*Intelligent Automation & Soft Computing*
DOI: 10.32604/iasc.2023.029412
***Article***

# Assessing Conscientiousness and Identify Leadership Quality Using Temporal Sequence Images

**T. S. Kanchana* and B. Smitha Evelin Zoraida**

Department of Computer Science, Bharathidasan University, Khaja Mali Campus, Tiruchirappalli, India
*Corresponding Author: T. S. Kanchana. Email: kanchanats79@gmail.com
Received: 03 March 2022; Accepted: 19 April 2022

**Abstract:** Human Facial expressions exhibits the inner personality. Evaluating the inner personality is performed through questionnaires during recruitment process. However, the evaluation through questionnaires performs less due to anxiety, and stress during interview and prediction of leadership quality becomes a challenging problem. To the above problem, Temporal sequence based SENet architecture (TSSA) is proposed for accurate evaluation of personality trait for employing the correct person for leadership position. Moreover, SENet is integration with modern architectures for performance evaluation. In Proposed TSSA, face book facial images of a particular person for a period of one month and face images collect from different social environments and forms the sequential facial image database are analysed for personality trait estimation. Now a days, Facebook plays a vital role, where people express their emotions by posting images and updating their profile pictures. In TSSA method, 50 Facebook temporal sequence of images of person with answered questionaries during the face image collection forms as a Temporal sequence image (TSI) database for prediction of the Big Five personality trait. In order to get precise prediction, we have analysed the face images that were posted in a period of one month and validated the result with the next month face images from face book. Face images for predicting the personality, where asked to fill the Questionnaires through Google Forms increase the accuracy in prediction. The TSSA prediction results are utilized for assessment of a person's conscientiousness for leadership quality suitability. The study implements Deep Learning algorithm with SENet architecture and compares with traditional algorithms. From the validation results the proposed TSSA method performs 96% of accuracy in conscientiousness prediction.

**Keywords:** Big five; ocean; deep learning; set; personality traits

## 1 Introduction

Humans differ from one person to other due to appearance and personality traits. Personality traits patterns are attitudes, emotions, actions, reactions and behaviours of an individual. People use social networking sites for a variety of reasons, and this usage may also have led in addictive behaviours due to the continuous use of site. The study, examine into factors which can influence social media addiction by using regression analysis [1]. Personality trait patterns vary in person during different circumstances such as social, family, friends and different time period age of a person. To explain variations in Facebook addiction, a regression analysis was applied with personality traits, societal, family, personal loneliness, and life satisfaction with predictor factors [2]. The impact of social media influencer endorsements on purchase intent is investigated, with a focus on the role of advertising disclosure and source legitimacy in this process [3]. The Pearson correlation coefficient (PCC), correlation-based feature subset (CFS), information gain (IG), symmetric uncertainly (SU) evaluator, and chi-squared (CHI) technique were used to compare the performance of five feature selection algorithms [4]. Presents an overview of personality prediction based on linguistic features [5]. Using my Personality project data set, investigate the presence of social network structures and language features in connection with personality relationships. To compare and contrast four machine learning models, as well as determine the relationship between each feature set and personality attributes [6]. This survey attempts to discuss how text analytics and text mining techniques have been used in social media studies to identify key themes from the data [7]. Personality trait is called as five factor model and which consists of Openness (O), Conscientiousness(C). Extraversion (E), Agreeableness (A), and Neuroticism (N). Openness (O) is the inclination to enjoy and admire new creations, opinions, values, attitudes, and ethics. The ones who possess openness have the brains to think outside the box. A person who possesses conscientiousness (C) tends to be accurate, punctual for appointments, follow and obey the rules, and hardworking. Extraversion (E) or extroversion is distinguished by introducing one’s enthusiasm and strengths toward the outer universe of people. The framework processes the likes, comments, and shares as input and maps them to a personality trait [8]. Generally, extraversion is correlated with the importance of accomplishment and gratification and intentions associated with an impressive lifestyle. The individuals who possess agreeableness (A) tend to agree and go along with others, preferably asserting their own ideas and preferences. People who own neuroticism (N) have pessimistic qualities, including agitation, anxiety, self-consciousness, impatience, emotional vulnerability, and depression. Human character is a combination of body and mind. Human express the emotions through our facial and physical expressions. Loneliness was found to be significantly associated with Facebook addiction, and it was found to be a great indicator of Facebook addiction [9]. Facial expressions have impact in behaviour regardless of culture, language, or region. Predicting a person’s facial expression helps to understand his/her psychological traits. The facial and physical expressions of a particular person can be obtained through Social Networking Sites (SNS). Among SNS, Facebook is one of the notable sites where people express their emotions through photos or status.

