IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Beyond the Surface: Text-Based Personality Prediction Using Bi-LSTM and CNN2D

[1]**VADAPALLI GOWRI PRASAD,**
Student in Dept. Of Master of Computer Applications, at Miracle Educational Society Group of Institutions
[2]E MAHENDRA ROY, Miracle Educational Society Group of Institutions
[3]P.APARNA, Miracle Educational Society Group of Institutions
[1]prasadvadapalli553@gmail.com

ABSTRACT:

This research aims to predict the extroversion personality trait through the application of deep learning techniques on social media text data. Leveraging modern NLP techniques and sentence embeddings, the model analyzes large data sets of text to discern intricate patterns of user behavior. Performance is evaluated with various algorithms, and Bi-LSTM is confirmed to have the highest accuracy. In this study, Bi-LSTM is applied to the MBTI dataset, where text is converted to embeddings with models like MiniLM. The results show deep learning's potential in personality evaluation, which can be used in marketing, recruitment, and even mental health evaluation. This study showcases AI's strides in accurately and meaningfully understanding human traits.

Keywords: Deep Learning, CNN2D, AI

INTRODUCTION

In today's world, social media is a treasure trove of information that can be exploited to get a glimpse into a person's thoughts and character. Every comment, tweet, and message pulls together the essence of a personality. It opens doors to a unique dimension where machines can analyze a person's character. This project aims to evaluate the extroversion trait by predicting through text data whether a person is an extrovert or introvert. Step into the shoes of an extrovert: they will typically engage in expressive, interactive forms of language. In contrast, introverted individuals craft their thoughts in a much more introspective manner. Though personal attributes can be useful for NLP instruments and Bi-LSTM and CNN2D models, analysis distinguishing them individually is not very useful. A MiniLM and TF-IDF embedding methods were applied to the MBTI dataset in the study. This study, along with tailored advertising and early intervention in mental health, has applications in career advice. It is essential, however, to address issues of ambiguous language, imbalanced data, and ethics to ensure accuracy and responsible application.

RELATED WORK

Research in past has focused on predicting personality traits with the help of classical ML techniques and analyzing text data. User-generated content has shown the application of deep learning personality traits models by Yang et al. (2023), who demonstrated the importance of context-aware embeddings in comparison to simple keyword models. Zim et al. (2024) proposed a hybrid deep learning model to detect mental health indicators from social data, using a combination of CNN and LSTM. Sánchez-Fernández et al. (2023) analyzed the performance of classical ML methods and sophisticated deep learning techniques in the task of personality prediction. They asserted that deep learning models, particularly those employing transformer embeddings, provided higher accuracy in the predictions. Bowden-Green et al. (2020) reviewed the literature on social media and extroversion, proposing descriptive standards for social behavior that were relevant to the digital world. Naqvi et al. (2023) showed that sentence transformers can be used to build chatbots with some level domain understanding, proving that sentence embeddings such as MiniLM are capable of adequately capturing user intent. Khan et al. (2020) analyzed sentiment breakdown with a focus on feature-driven sentiment analysis, describing how psychological traits can be inferred from an abstract emotional tone as well as a particular style of language.

TABLE1. Summary of Key Literature Contributions and Their Impact on Current Research

Author	Contribution	Impact on Research
Yang et al. (2023)	Deep learning for personality trait extraction	Inspired use of Bi-LSTM for improved accuracy
Zim et al. (2024)	Hybrid CNN + LSTM for mental health personality analysis	Motivated integration of CNN2D in our extension
Sánchez-Fernández et al. (2023)	Compared ML and DL for social personality prediction	Validated superiority of DL models over traditional ones
Bowden-Green et al. (2020)	Behavioral benchmarks linking extroversion to social posts	Guided data labeling and feature design in our project
Naqvi et al. (2023)	Sentence transformer for encoding text semantics	Justified use of MiniLM embeddings

