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A Classification Pipeline Methodology for Predicting Personality Traits

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Abstract: ***With multiple advancements in machine learning and deep learning a multitude of tasks that were either too complex to hardcode or even regarded as impossible can now be performed. This technology can be used to our advantage to determine someone's personality based solely on their perception and opinions. Nowadays, a lot of tasks involving the victim's personality are necessary for criminal activity surveillance, personality has started to play a significant role in mental health therapy as well as hospitality businesses are trying to monitor the personality of customers to provide better services. We can assist in the completion of such a work by combining deep learning with a classification-based machine learning model connected by a data pipeline. The use case can also be extended to hospitality businesses to understand the mindset of the patient and is also useful during selection of candidates for a particular job profile based on their personality traits. It is also used in many successful marketing campaigns to target specific audiences. We propose a combined classification pipeline that employs both unsupervised and supervised deep learning approaches such as K-Means along with LSTM, GRU, RNN and Autoencoders (Deep Embedded Clustering) to draw a comparative analysis between these approaches to analyze personalities successfully.***

Keywords: Deep learning, RNN- Recurrent Neural Network, LSTM – Long Short-Term Memory, GRU – Gated Recurrent Unit, DEC – Deep Embedded Clustering, Autoencoder, Personality Prediction, OCEAN- Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism

I. INTRODUCTION

The various traits make a person unique. The list includes fundamental characteristics, as well as interests, desires, beliefs, skills, and emotional elements. It is a biological and environmental phenomenon that lasts for the bulk of lifespan.

A personality prediction system is used to determine the personality of a person based on a questionnaire. As we all know, a person's personality is a major factor in deciding a lot of things about that individual. Nowadays, both criminal activity monitoring and mental health therapy call for a number of activities pertaining to the victim's personality. We can assist in the accomplishment of such a task by integrating a classification-based machine learning model with natural language processing via a data pipeline. Automating mental health monitoring is the following step towards greater accessibility. Learning from datasets has enabled machine learning and deep learning to predict a number of human attributes.

The subsequent stage towards better accessibility is the automation of mental health monitoring. By learning from datasets, algorithms have made it possible to predict a variety of human attributes. As a consequence, interactions with systems may be streamlined and made more approachable for people who might not normally feel comfortable using them. High-speed internet became widely accessible, ushering in the era of machine learning.

Psychologists have created a number of psychological tests to categorize personality. The Big Five personality test, the MBTI exam, the DISC assessment, and other well-known psychological tests are used widely around the globe. In this study, we suggest using the Big Five personality test to categorize personality into any one of the five different types that the Big Five Test's creators have identified.

To predict the personalities from the provided dataset, we will use the Gated Recurrent Units (GRUs) and Autoencoders. After receiving the results from the GRU and the Autoencoder, we will evaluate the accuracy of the RNN, LSTM, GRU, and Autoencoder to see whether any hyperparameter adjustment is necessary to enhance them. With our future advancements, we may include various input methods, including audio and video, to collect more data and present it in a comprehensible and understandable manner.

The main aim is to draw a comparative analysis between various approaches to analyze personalities successfully. The comparison is based on the total number of parameters used per model, number of epochs, best accuracy and least lost. The algorithms used for comparison are: RNN, LSTM, GRU and semi supervised DEC.

II. LITERATURE SURVEY

The classification of personality traits from text was done using a mixed deep learning technique [1]. The model proposed a combination of convolutional neural networks along with LSTM for personality trait classification. Deep learning models help overcome drawbacks of using machine learning approaches as a method of feature selection. For a more precise classification of personality traits, the issue of context information processing must be addressed utilizing hybrid DL models helped by feature selection. This is supported by making effective use of a deep neural network to extract features. The accuracy of the results was 88% [2]. A. Pulver and S.

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Lyu proposed an LSTM like architecture which outperforms the vanilla RNN and LSTM model. RNN performance test that emphasizes various crucial network characteristics while using handwritten numbers [5]. Numerous techniques ranging from fundamental procedures to cutting-edge methods such as the LSTM neural network are employed in the prediction process. It will be possible to anticipate product sales using neural networks as a model for prediction of time series, with a focus on the LSTM neural network architecture.