Organisations can use personality tests to hire quality and talented employees. Leadership quality, team bonding, honesty, innovative ideas, creativity, and positive attitude of a person can be identified using personality traits. The findings were in accordance with demographic predictions and associations drawn from central addiction theories, implying that women are more likely than men to become addicted to social interactions [10]. Personality tests provide recruiters a constructive perception about how a candidates’ personality will have an impact in their working environment. One of the advantages of personality tests is that it can avoid the possibilities of making biased decisions while recruiting a candidate for a specific job. These tests are more feasible and are implemented effectively. Through personality tests HRs will get a foresight whether a particular candidate is suitable to achieve the organisations future roles. Candidates who exhibit creativity, critical thinking and strong goat setting abilities can be selected for administration role.

### *1.1 Problem Statement*

Multiple personality prediction tools are available in the market and not every tool is perfect. The outcome of an imperfect prediction may be misleading and will fail to choose the right talent person. The attributes of a personality tests may vary from every job and the selection of the same should be handled in a wise manner. When an addicted Facebook user is asked to disclose his/her real behaviour, he may tend to report a false answer which may lead to misconceptions. Assessment of personality traits only through questionnaires will not give a proper measurement of OCEAN. By targeting only, the face the Personality traits based on dress style can never be identified. We need to access how a person is engaged with the social environment.

### *1.2 Contributions*

In recent years Social Networking Sites (SNS) have been used by wide range of people and Facebook is one among that. Users express their emotions by uploading pictures and updating their status in Facebook. This article specifies a method to predict the personality traits of a person by their interactions in Facebook. People share pictures on different occasions such as a marriage function, cultural activities, on their birthdays and so on. By using SENet deep learning algorithm we analyse the OCEAN personality trait obtained from the face images and queries from the same person. This analysis can be used by organisations to recruit and to identify the talent of a particular person. To the above problem,

i) To propose, Temporal sequence based SENet architecture (TSSA) is proposed for accurate evaluation of personality trait for employing the correct person for leadership position through facial images of a particular person for a period of one month and face images collect from different social environments and forms the sequential facial image database are analysed for personality trait estimation through SENet Integration with modern architectures such as SE-Inception-ReseNet-v2
ii) To collect, 50 Facebook temporal sequence of images of person with answered questionaries during the face image collection forms as a Temporal sequence image (TSI) database for prediction of the Big Five personality trait.
iii) To predict, personality traits the face images collected for a period of one month and validated the result with the next month face images from Facebook and Questionnaires in Google Forms and increase the accuracy in prediction through Deep Learning algorithm with SENet architecture in TSSA
iv) To compare, the proposed TSSA with traditional algorithms and evaluated for the accuracy in conscientiousness prediction.

## 2 Literature Survey

Experiments show that two of the offered LDL approaches outperform others in terms of predictive ability, and that the best predictive algorithms also outperform others in terms of operational performance [11]. To provide novel computational aesthetics-based methodologies to inferring Flickr users' personality attributes from their galleries. Low-level features extracted from the images are mapped into numerical scores matching to the Big-Five Traits, both self-assessed and assigned, in the techniques [12]. Presents a deep learning-based approach for assessing the author's personality type from text: the presence or absence of the Big Five traits with in author's psychological profile is discovered with the text. The performance was improved by filtering out emotionally neutral input sentences [13]. Based on Facebook information, this study attempts to predict a person's personality. The Big Five Personality Model is adopted for the study [14]. This research examined into whether personality influences profile and image choices on Twitter and Facebook, respectively. There are some indications that personality does impact profile image selection, not always in the direction that predicted [15]. Huge differences in profile picture choice among personality types can be used to predict personality traits [16]. Identify the relationship between personality differences as evaluated by the Big Five model and profile image selection. This reduces the prediction error for personality attributes for each model [17]. Show how to use Facebook to recruit participants, motivate them, and engage them [18]. Automatic classifiers were trained using machine learning techniques on the acquired data to search for interaction patterns that indicate user personality traits [19]. This work attempts to model personality attributes of individuals using images labelled as favourite or liked on Flickr [20].