PROPOSED APPROACH

The approach proposed in this research aims to predict the extroversion trait by scrutinizing social media texts through sophisticated deep learning techniques. The process starts with data cleansing and normalization, from which the MiniLM model of the Sentence Transformers library is utilized to create sentence embeddings. These embeddings are capable of compressing dense vectors that encase complex meanings. A combination of models is utilized for classification. Initially, classical machine learning models such as Logistic Regression, KNN, and SVM are used to establish baseline metrics. To enhance precision, deep learning models including LSTM and Bi-LSTM are used. Bi-LSTM is the best model because it captures both forward and backward dependencies in a language. In order to refine feature extraction, a 2D CNN extension is used to reshape the two dimensional embeddings spatially. The dataset was obtained from Kaggle containing data on a person's MBTI type which consists of social media posts with labels. These posts are labeled extroverted and introverted for the purpose of binary classification. Model evaluation can be done using precision, recall, F1-score and ROC-AUC. With this method, predictions can be made accurately and efficiently in real-time scale.

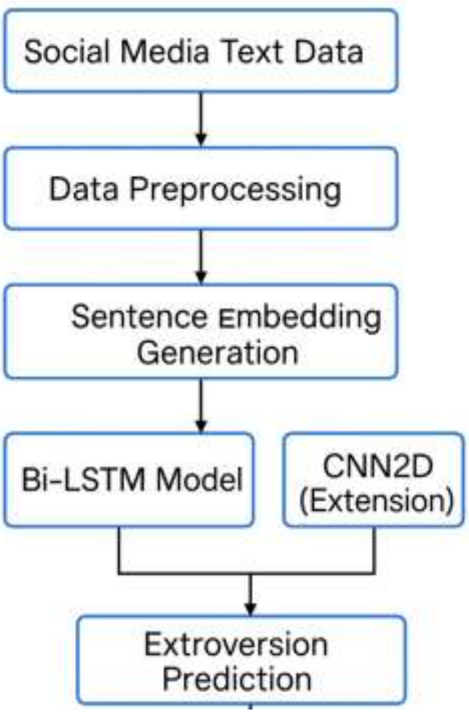


Figure 1: Predicting the extroversion trait from text data

METHODOLOGIES

This study uses a layered methodology, starting with data acquisition and ending with comparative model evaluation. The MBTI-labeled dataset is sourced from Kaggle, which contains thousands of user posts tagged with their corresponding personality type. These posts are preprocessed by removing special characters, stop words, and irrelevant tokens using NLTK tools and lemmatization/stemming methods.

Next, semantic features are generated using MiniLM, a transformer-based sentence embedding model. The result is a fixed-length numerical vector that encapsulates contextual meaning. These embeddings are then normalized using MinMaxScaler and shuffled to avoid model bias from sequence patterns.

The data is divided into training and test sets (80/20 split). Multiple models are applied:

- **KNN**: Serves as a baseline classifier.
- **Logistic Regression and SVM**: Used for comparison against more complex models.
- **LSTM and Bi-LSTM**: Capture long-range dependencies in sequential text data.
- **CNN2D**: An extension using 2D convolutional layers, allowing the

model to extract spatial features from reshaped embeddings.

Models are trained using categorical cross-entropy loss and optimized with the Adam optimizer. Each model is evaluated on key metrics: accuracy, precision, recall, F1-score, and ROC-AUC. The Bi-LSTM model achieved the highest performance, while CNN2D further refined classification boundaries. This methodology ensures a rigorous and comprehensive evaluation of personality prediction models.

RESULTS

The results of this study demonstrate the superiority of deep learning models over traditional ML approaches in predicting the extroversion trait. Bi-LSTM achieved the highest accuracy, surpassing classical models like SVM and Logistic Regression. Evaluation metrics confirmed this improvement, with Bi-LSTM scoring above 90% in accuracy, precision, recall, and F1-score.