Recurrent neural networks are more practical than artificial neural networks because they can represent a series of data such that each data point may be taken to be dependent on the previous one [7]. Yet, ANN is unable to model a series of data. So long as each data point is supposed to be independent of the preceding and subsequent ones, ANN is favorable [8]. Another application of RNN to the study of hate speech shows its potential. The categorization of hate speech is divided into two categories (hate speech or non hate speech). More training resulted in better accuracy. Testing results for system performance showed an average accuracy of 91%, recall of 90%, and precision of 91% [9]. Social media content used for the detection of mental disorders has been implemented using CNNs and LSTMs. Features extraction was based on two methods namely, facial expression and textual information. With a performance accuracy of 97.56%, CNN+LSTM with word embeddings outperformed the competition, while LSTM came in second with a 97.48% accuracy.

Facebook profile data is automatedly collected by web scraping and stored in MongoDB [3]. Personality prediction is carried out based on random forest regressor and classifier algorithms [6]. Several studies have found a connection between face features and personality. It has been proven that people can infer some personality qualities about one another very accurately from their appearances. Algorithms like MobileNetv2, ResNeSt50, and S-NNPP were used. Using a person's facial expressions, one might infer their personality. It was found that the accuracy was higher than 70% as a result. Deep learning methodologies were implemented in order to automate the process of personality prediction using posts and profile pictures for social media [10]. Algorithms used were face detection and smile detection for facial expression recognition and Word2Vec for text preprocessing. The conclusion obtained was that picture characteristics are more accurate in predicting personality than text features alone or when combined with text and image features.

The classification of personalities was performed using CNN. The method was used to categorize five different personality characteristics. Word vectorization using Word2Vec is done in the first layer. Using the Word2Vec Word embeddings library from Google, word-level feature extraction was carried out. To extract n-gram features from each phrase in the document, convolutional filters and max pooling were used in the second layer. In order to create document vectors, the phrase vectors from Layer 3 were concatenated. The document vector was enhanced using Mairesse characteristics that were concatenated with the document features acquired in Layer 3. In the fifth layer, activation functions such as Sigmoid, Tanh, and ReLU have been applied. The presence or absence of a particular personality trait is determined by the sixth layer [11].

Various machine learning approaches are used for the analysis of personality prediction using different datasets [4]. At a 60% accuracy rate, Naive Bayes marginally outperforms SVM and KNN. Gray prediction model, the multitasking model, and multiple regression may be used since accuracy rate is high but it is uncommon for researchers to use the gray prediction approach [12]. Utilizing information from the candidate's résumé as well as results from various personality tests, the Applicant Personality Prediction System (APPS) forecasted the candidate's personality [13]. By rating the resume on several parameters, including experience, talents, and other factors, personality prediction systems choose the best applicant for the desired job description. This approach is also applicable to other industries where it is necessary to select people quickly through the use of screening procedures. To evaluate, summarize, and compare the similarities between a CV and a job description, our programme employs the Spacy module.

Despite the fact that there are countless publications devoted to our issue, there are far too few that have really undertaken any type of study, including many different models carrying out various activities that are pertinent to what we want. Machine learning models are employed in a lot of studies. These studies' findings frequently have very poor accuracy. Large datasets are frequently used in articles utilizing deep learning algorithms. Despite the fact that the Big Five personality test has utilized a variety of algorithms, the DEC method has never been employed to predict personality in this dataset.

III. PROPOSED WORK

While understanding the workings and functionalities of worked upon algorithms: Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Recurrent Neural Network (RNN) and Deep Embedded Clustering (DEC), a comparison was drawn amongst them in order to be best applicable in case of use of the mentioned Big five personality dataset for serving to a multitude of applications. Elaborately it was clearly acknowledged that DEC performed better than its competitors [24].

Deep Embedded Clustering known as DEC is a kind of unsupervised machine learning algorithm that combines and fully amalgamates deep learning with clustering. It involves a deep neural network architecture that learns and understands a low-dimensional representation of the input data and uses this representation to cluster the data points. Long Short-Term Memory or LSTM, Gated Recurrent Unit or GRU, and Recurrent Neural Network or RNN are all different kinds of neural networks that are usually used in natural language processing and the time series analysis [25]. They are designed to manage sequential data and are able to remember information from previous time steps. LSTM and GRU are types of RNNs that were developed to aid the observed problem of vanishing gradients in traditional RNNs. Both LSTM and GRU have additional mechanisms, called gates, that manage the flow of information within the network [26]. LSTM has three