## 3 Proposed Methods

In this article, prediction of the personality of a person using his/her Facebook face images is proposed through TSSA method. As mentioned early a person's face expressions talks about his emotions which can be used to predict their personality. Here we chose only the face images from Facebook for identifying the personality, leaving other features such as status updates, likes or comments and questions. The data are obtained from questionnaires obtained from the link from https://openpsychometrics.org/tests/IPIP-BFFM/1.php, whenever the face images are collected from the same person. A person's facial expressions and his emotions are a time-varying factor and to predict a person's personality we need to analyse the facial images that are uploaded in a series of time. We can't predict a person's inner personality by viewing one or two pictures which may give an unreliable result. We need to use plural images that can stabilize the recognition of a person's personality. To achieve this stabilization, we use a temporal sequence of images in which we extract the facial expression of the people through a sequence of events in a period of time. By this process of temporal sequencing, we are able to avoid the flaws in predicting the personality trait of a person. In this study, we've taken the data of facial images of a particular person for a period of one month. The Fig. 1 shows the methodology block diagram of the proposed method.

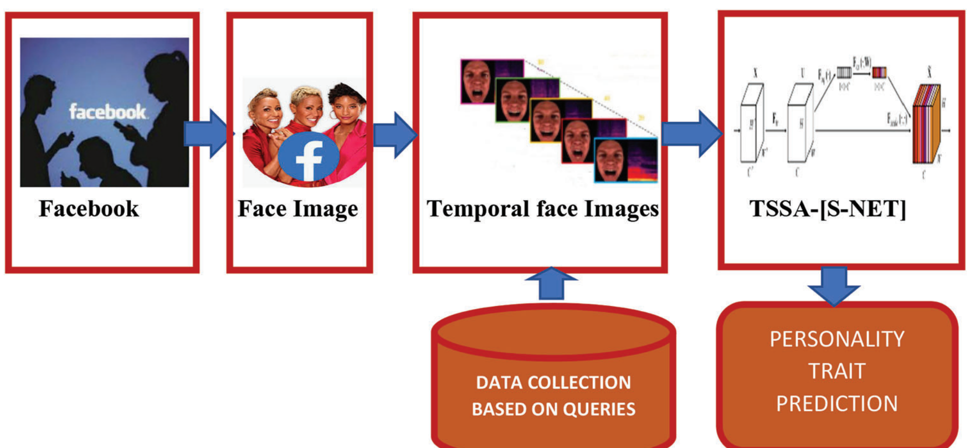


**Figure 1:** Proposed tssa method for evaluated for conscientiousness prediction

### *3.1 Face Image and Personality Trait Data Collection for Ocean Personality Prediction*

In order to increase accuracy of the prediction from facial expressions, data is also collected through queries from the same person whose face is taken into account. Google Forms are given to the participants and data were collected through standardized questionnaires. Collecting information regarding what a participant shares, what kind of content they like, whom they follow, the groups they interact with will provide an overall view of a person's behaviour. The responses which are gained through google forms are fused with their facial expressions and mapped with the Big Five Factor model to predict the personality traits. This method of compound data collection gives more precise information about a person's personality which results in a flawless prediction. For the prediction of the ocean personality the facial images and data collected from the questionnaires in google form are applied with proposed TSSA. A Combination of image and questionary data are termed as my personality dataset.

### *3.2 Se-Net for Classification and Conscientiousness Prediction From Face Images Acquired From Facebook*

Deep Learning (DL) is a subset of Machine Learning (ML) which in turn is a subset of Artificial Intelligence (AI). The deep learning algorithm is an iterative progress to artificial intelligence (AI) that uses machine learning algorithms. Accuracy is one of the main advantages of the deep learning algorithm. This is the most widely distributed AI architecture in recent days. In this algorithm, each level is processed by applying the knowledge that is acquired in the previous level. An input image is taken and the various features in it are assigned weights to differentiate each other. Moreover, there are three layers, the input layer, the hidden layer and the output layer. Each layer has neurons, which are the core entity of a neural network. S-net (scalable net) is a Convolutional Neural Network (CNN) architecture which uses Deep Learning algorithm. Deep Learning uses Graphical Process Unit (GPU) for processing and it also requires a massive data to get the desired output.

