results in our experiment (without balancing) A	Results on Balanced dataset experiment (%)		
					P	R	F
Alam <i>et al.</i> (2013) [22]	SVM, NB	SVM: C=0.7, kernel='linear', verbose='False', random_state='None' NB: alpha=5.0, fit_prior=True, class_prior=None	78	71.2	75	76	70
Chaudhary <i>et al.</i> (2018) [18]	NB	NB: alpha=1.0, fit_prior=True, class_prior=None	65	73	78	76	77
Ilmini and Fernando, (2016) [24]	SVM and ANN	SVM: C=0.05, kernel='linear', max_iter=-1, verbose='False', degree=3 ANN: Kernel_size=2×2, padding=valid, filters=7, pool_size=4×4, vocab_size=2000	98.5	81.72	91	90	90
Kedar <i>et al.</i> (2015) [23]	ANN	ANN: vocab_size=2000, embed_dim=128, Kernel_size=3×3, padding=same, filters=32, pool_size=2×2,	90	82	91	90	90
Celli and Rossi (2012) [35]	Un-Supervised, score-based technique	tweets=12246, following=838, followers=34502, listed=385, favorites=157	81.43	71.45	80	78	78
Liu <i>et al.</i> (2016) [49]	RNN	RNN: units=100, vocab_size=5000, embed_dim=300, batch_size=7, ephocs=10	72.67	75	89	91	90
Hernandez and Scott (2017) [47]	RNN	RNN: units=100, vocab_size=2000, embed_dim=128, batch_size=5, ephocs=7	86.72	72	91	88	90
Majumder <i>et al.</i> (2017) [1]	CNN model	CNN: vocab_size=10000, embed_dim=128, Kernel_size=2×2, padding=same, filters=16, pool_size=4×4, activation= Relu, strides=1.	83.2	88	91	90	90
Xue <i>et al.</i> (2018) [45]	Attn.-RCNN	Attention: units=100 RCNN: units=200, vocab_size=2000, embed_dim=100, attention batch_size=7, ephocs=10	89	93	95	95	95

formance of the existing approaches, using a personality dataset that contained 12,000 items for different personality traits. The results of the evaluation can be seen in Table 8, which illustrates the reported accuracy in the original papers and the accuracy when implemented by this paper. As mentioned previously, the lack of detail in the original publication may have prevented exact reproduction of the techniques from the original studies, which could account for discrepancies in the accuracy figures. The fact that this paper conducted the experiments using different tools, data and settings also affected the reported results; for example, [49] reported 72.67 percent accuracy and this paper obtained 75 percent, and this paper obtained 72 percent to Hernandez and Scott's [47] 86.72 percent.

5 Experiment on Balanced Dataset

In the process of comparing classifiers. The only metric used is accuracy. However, in the case of imbalanced classes, its application does not make it possible to evaluate the quality of the classifier. To address this issue, we have balanced the dataset by applying a SMOTE in Ana-

conda Framework, which is an over-sampling technique [53]. We choose to use over-sampling technique due to its performance efficiency reported by [20]. After balancing the dataset by using the above-mentioned technique, we get improved results, as reported in the Table 8 (P, R, F). The acquired results show the performance of different machine learning algorithms used in this study. RCNN yielded the best performance outcomes and proves the superiority as compared to other Classifiers.

6 Trends in Personality Detection

This section presents trends that have been identified with regard to personality detection.

6.1 Year-wise article publication

This trend saw the identification of the number of articles based on year. Figure 5 is a bar chart that presents the number of articles alongside the year that they were published. There were few articles on semi-supervised & hybrid, a

Figure 5: The no. of articles with respect to four dimensions: supervised, unsupervised, semi-supervised & hybrid and deep learning

moderate number on unsupervised and deep learning and the majority concerned supervised learning.