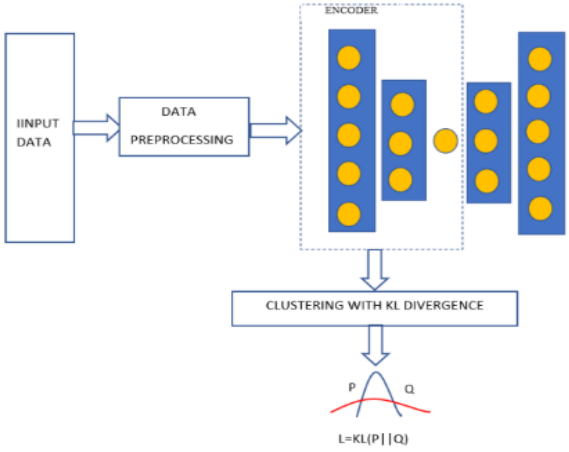
observed gates, which are the input gate, output gate, and forget gate, while GRU has two gates, including an update gate and reset gate. In summary, DEC is a clustering algorithm that combines deep learning with clustering, while LSTM, GRU, and RNN are types of neural networks designed to handle sequential data. LSTM and GRU are both types of RNNs that help with the issue of vanishing gradients in regular and traditional RNNs by including additional mechanisms, known as gates, that manage the flow of information and data within the network [27].

A. Semi Supervised Embedded Clustering

The input data is clustered in a semi-supervised way with the help of the Semi-Supervised DEC algorithms on the basis of a small portion of previous information. More precisely, an autoencoder paradigm and deep clustering are put to use to formulate a deep semi- supervised clustering network. By helping the prevention of shift of labels in DEC, this network is designed to efficiently mine the clustering representation and clustering assignment. Post that, a back-propagation-based method with adaptable labels is described. This method trains the parameters of the deep semi-supervised clustering network using the pretrain and fine-tune techniques.

One of the main causes for its popularity is that deep embedding clustering (DEC) outperforms end-to-end clustering by a wide margin.

Nevertheless, due to the extremely small amount of a priori knowledge that is included in the vast amount of data, DEC is unable to take advantage of it. Figure 1 shows a semi-supervised deep embedded clustering algorithm with adaptive labels that has been developed to get around this problem.



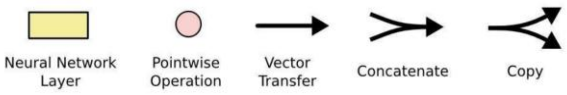
[Fig.1: Semi-Supervised Deep Embedded Clustering]

In the semi-supervised DEC, a model is simultaneously trained using clustering and measuring representation learning. The initial part of the system does representation learning, which seeks to make data less dimensional and produce results that are as similar as possible to the input.

In contrast to clustering, where the model is trained to minimize both reconstruction loss and clustering loss, DEC is semi-supervised. It calculates soft assignment values between the cluster centroids and the embedded locations.

In more generic ways it is identified that DEC performs far better than its peers.

B. Notations used

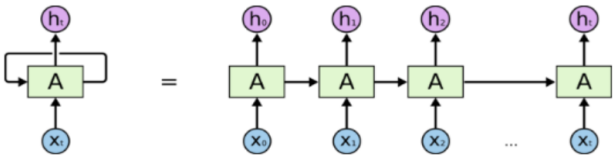


[Fig.2: Notations used]

C. Other Methods Implemented for Comparison

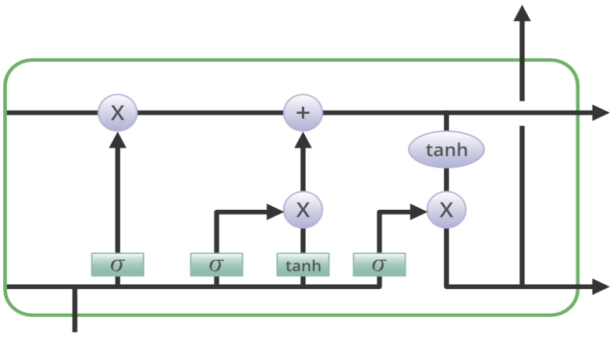
For the study of adequate performance of the DEC Model, other algorithms were studied to draw comparison with DEC and between themselves in terms of accuracy and usability.