Artificial Intelligence (AI) is the process in which the computers or machines are simulated to work like or to work beyond a human brain. Artificial Neural Network (ANN) is an effort taken to simulate a machine by using the neuron network that will help the computer to learn and think like a human brain. They are programmed in such a way like how human brain cells are interconnected. ANN is a network of neurons to resemble a human brain and are fully connected. This fully connected network requires a lot of data and the result is not accurate always. To overcome the limitations of ANN a new architecture called Convolutional Neural Network (CNN) is used. A Convolutional Neural Network (CNN) implements Deep Learning algorithm, in which an input image is taken and weights are assigned based on the importance of the feature to differentiate one another. There is Input layer, hidden layer and the output layer. We can have n number of hidden layers depending upon our requirements. The CNN architecture is a simulation of the pattern of how neurons are interconnected in the Human brain. "Convolution" term refers to a function in mathematics which is a linear operation where we multiply two functions in order to get the third function which states the way how one function's shape is modified from another. Simply stating that, two images can be identified as matrices that are multiplied to get an output matrix which extract the features in the given input image. There following are the two main objects of CNN Architecture such as (i) Convolution tool: This tool is used to separate and identify the several features of the image in the process of Feature Extraction for analysis. (ii) Fully Connected Layer: This layer uses the output that is obtained in the above convolution process to predict its class that is based on the extracted features in the previous stages. Researches that are carried out recently indicates that the illustrations that are produced by CNN are strengthened through integration of learning mechanisms in the network which will help in capturing spatial correlations among the features. In this study, we have implemented a different view of network design to find the relationship between channels. Here we introduce a new architecture and the term Squeeze-and Excitation (SE) block, with the aim to improve the quality of representations that are produced by the network modelling the interdependencies explicitly between the channels of its convolutional features. The squeeze and Excitation block of S-net is as in Fig. 2.

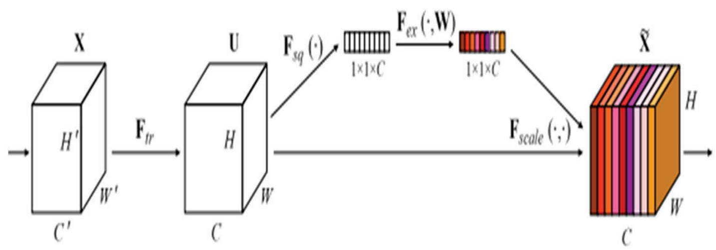


**Figure 2:** Squeeze and excitation block in proposed tssa method

The computational unit "squeeze and excitation block" is built on a transformation say, $F_{tr}$ which is mapped to an input X ∈ R H0 × W0 × C 0 to the feature maps U ∈ R H × W × C. In this notation we've taken $F_{tr}$ as the convolutional operator, then we use V = [v1,v2…vC] to specify the learned set of filter kernels. Here vc denotes the parameter in the c-th filter. Now the output is given as U = [u1,u2,…uC], in which

$$u_c = v_c * X = \sum_{s=1}^{C'} v_c^8 * x^8 \tag{1}$$

In the above equation, * indicates convolution, vc $= [v_c^1, v_c^2, \ldots . v_c^{C'}]$,

X $= x^1, x^2, \ldots . x^{C'}$ and $u_c \in R^{H \times W}$. $v_c^s$ is the 2-dimensional spatial kernel which represents the single channel that acts upon the channel of x. In order to evaluate the impact of SE blocks in TSSA method, experiments are performed on myPersonality dataset which constitutes 50 training images and 25 validation images from five various classes such as O, C, E, A and N. facial images are trained and reported the top-1 and top-5 error on the validation set. Each baseline network architecture and its respective SE counterpart in TSSA are trained with same optimisation schemes. Standard practices are followed and data augmentation are performed along with random cropping by using scale and aspect ratio to bring image into a size of 224 × 224 pixels (or 299 × 299 for Inception-ResNet-v2 and SE-Inception-ResNet-v2 and performed random horizontal flipping. Using mean RGB-channel subtraction the given input image is normalized. The Fig. 3 shows the top-1 error for the Inception-ResNEt-v2 and SE-Inception-ReseNet-v2 training. The Fig. 4 shows the top-5 error for the Inception-ResNEt-v2 and SE-Inception-ReseNet-v2 validation.