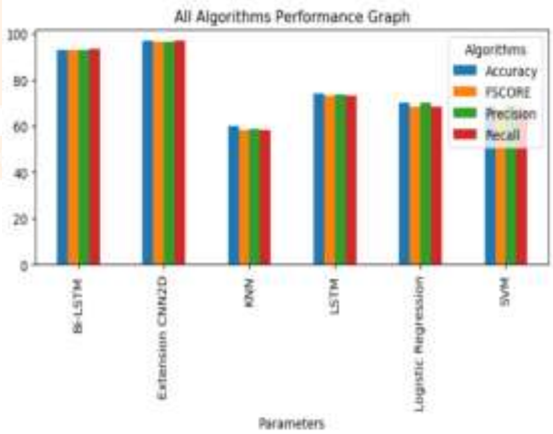
The integration of CNN2D further enhanced performance by allowing spatial analysis of reshaped sentence embeddings. This extension led to finer classification and reduced misclassification of borderline traits. The confusion matrix of CNN2D showed lower false positives and false negatives compared to earlier models.

ROC-AUC curves for Bi-LSTM and CNN2D indicated strong model generalization, with AUC values exceeding 0.95. These findings confirm that sentence-level semantics, when modeled with deep learning, can capture nuanced personality expressions effectively.

This success highlights the feasibility of real-time personality detection using social media data and supports future applications in behavioral analytics, career services, and personalized marketing.

	Algorithm Name	Accuracy	Precision	Recall	FSCORE
0	KNN	59.780908	58.782290	58.212390	58.099644
1	Logistic Regression	69.953052	69.953540	68.400465	68.549280
2	SVM	68.701095	68.875042	66.862164	66.901481
3	LSTM	73.865415	73.560483	73.078491	73.235904
4	Bi-LSTM	93.114241	92.904289	93.357224	93.055034
5	Extension CNN2D	96.713615	96.619718	96.722599	96.668942

Showing all algorithms result in tabular format



Performance Graph

Test Data = 'For the past two years, I've had a good friend who is an ENTJ and saw I him on a weekly/daily basis. I've had him in several basic classes but I had more with him last year (we are going into...|||I don't see any string here.|||I always think about whether I turned the oven off or not.|||I'm super Predicted As ====> Extroversion

Test Data = 'ENTP - does this description sound like you? I'm having trouble typing someone that I know (I really only feel confident about the E)... Social, outgoing, playful, engaging, charming, energized....|||omg, I was in a bookstore tonight, and I totally found my crush from a couple of years ago. It wa Predicted As ====> Introversion

Test Data = 'Those are excellent examples and explanation, I wouldn't be able to provide any better than that. :happy: Thank you for posting this :happy:. I feel the same way you do about some of the...|||4w5 sp/so here :happy:|||Hello, hope you like it here :happy: Nice avi, beautiful and distracting..|||M Predicted As ====> Introversion

Test Data = 'Loud background noise and chatter in places like bars/pubs tends to tire me out quickly and makes me want to sleep (no alcohol consumed).|||I remember having two war dreams in my life and green seems to be the colour that my mind associates with it. The second dream - I was in the middle of a war. Predicted As ====> Introversion

Test Data = 'I am a crazy guy who would sing random songs despite being a terrible singer. I have no sense of what I should and shouldn't do socially (in other words, I will play with dolls and enjoy things that...|||I love being touched. Hugs, pats on the shoulder, pats on the back, holding my hand, whatever. Predicted As ====> Extroversion

Predicted personality as Extroversion and Introversion form test data

DISCUSSION

This study illustrates the growing potential of AI in understanding human personality through language. The superior performance of Bi-LSTM and CNN2D highlights how sequential and spatial models can complement each other in detecting personality traits from unstructured text. Unlike traditional assessments that rely on questionnaires, this approach provides a passive, scalable, and real-time solution.