A **Recurrent Neural Network or RNN** is a kind of neural network which is created in order to process and evaluate sequential data such as the time-series data, text, and speech signals. Unlike feedforward neural networks that process data inputs in a fixed order, RNNs allow feedback connections between their nodes, allowing them to maintain a memory of past inputs. The RNN takes an input and produces an output, as well as a hidden state that is fed back into the network to influence the processing of the next input at every time step. On the basis of the present input and the previous hidden state the hidden state is updated , further permitting the network to encode information about the previous inputs.They are particularly useful for tasks where context and temporal dependencies are important. Recent advances in RNN architectures such as LSTM networks and GRUs have further improved the performance of RNNs on a range of sequential data tasks.



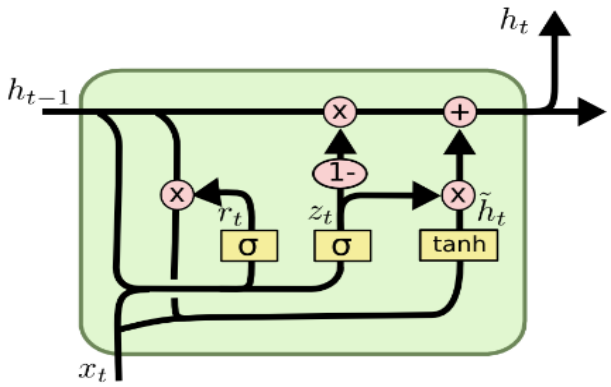
[Fig.3: An Unrolled Recurrent Neural Network]

Long Short-Term Memory or LSTM is a kind of RNN architecture that is specifically created in order to address the problem of vanishing gradients that can be seen during the training of regular RNNs. LSTMs first were brought to light in 1997 by Hochreiter and Schmidhuber [14]. The central innovation of LSTMs relies on the use of cells which are memory cells that can maintain information for a long span of time, enabling the network to selectively choose to forget or remember information as per requirement [15]. This is successfully possible with the use of a series of gates that maintain and manage the flow of information into and out of the memory cell [16]. One of these gates is an input gate that regulates the flow of information into the memory cell, then there's a forget gate that determines the information that should be removed from the cell, and an output gate that regulates the flow of information moving out of the cell. During training, the LSTM learns to adjust the weights of the respective gates based on the input data and the desired output [17]. This permits the network to capture long-term dependencies and certain temporal patterns in the input data [18].



[Fig.4: Long Short-Term Memory]

Gated recurrent units or GRUs are a variation of recurrent neural network (RNN) architecture that was developed by Cho et al. in 2014 [19]. Like LSTMs, GRUs are created to amend the problem of vanishing gradients that can be seen during training of traditional RNNs. GRUs present an easier architecture as compared to LSTMs [20]. In GRUs there are two gates known as the reset gate and the update gate. These gates are responsible for regulating the flow of information in the network. The reset gate determines how much of the prior information needs to be forgotten, and on the other hand the update gate decides what amount of new information can be necessarily retained. The advantage of GRUs is that they need fewer parameters than LSTMs and are therefore faster to train and need less memory. Additionally, in some cases, they have been found to perform better than LSTMs.



[Fig.5: Gated Recurrent Unit]

D. Dataset

Kaggle Dataset – Big Five Personality Test (1M answers to 50 personality questions). In the respective dataset 1,015,342 questionnaire responses were collected and amalgamated online by Open Psychometrics. Size of dataset – 416.27MB.

A technique for categorizing personality traits is called the five-factor model (FFM), sometimes referred to as the OCEAN model and the Big Five personality traits. Many labels used to characterize personality qualities are frequently assigned to the same person when personality survey data is subjected to factor analysis. You must rate each of the fifty items on a five-point scale (where one means disagree, three means neutral and 5 means agree) based on how well it characterizes you. The test can be finished in a few minutes by most individuals. According to this theory, which describes the human mentality and psyche using adjectives from everyday language, there are five main groups.

Table 1: Personality Traits

S. No.	Trait	Description
1	Openness	Includes personality attributes like inspiration, creativity, and impartiality.
2	Conscientiousness	Consist of character traits including tenacity, strictness, and dedication to their work.
3	Extraversion	Individuals that enjoy being with other people and are enthusiastic.
4	Agreeableness	Includes qualities like kindness, love, support, and good humor..
5	Neuroticism	includes personality qualities such anxiety, worry, fear, rage, and irritation as well as feelings of envy, jealousy, remorse, and loneliness.