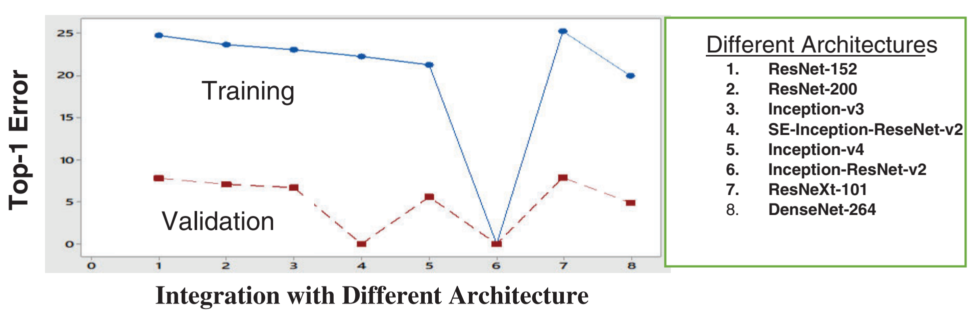


**Figure 3:** Top-1 error for the inception-resnet-v2 and se-inception-resenet-v2 training and validation

From Fig. 5, the SE-Inception-ReseNet-v2-TSSA method can handle efficiently the parallel training of huge facial images. Optimisation is done with the momentum of 0.9 and the size of the minibatch is 1024. The learning rate is initially set to 0.6 and for every 30 epochs it's decreased by a value of 10. The default value of the reduction ratio is set to 16. Weight initialization method is used to train the models for 100 epochs from scratch.