6.2 Methods for classification

Research work on machine learning and deep learning perspectives were distinguished for this trend. Figure 6 shows that most of the work has been done in machine learning, using SVM (27%), Naïve Bayes (20%), Random Forest (13%), Decision Tree Classifier (20%), and K-Nearest Neighbour (13%). Deep learning (Figure 7) was also found, using RNN (29%), LSTM (14%), Convolutional neural network (15%), GRU (14%), Glove (14%) and AttRCNN (14%).

Figure 6: Percentage of articles applying Machine learning approaches

Figure 7: Percentage of articles applying Deep learning approaches

6.3 Open Problems

More Focus on deep learning: the review of existing literature found that the majority of prior work endeavored to discover personality traits through machine learning algorithms in which features were manually extracted. This is a time-intensive and labor-intensive task, so deep learning is a reasonable alternative. This paper's authors encourage future researchers to focus on deep neural models, as this delivers superior performance to machine learning algorithms by effectively capturing the hidden representations [45].

Lack of a shared dataset: there is a lack of publicly available data for the development of generic personality detection [31], which is a limitation that could be overcome by researchers collaborating to build a shared dataset.

Limited set of personality model: the existing personality-related models are based on basic set of personality features, providing a limited coverage of personality traits for textual content available on social media sites.

6.4 Qualitative Evaluation

A considerable number of researchers have produced work that considers the topic of how personality may be predicted by language features, and much of this is driven by the *lexical hypothesis*, which states that an individual's choice of words reveals their personality traits. Several such studies have determined important results [19, 45, 48] Users' behavior on social media platforms reflects several real-life aspects such as personality, so these platforms provide an abundant source of textual data [1]. Social media platforms are an environment where individuals appear to feel comfortable sharing their opinions, emotions and feelings, which results in an in-depth accumulation of personal data that has a broad range of applications.

The fact that people share such information with their networks without being cognizant of the nature of this sharing, means that it is sometimes referred to as subconscious crowdsourcing information [54]. Participation in social media has undergone exponential growth over the past decade, which makes users of these platforms ideal candidates for predicting personality traits, although [55] caution that the specific characteristics of individual social media platforms may impact the efficacy of predictions. These individual characteristics involve whether or not the author is identified, as well as the length and number of entries and the word choice and grammar used. It is vital that the characteristics of each platform and their individual biases are considered when they are used as sources for analysing textual data in an experimental setting like the one used by [40].

For example, tweets tend to be short, which means that they use a great number of abbreviations and also contain links to other textual sources such as blogs. The particular nature of tweets thus presents particular issues when attempting to profile personality types from text. Prior studies on this topic have demonstrated that the traits of neuroticism and extraversion have a strong correlation with the number of friends that an individual has in real life, as well as on Facebook [56]. People who are low in neuroticism and high in extraversion usually keep consistent contact with friends, while individuals who are extroverted tend to feel comfortable using these platforms [57]. The homophily principle asserts that people tend to form ties with individuals who are of a similar age and have similar attributes, including personality and interests [54]. This means that in general, social media users connect with friends online who have higher levels of Agreeableness and choose others who have comparable levels of Extraversion and Openness [54].

7 Conclusion and Future Work

User's behaviour and personality detection is a challenging and highly focused area in cognitive-based sentiment analysis. Predicting personality from online text is a growing trend for researchers. Several studies have already been conducted on predicting personality from the input text. In this review paper, we provided an insight to the following issues of personality recognition: (i) Personality models; (ii) machine learning approaches for personality recognition; and (iii) deep learning approaches for personality recognition. We also provided open issues and their probable solutions. We propose guidelines for future

work to acknowledge and incorporate the following key points: (i) To increase the accuracy of machine learning approaches for personality trait classification, dimensionality reduction techniques need to be addressed; (ii) Most of the reviews posted on social media sites are written in different languages. Therefore, this requires thorough investigation using supervised, unsupervised and hybrid classification schemes, applied on multilingual datasets; (iii) Reinforcement learning is least addressed dimension for detecting personality traits using deep learning, needing further attention; (iv) Emotion and slang based personality detection and classification is to be acknowledged as a challenging task; and (v) personality recognition and multimedia content posted on social media sites is to be acknowledged as a challenge.

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