E. Hardware and Software Requirements

Hardware Requirements: Graphics Processing Unit (GPU)

Software Requirements: Google collaboratory or Jupyter Notebook, Anaconda, Python

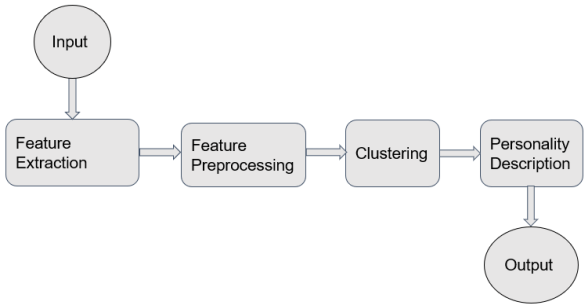
F. Experimental Setup

Tensor-flow was used to code all architectures, and the NVIDIA P4 GPU with CUDA integration was used to train them. A data collection of responses from 200000 test participants was utilized to train the models, and some of the responses were also used for cross-validation [21].

G. System Architecture

A system architecture is a collection of rules that outline the creation and development of software [22]. The organization and structure of the software system are determined by its architecture. It also explains the various levels of abstraction and the interactions between the various parts of the software system.

An architecture can be used to define a project's objectives or to serve as a blueprint for the design and development of a new system [23].



[Fig.6: System Architecture]

IV. RESULTS AND CONCLUSION

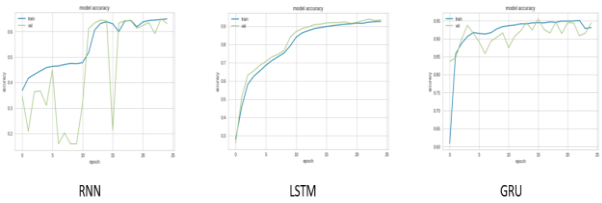
The paper attempts to provide an in-depth understanding and comparison between various deep learning approaches in order to aid better use and application of the respective approaches. The proposed semi-supervised DEC classifier model has been extensively tested on the Kaggle personality datasets. Firstly, based on reconstruction error, the autoencoder method helped in the extraction of the features.

Post this, predictions were made using the extracted features from the autoencoder which were fed to the clustering model. In an improved feature space, the clustering model progressively clusters the provided data points based on KL-divergence and predicts the personality of the person.

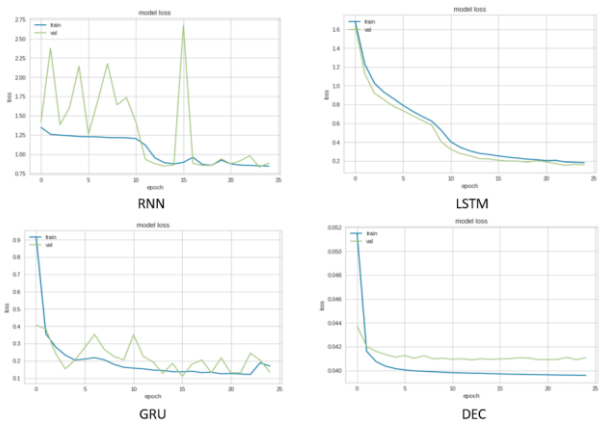
The outcomes of the suggested model were contrasted with current state-of-the-art findings in the literature, and the findings demonstrated that our proposed model develops an advanced computational method by offering a creative framework for forecasting people's personalities. In semi-supervised and unsupervised applications, when cross validation is not available, the Semi-supervised DEC offers improved performance as well as flexibility with regard to hyperparameter settings. The Semi-supervised DEC can expand to huge datasets since it can manage both clustering loss and reconstruction loss. The suggested work may be expanded in the future to incorporate automated mental health monitoring.

Table 2: Comparison of Algorithms

S. No	Algorithm	Accuracy	Loss
1	RNN	65.01%	0.8332
2	LSTM	93.85%	0.1538
3	GRU	95.50%	0.01099
4	DEC	-	0.04089



[Fig.7: Comparison of Accuracy of Various Models]



[Fig.8: Comparison of Loss of Various Models]

V. FUTURE SCOPE

Machine Learning is fast evolving and hence, with it there is always a scope of improvement. This model can be improved by incorporating more layering in the LSTM architecture and then testing the accuracy for the models. The regular LSTM can be replaced by Bi-LSTM or Gated Recurrent Units (GRUs).