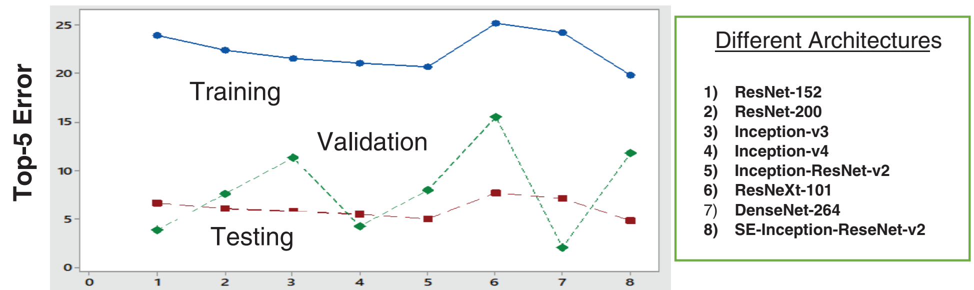


**Figure 4:** Top-5 error for the inception-resnet-v2 and se-inception-resenet-v2 training, validation

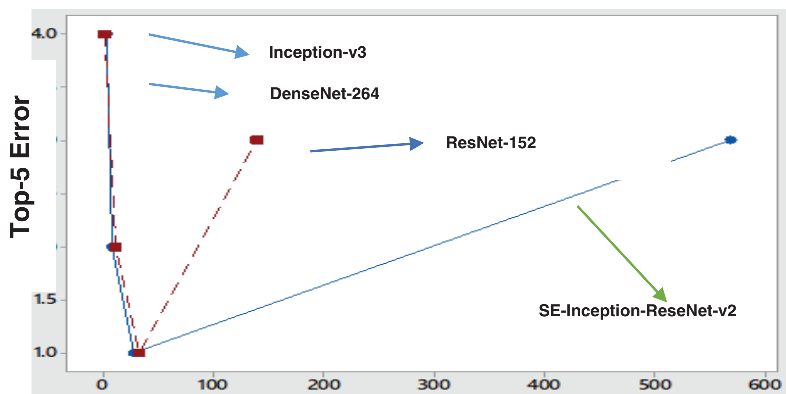


**Figure 5:** Top-5 error for the resnet and se-inception-resenet-v2 with different epoch

During face (model) evaluation centre-cropping method is applied in order to crop 224 × 224 pixels from every image, whose shorter edge is first resized to 256. Network depth is visible in Squeeze and Excitation block has a better performance in various depths adding feeble increase in the computational complexity. Remarkably, SE-ResNet-50 gains a single-crop top-5 validation error of 6.62%, which exceeds ResNet-50 (7.48%) by 0.86% and nearing the performance achieved by the much deeper ResNet-101 network (6.52% top-5 error) with only half of the total computational burden. This pattern is repeated at greater depth, where SE-ResNet-101 (6.07% top-5 error) not only matches, outperforms the deeper ResNet-152 network (6.34% top-5 error) by 0.27%. It's noticed that SE blocks add depth in an efficient manner of computation and gained better returns while the base architectures yield diminishing returns during depth extension. In addition, the returns are consistent for a wide range of facial image (network) depths, saying that the improvisations contributed by SE blocks are better (complementary to the ones that are gained by simply increasing the depth of the base architecture.).Integration with modern architectures is also study the impact of the integration of SE blocks with other important architectures namely, Inception ResNet V2 and ResNet, where computational building blocks are added with the base network. With the construction of SENet equivalent network called SE Inception ResNet V2 and SE ResNet where the SE block is introduced, and observe that, there is a significant improvement in the performance due the establishment of SE blocks into both the architectures. Especially the top-5 error of SE ResNet 50 is 5.49% which is better than ResNet 50 (5.90%) and deeper ResNet 101 (5.57%) which are models that have more parameters and the computation is also difficult. It's observed that there is a small difference in performance between our re-implementation of Inception-ResNet-v2. The impact of SE blocks on non-residual network was also assessed and experiments were conducted with the architectures namely VGG-16 and BN-Inception. The training of VGG-16 is done by adding Batch Normalization layers after completing each convolution. Similar schemes are implemented for both VGG-16 and SE-VGG-16, and the comparative results are shown in Tab. 2. As observed in the earlier cases of Residual Baseline Architectures it is clearly visible that the addition of SE block yields performance improvisations in non-Residual Architectures.

### *3.3 Single Crop Error Rates During Face Image Cropping From Facebook Page*

During acquisition of the face image overlapping other objects in the image need the Single Crop. The single cropping of the image leads to Error Rates in the proposed TSSA method. The image size cropping of image size 224 × 224 pixels and resized and applied to the TSSA method, since the face book images are not equal in size during extraction of face images from Facebook. The size of pixels are reduced from one to two range of the original image and optimized results are obtained from the TSSA method. The Fig. 6 shows the image cropping and Error plot for two different image pixel size.

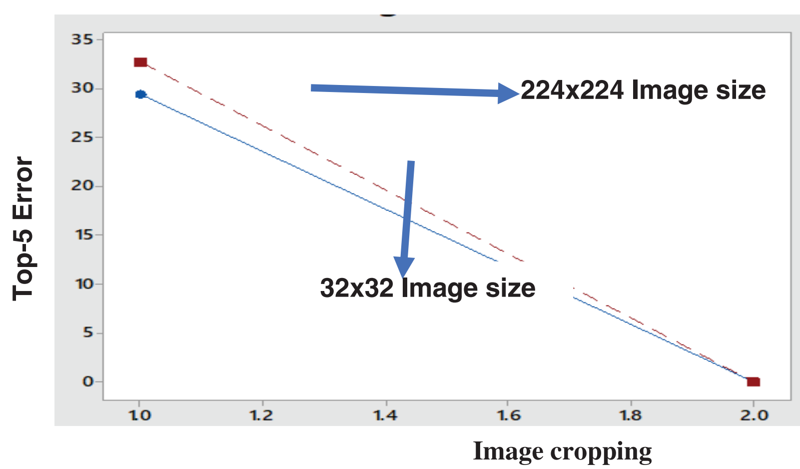


**Figure 6:** Image cropping and error rate for smaller size of face image extracted from Facebook page

From the plot, the TSSA method performs better for the different size of image obtain from facebook page and whereas other method performs less. TSSA method exhibit improved optimisation characteristics and produce consistent gains in performance which are sustained throughout the training process. The above Fig. 6 shows the impact of SE blocks while optimising these models. The training curves of the Base line Architectures and their corresponding SE Architectures observed that there is a constant improvement through the procedure of optimisation. Tab. 1 shows the Top 1 error for Integration with modern architectures and temporal face images from facebook page. Tab. 2 shows the Top 5 error for Integration with modern architectures and temporal face images from facebook page. The overall training process needed ~400 epochs. The results depicted in Tab. 2 indicates that SE block has improved the accuracy consistently in a wide margin while the elevation in the computational cost is minimized.