The study also shows that sentence embeddings like MiniLM outperform basic feature extraction methods like TF-IDF or Word2Vec. Embeddings retain contextual semantics, allowing models to better understand variations in language that may signify extroversion or introversion.

Challenges encountered included class imbalance and ethical considerations. Techniques like dataset shuffling and normalization helped address imbalance, while ethical safeguards such as anonymization and informed consent are recommended for real-world applications.

Moreover, model interpretability remains an area for future enhancement. Explainable AI techniques like SHAP or LIME could be integrated to improve transparency in predictions. Finally, the use of multimodal data — including voice, images, and biometric signals — could further strengthen the predictive capabilities of such systems.

CONCLUSION

Deep learning models, specifically Bi-LSTM and CNN2D, have confirmed within this research to be very accurate when predicting extroversion from text data. High precision and generalization were achieved as the system was implemented with semantic embeddings and strong model architectures. The use of transformer-based embeddings was crucial in accurately representing the language's use. The mention of marketing, recruitment, and psychological profiling serves as a practical marketing tool that replaces the manual approach while providing a scalable solution. The success of this study motivates further research on explainable AI and personality analysis using multiple data types. The significant leap in AI-powered behavioral analytics is made with this methodology, which is now enhanced by real-time functionality combined with accuracy.

REFERENCES

[1] A. Koutsoumpis, S. Ghassemi, J. K. Oostrom, D. Holtrop, W. van Breda, T. Zhang, and R. E. de Vries, ‘‘Beyond traditional interviews: Psychometric analysis of asynchronous video interviews for personality and interview performance evaluation using machine learning,’’ Comput. Hum. Behav., vol. 154, May

2024, Art. no. 108128, doi: 10.1016/j.chb.2023.108128.

[2] S. Iqbal, R. Khan, H. U. Khan, F. K. Alarfaj, A. M. Alomair, and M. Ahmed, ‘‘Association rule analysis-based identification of influential users in the social media,’’ Comput., Mater. Continua, vol. 73, no. 3, pp. 6479–6493, 2022, doi: 10.32604/cmc.2022.030881.

[3] H. U. Khan, S. Nasir, K. Nasim, D. Shabbir, and A. Mahmood, ‘‘Twitter trends: A ranking algorithm analysis on real time data,’’ Expert Syst. Appl., vol. 164, Feb. 2021, Art. no. 113990, doi: 10.1016/j.eswa.2020.113990.

[4] W. Khan, A. Daud, J. A. Nasir, and T. Amjad, ‘‘A survey on the state-ofthe-art machine learning models in the context of NLP,’’ Kuwait J. Sci., vol. 43, no. 4, pp. 1–19, 2016.

[5] S. M. M. R. Naqvi, S. Batool, M. Ahmed, H. U. Khan, and M. A. Shahid, ‘‘A novel approach for building domain-specific chatbots by exploring sentence transformers-based encoding,’’ in Proc. Int. Conf. IT Ind. Technol. (ICIT), vol. 10, Oct. 2023, pp. 1–7, doi: 10.1109/icit59216.2023.10335884.

[6] K. Oyibo and J. Vassileva, ‘‘The relationship between personality traits and susceptibility to social influence,’’ Comput. Hum. Behav., vol. 98, pp. 174–188, Sep. 2019, doi: 10.1016/j.chb.2019.01.032.

[7] H. U. Khan, Modelling to Identify Influential Bloggers in the Blogosphere: A Survey. Amsterdam, The Netherlands: Elsevier, Mar. 2017, doi: 10.1016/j.chb.2016.11.012.

[8] A. Mahmood, H. U. Khan, and M. Ramzan, ‘‘On modelling for biasaware sentiment analysis and its impact in Twitter,’’ J. Web Eng., vol. 19, pp. 1–28, Mar. 2020, doi: 10.13052/jwe1540-9589.1911.