Audio Input and Video Input format can also be considered for personality prediction by the use of audio processing and capturing of facial features along with audio signals.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been sponsored or funded by any organization or agency. The independence of this research is a crucial factor in affirming its impartiality, as it has been conducted without any external sway.
- **Ethical Approval and Consent to Participate:** The data provided in this article is exempt from the requirement for ethical approval or participant consent.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Authors Contributions:** The authorship of this article is contributed equally to all participating individuals.

REFERENCES

1. Ahmad, H., Asghar, M. U., Asghar, M. Z., Khan, A., & Mosavi, A. H. (2021). “A hybrid deep learning technique for personality trait classification from text” IEEE Access, 9, 2021. DOI: https://doi.org/10.1109/ACCESS.2021.3121791
2. A. Pulver and S. Lyu, "LSTM with working memory," 2017 International Joint Conference on Neural Networks (IJCNN), 2017. DOI: https://doi.org/10.1109/IJCNN.2017.7965940
3. G. V. Rohit; K Rakesh Bharadwaj; R Hemanth; Bariti Pruthvi; M.V. Manoj Kumar, “Machine intelligence based personality prediction using social profile data ” 2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT), 2020. DOI: https://doi.org/10.1109/ICSSIT48917.2020.9214175
4. Aditi V. Kunte, Suja Panicker “Analysis of Machine Learning Algorithms for Predicting Personality: Brief Survey and Experimentation” Global Conference for Advancement in Technology (GCAT), 2019. DOI: https://doi.org/10.1109/GCAT47503.2019.8978469
5. N. S. Malinović, B. B. Predić and M. Roganović, "Multilayer Long Short-Term Memory (LSTM) Neural Networks in Time Series Analysis," 2020 55th International Scientific Conference on Information, Communication and Energy Systems and Technologies (ICEST), 2020. DOI: https://doi.org/10.1109/ICEST49890.2020.9232710
6. Jia Xu, Weijian Tian, Guoyun Lv, Shiya Liu, Langyu Fan, “Prediction of the Big Five Personality Traits Using Static Facial Images of College Students With Different Academic Backgrounds” IEEE Access, 2021. DOI: https://doi.org/10.1109/ACCESS.2021.3076989
7. M. Kaur and A. Mohta, "A Review of Deep Learning with Recurrent Neural Network," 2019 International Conference on Smart Systems and Inventive Technology (ICSSIT), 2019. DOI: https://doi.org/10.1109/ICSSIT46314.2019.8987837
8. A. S. Saksesi, M. Nasrun and C. Setianingsih, "Analysis Text of Hate Speech Detection Using Recurrent Neural Network," 2018 International Conference on Control, Electronics, Renewable Energy and Communications (ICCEREC), 2018. DOI: https://doi.org/10.1109/ICCEREC.2018.8712104
9. R. Kanaan, B. Haidar and R. Kilany, "Detecting Mental Disorders through Social Media Content," 2021 IEEE 3rd International Multidisciplinary Conference on Engineering Technology (IMCET), 2021. DOI: https://doi.org/10.1109/IMCET53404.2021.9665555
10. Nicholaus Hendrik Jeremy, George Christian, Muhammad Fadil Kamal, Derwin Suhartono, Kristien Margi Suryaningrum, “Automatic Personality Prediction using Deep Learning Based on Social Media Profile Picture and Posts”, International Seminar on Research of Information Technology and Intelligent Systems (ISRITI), 2021. DOI: https://doi.org/10.1109/ISRITI54043.2021.9702873
11. Nilugonda, M., Madhavi, K., & Nagaraju, K. C., “Big Five Personality Traits Prediction Using Deep Convolutional Neural Networks” International Conference on Advanced Informatics for Computing Research, pp. 446-455, Springer, 2020. DOI: https://doi.org/10.1007/978-981-16-3660-8_42