**Table 1:** Top 1 error for integration with modern architectures and temporal face images from facebook page

| Epoch values | % of Top 1 Error | | | |
|---|---|---|---|---|
| | ResNet-50 training | ResNet-50 validation | SE-Inception-ReseNet-v2 training (TSSA) | SE-Inception-ReseNet-v2 (TSSA) |
| 5 | 60 | 60 | 58 | 55 |
| 30 | 58 | 55 | 50 | 50 |
| 35 | 38 | 35 | 36 | 32 |
| 60 | 35 | 30 | 27 | 25 |
| 80 | 28 | 26 | 25 | 23 |
| 100 | 27 | 27 | 23 | 24 |

**Table 2:** Top 5 error for integration with modern architectures and temporal face images from facebook page

| Epoch values | % of Top 1 Error | | | |
|---|---|---|---|---|
| | ResNet-152 training | ResNet-152 validation | SE-Inception-ReseNet-v2 training (TSSA) | SE-Inception-ReseNet-v2 training (TSSA) |
| 5 | 60 | 60 | 58 | 55 |
| 30 | 58 | 55 | 50 | 50 |
| 35 | 38 | 35 | 36 | 32 |
| 60 | 35 | 30 | 27 | 25 |
| 80 | 28 | 26 | 25 | 23 |
| 100 | 27 | 27 | 23 | 24 |

At last, let's consider two more representative architectures namely ResNet-152 and SE-Inception-ReseNet-v2 which belong to the class of optimized network. A minibatch of size 256 and the size of the aggressive data argumentation is reduced slightly and regularisation. The models are trained across and momentum set to 0.9 along with the learning rate as 0.1 which will be reduced by 10 every time the validation loss is saturated. Tab. 3 shows the Comparison of Temporal face images from Facebook page (TSSA) and Traditional query-based methods.

**Table 3:** Comparison of temporal face images from facebook page (tssa) and traditional query-based methods

| Personality traits | TSSA-(SE-Inception-ReseNet-v2)-Facebook face images (% Prediction) Proposed | www.truity.com/test/big-five-personality-test | www.123test.com/personality-test/ | https://bigfive-test.com/ |
|---|---|---|---|---|
| 0 | 96 | 75 | 81 | 82 |
| C | 92 | 79 | 78 | 85 |
| E | 91 | 80 | 87 | 75 |
| A | 95 | 82 | 79 | 74 |
| N | 94 | 79 | 85 | 86 |

## 4 Conclusion

This article provides an analysis of the personality traits of Facebook users through their behavioural features in the Social Network Facebook. This article implements the user-generated Facebook face images and their corresponding feedback through questionnaires in google forms and extracted their personality traits. We analysed whether the advantages of SE blocks are common to other datasets also. In this paper, experiments are performed with many baseline architectures like ResNet–110, ResNet-164, WideResNet-16-8, Shake-Shake and Cutout with the datasets namely CIFAR-10 and FIFAR-100 datasets. In this analysation a group of 50 training and 10 testing images of size 32 × 32 pixel RGB images are marked with 10 and 100 class respectively. The facial images (images) are randomly flipped horizontally and zero padded on the sides with 4 pixels before 32 × 32 crop. The training hyperparameters say, minibatch size, weight decay and initial learning rate settings are matched with original image. Analysing the addition of SE block in other datasets its clear that the SENet yield better results than other architectures and performs better for prediction results are utilized for assessment of a person's conscientiousness for leadership quality suitability. The study implements Deep Learning algorithm with SENet architecture and Integration with modern architectures compares with traditional algorithms. From the validation results the proposed TSSA method performs 96% of accuracy in conscientiousness prediction. The induction of SENet algorithm with deep learning gives more accurate predictions of the user's personality. The result for the combination of all the features of Big five model the predicted personality trait has and average accuracy of 92%.

**Funding Statement:** The authors received no specific funding for this study.

**Conflicts of Interest:** The authors declare that they have no conflict of interest to report regarding the present study.

### References

[1] H. S. Hwang, "The influence of personality traits on the facebook addiction," *KSII Transactions on Internet and Information Systems (TIIS)*, vol. 11, no. 2, pp. 1032–1042, 2017.

[2] R. Biolcati, G. Mancini, V. Pupi and V. Mugheddu, "Facebook addiction: Onset predictors," *Journal of Clinical Medicine*, vol. 7, no. 6, pp. 118, 2018.

[3] J. Weismueller, P. Harrigan, S. Wang and G. N. Soutar, "Influencer endorsements: How advertising disclosure and source credibility affect consumer purchase intention on social media," *Australasian Marketing Journal, Elsevier*, vol. 28, no. 4, pp. 160–170, 2020.