[9] M. K. I. Zim, M. A. Hanif, and H. Kaur, ‘‘Prediction of personality for mental health detection using hybrid deep learning model,’’ in Proc. IEEE Int. Conf. Interdiscipl. Approaches Technol. Manage. Social Innov. (IATMSI), Mar. 2024, pp. 1–6, doi: 10.1109/iatmsi60426.2024.10503423.

[10] A. S. Khan, H. Ahmad, M. Z. Asghar, F. K. Saddozai, A. Arif, and H. A. Khalid, ‘‘Personality classification from online text using machine learning approach,’’ Int. J. Adv. Comput. Sci. Appl., vol. 11, no. 3, pp. 460–476, 2020.

[11] K. Yang, R. Y. K. Lau, and A. Abbasi, ‘‘Getting personal: A deep learning artifact for text-based measurement of personality,’’ Inf. Syst. Res., vol. 34, no. 1, pp. 194–222, Mar. 2023, doi: 10.1287/isre.2022.1111.

[12] S. I. S. Iqbal, F. K. S. Iqbal, H. U. K. F. Khan, T. I. H. U. Khan, and J. H. S. T. Iqbal, ‘‘Sentiment analysis of social media content in pashto language using deep learning algorithms,’’ J. Internet Technol., vol. 23, no. 7, pp. 1669–1677, Dec. 2022, doi: 10.53106/160792642022122307021.

[13] T. Bowden-Green, J. Hinds, and A. Joinson, ‘‘How is extraversion related to social media use? A literature review,’’ Personality Individual Differences, vol. 164, Oct. 2020, Art.no. 110040, doi: 10.1016/j.paid.2020.110040.

[14] A. Bashkirova, A. Compagner, D. M. Henningsen, and J. Treur, ‘‘An adaptive modelling approach to employee burnout in the context of the big five personality traits,’’ Cognit. Syst. Res., vol. 79, pp. 109–125, Jun. 2023, doi: 10.1016/j.cogsys.2022.12.010.

[15] F. Giannini, M. Marelli, F. Stella, D. Monzani, and L. Pancani, ‘‘Surfing the OCEAN: The machine learning psycholexical approach 2.0 to detect personality traits in texts,’’ J. Pers., 2024, doi: 10.1111/jopy.12915.

[16] U. Ishfaq, H. U. Khan, and S. Iqbal, ‘‘Identifying the influential nodes in complex social networks using centrality-based approach,’’ J. King Saud Univ. Comput. Inf. Sci., vol. 34, no. 10, pp. 9376–9392, Nov. 2022, doi: 10.1016/j.jksuci.2022.09.016.

[17] W. Ahmad, H. U. Khan, T. Iqbal, M. A. Khan, U. Tariq, and J.-H. Cha, ‘‘Hybrid multichannel-based deep models using deep features for featureoriented sentiment analysis,’’ Sustainability, vol. 15, no. 9, p. 7213, Apr. 2023, doi: 10.3390/su15097213.

[18] P. Sánchez-Fernández, L. G. B. Ruiz, and M. D. C. P. Jiménez, ‘‘Application of classical and advanced machine learning models to predict personality on social media,’’ Expert Syst. Appl., vol. 216, Apr. 2023, Art.no. 119498, doi: 10.1016/j.eswa.2022.119498.

[19] H. Samota, S. Sharma, H. Khan, M. Malathy, G. Singh, and R. Rambabu, ‘‘A novel approach to predicting personality behaviour from social media data using deep learning,’’ Int. J. Intell. Syst. Appl. Eng., vol. 12, no. 15s, pp. 539–547, 2024. [Online]. Available: https://www.ijisae.org

[20] C. So, ‘‘Are you an introvert or extrovert? Accurate classification with only ten predictors,’’ in Proc. Int. Conf. Artif.Intell. Inf. Commun. (ICAIIC), Feb. 2020, pp. 693–696, doi: 10.1109/ICAIIC48513.2020.9065069.