12. M. Karnakar, H. U. Rahman, A. B. J. Santhosh, and N. Sirisala, "Applicant Personality Prediction System Using Machine Learning," 2021 2nd Global Conference for Advancement in Technology (GCAT) IEEE Xplore, 2021. DOI: https://doi.org/10.1109/GCAT52182.2021.9587693
13. Kingma, D. P., & Ba, J., Adam: A method forstochastic optimization, 2014. DOI: https://doi.org/10.48550/arXiv.1412.6980
14. Hochreiter, S., & Schmidhuber, J., LSTM can solve hard long time lag problems. Advances in neural information processing systems, 9, 1996. https://proceedings.neurips.cc/paper_files/paper/1996/file/a4d2f0d23dcc84ce983ff9157f8b7f88-Paper.pdf
15. Zaferani, E. J., Teshnehlab, M., & Vali, M. Automatic Personality Traits Perception Using Asymmetric Auto-Encoder. IEEE Access, 9, 68595-68608, 2021. DOI: https://doi.org/10.1109/ACCESS.2021.3076820
16. Mehta, Y., Majumder, N., Gelbukh, A., & Cambria, E., Recent trends in deep learning-based personality detection. Artificial Intelligence Review, 2020, 53(4), 2313-2339. DOI: https://doi.org/10.1007/s10462-019-09770-z
17. Başaran, S., & Ejimogu, O. H., A neural network approach for predicting personality from Facebook data, 2021. DOI: https://doi.org/10.1177/21582440211032156
18. Nilugonda, M., Madhavi, K., & Nagaraju, K. C., Big Five Personality Traits Prediction Using Deep Convolutional Neural Networks. In International Conference on Advanced Informatics for Computing Research, 2020, pp. 446-455, Springer. DOI: https://doi.org/10.1007/978-981-16-3660-8_42
19. Thieme, A., Belgrave, D., & Doherty, G., Machine learning in mental health: A systematic review of the HCI literature to support the development of effective and implementable ML systems. ACM Transactions on Computer-Human Interaction (TOCHI), 2020. DOI: https://doi.org/10.1145/3398069
20. B. K. Singh, M. Katiyar, S. Gupta, and N. G. Ganpatrao, "A Survey on: Personality Prediction from Multimedia through Machine Learning," 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), 2021. DOI: https://doi.org/10.1109/ICCMC51019.2021.9418384
21. Xie, J., Girshick, R., & Farhadi, A., Unsupervised deep embedding for clustering analysis. In the International conference on machine learning (pp.478-487). PMLR, 2016. DOI: https://doi.org/10.48550/arXiv.1511.06335
22. Kamalesh, M. D., & Bharathi, B. Personality prediction model for social media using machine Learning Technique. Computers and Electrical Engineering, 100, 107852, 2022. DOI: https://doi.org/10.1016/j.compeleceng.2022.107852
23. Muralidharan, R., Kuriakose, N., & J, S. (2023). Myers-Briggs Personality Prediction. In Indian Journal of Data Mining (Vol. 3, Issue 1, pp. 11–19). DOI: https://doi.org/10.54105/ijdm.b1630.053123
24. Bhamare, M., & Kumar, Dr. K. A. (2019). Personality Prediction from Social Networks text using Machine Learning. In International Journal of Recent Technology and Engineering (IJRTE) (Vol. 8, Issue 4, pp. 2384–2389). DOI: https://doi.org/10.35940/ijrte.d7146.118419
25. Maloji, S., Mannepalli, K., Sravani, N., Sri, J., K. Bhavya, & Sasidhar, C. (2020). Big Five Personality Prediction from Social Media Data using Machine Learning Techniques. In International Journal of Engineering and Advanced Technology (Vol. 9, Issue 4, pp. 2412–2417). DOI: https://doi.org/10.35940/ijeat.d7946.049420
26. Lal, M., & Agarwal, S. (2020). Natural Convection MHD Effect on Heat Transfer in Vertical Cylinder. In International Journal of Innovative Technology and Exploring Engineering (Vol. 9, Issue 4, pp. 237–240). DOI: https://doi.org/10.35940/ijitee.d1318.029420
27. Mukherjee, P., Palan, P., & Bonde, M. V. (2021). Using Machine Learning and Artificial Intelligence Principles to Implement a Wealth Management System. In International Journal of Soft Computing and Engineering (Vol. 10, Issue 5, pp. 26–31). DOI: https://doi.org/10.35940/ijsce.f3500.0510521