[4] A. Marouf Ahmed, Md. Kamrul Hasan and H. Mahmud, "Comparative analysis of feature selection algorithms for computational personality prediction from social media," *IEEE Transactions on Computational Social Systems*, vol. 7, no. 3, pp. 587–599, 2020.

[5] Z. M. M. Aung and P. H. Myint, "Personality prediction based on content of facebook users: A literature review," in *2019 20th IEEE/ACIS Int. Conf. on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD)*, Toyama, Japan, pp. 34–38, 2019.

[6] M. M. Tadesse, H. Lin, B. Xu and L. Yang, "Personality predictions based on user behavior on the facebook social media platform," *IEEE Access*, vol. 6, pp. 61959–61969, 2018.

[7] S. A. Salloum, A. Said, M. Al-Emran, A. A. Monem and K. Shaalan, "A survey of text mining in social media: Facebook and twitter perspectives," *Advances in Science, Technology and Engineering Systems Journal*, vol. 2, no. 1, pp. 127–133, 2017.

[8] M. Pramod, M. Raj Kumar, P. Anil Kumar, N. Naga Sarath and K. Vikas, "Identifying personality traits using social media," *Iconic Research and Engineering Journals*, vol. 1, no. 9, pp. 186–192, 2018.

[9] T. Rajesh and B. Rangaiah, "Facebook addiction and personality," *Heliyon*, vol. 6, no. 1, pp. e03184, 2020.

[10] C. S. Andreassen, S. Pallesen and M. D. Griffiths, “The relationship between addictive use of social media, narcissism, and self-esteem: findings from a large national survey,” *National Library of Medicine, Addictive Behavior*, vol. 64, pp. 287–293, 2017.

[11] D. Xue, Z. Hong, S. Guo, L. Gao and L. Wu, “Personality recognition on social media with label distribution learning,” *IEEE Access*, vol. 5, pp. 13478–13488, 2017.

[12] C. Segalin, A. Perina, M. Cristani and A. Vinciarelli, “The pictures we like are our image: Continuous mapping of favorite pictures into self-assessed and attributed personality traits,” *IEEE Transactions on Affective Computing*, vol. 8, no. 2, pp. 1–18, 2016.

[13] N. Majumder, S. Poria, A. Gelbukh and E. Cambria, “Deep learning-based document modeling for personality detection from text,” *IEEE Intelligent Systems*, vol. 32, no. 2, pp. 74–79, 2017.

[14] T. Tandera, D. Suhartono, R. Wongso and Y. L. Prasetio, “Personality prediction system from facebook users,” in *Computer Science and Computational Intelligence, 2nd Int. Conf., ICCSCI*, Bali, Indonesia, pp. 604–611, 2017.

[15] M. T. Whitty, J. Dodson, S. Creese and D. Hodges, “A picture tells a thousand words: What facebook and twitter images convey about our personality,” *Journal of Personality and Individual Differences*, vol. 133, no. 1, pp. 109–114, 2018.

[16] L. Lequi, D. Preotiuc-pietro, Z. Riahi Samani, M. E. Moghaddam and L. Ungar, “Analyzing personality through social media profile picture choice,” in *Web and Social Media, Tenth International Conference, ICWSM 2016. Proceedings: AAAI Conference*, Palo Alto, California, pp. 211–220, 2016.

[17] A. Lay and B. Ferwerda, “Predicting user’s personality based on their liked images on instagram,” *Journal of Humanize*, vol. 18, pp. 1–5, 2018.

[18] M. Kosinski, S. Matz, S. Gosling, V. Popov and D. Stillwell, “Facebook as a research tool for the social sciences: Opportunities, challenges, ethical considerations and practical guidelines,” *Journal of American Psychologist*, vol. 70, no. 6, pp. 543–556, 2015.

[19] A. Ortigosa, M. Carro, R. M. Carro and J. I. Quiroga, “Predicting user personality by mining social interactions in facebook,” *Journal of Computer and System Sciences*, vol. 80, no. 1, pp. 1–15, 2013.

[20] S. C. Guntuku, T. Joey Zhou, S. Roy, L. Weisi and I. W. Tsang, “Who likes what, and why? Insights into personality modeling based on image likes,” *Journal of IEEE Transactions on Affective Computing*, vol. 1, no. 1, pp. 99, 2016.