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Advancements in Personality Detection: Unleashing the Power of Transformer-Based Models and Deep Learning with Static Embeddings on English Personality Quotes

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ABSTRACT

Personality detection has garnered significant attention in recent years, with applications ranging from personalized user experiences to psychological analysis. This paper presents advancements in personality detection, focusing on the utilization of Transformer-based models and deep learning models with static embeddings to analyse English personality quotes. The research highlights the capabilities of advanced models such as ELECTRA and META OPT in comprehending contextual dependencies within text. Concurrently, it examines the significance of deep learning and embeddings in capturing semantic information and hidden personality traits. Leveraging the power of modern natural language processing techniques, the study explores the potential of these models in extracting latent personality traits from textual data. A diverse dataset of English quotes with personality dimension along the introversion-extroversion spectrum, supplemented by the concept of ambiverts is curated for training and evaluation, and the model's performance is assessed using accuracy, precision, recall and F1-score. The results reveal that the Transformer-based models significantly enhances personality detection accuracy compared to conventional methods. By exploiting these advanced techniques, the research contributes to a deeper understanding of individual personalities through their textual expressions, bridging the gap between human cognition and artificial intelligence to revolutionize personalized interactions.

Keywords: Personality traits, NLP, Transformer models, Deep Learning, word embeddings

Table 1 Taxonomy

Abbreviation	**Definition**
MBTI	Myers Briggs Type Indicator
NLP	Natural Language Processing
BERT	Bidirectional Encoder Representations from Transformers
RoBERTa	Robustly Optimized BERT Approach
GPT3	Generative Pre-trained Transformer 3
Meta OPT	Meta Open Pre-trained Transformers
BFI	Big Five Inventory
IPIP	International Personality Item Pool
ELMo	Embeddings from Language Model
ULMFiT	Universal Language Model Fine-Tuning
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
CNN	Convolution Neural Network
GRU	Gated Recurrent Unit
BiLSTM	Bidirectional Long Short-Term Memory
GloVe	Global Vectors
MCC	Mathew’s Correlation Coefficient

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INTRODUCTION

Psychologists acknowledge that studying human thinking and behaviour requires a multifaceted approach, as there is no one-size-fits-all, definitive technique. Nonetheless, the practical evolution of psychological studies continues to shape our understanding of the social and personality dimensions of human psychology as a legitimate subject of scientific inquiry. Personality psychology has played a significant role in driving research interest in understanding the behavioural foundations of an individual. Personality, in essence, refers to the distinctive patterns of thinking, feeling, and behaving that arise from a combination of inherent temperaments, inclinations, and external factors such as environments and experiences [1]. Personality traits serve as tangible psychometric measures for explaining human behaviour. There are numerous personality traits that collectively make up an individual's unique personality. These traits influence how people think, feel, and behave in various situations [2]. Here is a list of some common personality traits:

- *Openness to Experience:* This trait reflects a person's willingness to explore new ideas, experiences, and ways of thinking. High openness individuals are creative, curious, and open-minded.
- *Conscientiousness:* Conscientious individuals are organized, responsible, and reliable. They tend to be goal-oriented, diligent, and focused on details.
- *Extraversion:* Extraverts are outgoing, sociable, and energetic. They thrive in social settings, enjoy interactions with others, and often seek out new experiences.
- *Agreeableness:* Agreeable people are kind, compassionate, and cooperative. They value harmony, empathize with others, and are generally considerate of people's feelings.
- *Neuroticism (Emotional Stability):* This trait refers to emotional stability and how individuals handle stress and negative emotions. Low neuroticism individuals are emotionally resilient and tend to remain calm under pressure.
- *Adventurousness:* Individuals high in adventurousness are willing to take risks and try new things. They seek excitement and novelty in their experiences.
- *Assertiveness:* Assertive individuals are confident in expressing their opinions and standing up for their beliefs. They communicate their thoughts and needs clearly.
- *Empathy:* Empathetic individuals are attuned to the emotions and experiences of others. They can understand and share the feelings of those around them.
- *Resilience:* Resilient individuals are able to bounce back from challenges and setbacks. They have strong coping mechanisms and adapt well to adversity.
- *Creativity:* Creative individuals have a knack for generating original ideas and thinking outside the box. They often approach problems with innovative solutions.
- *Honesty:* Honest individuals value truthfulness and integrity. They are straightforward in their communication and behaviour.
- *Humour:* Humorous people have a tendency to find and appreciate humour in various situations. They use laughter as a way to connect with others and cope with stress.
- *Curiosity:* Curious individuals have a strong desire to learn, explore, and seek out new information. They are intellectually curious and enjoy discovering new things.
- *Patience:* Patient individuals can tolerate delays and challenges without becoming frustrated. They approach situations with a calm and composed demeanour.
- *Independence:* Independent people value self-reliance and autonomy. They are comfortable making decisions on their own and often prefer to work independently.
- *Sociability:* Sociable individuals enjoy interacting with others and being in social settings. They are skilled at building and maintaining relationships.
- *Trustworthiness:* Trustworthy individuals are reliable and can be counted on to keep their promises. They are seen as dependable and honest by others.

A visual depiction of these personality traits is presented through the use of a "Wheel of Personality Traits," as illustrated in figure1.This innovative personality traits wheel is a visual tool that can benefit researchers in psychology. It offers an accessible format to understand and organize various personality traits, aiding researchers in studying interactions and correlations among these traits.

The wheel intends to act as a framework to explore trait development over time, design assessment tools, and compare traits across individuals and cultures.

Additionally, it can guide research design, theory development, and clinical applications, aiding therapists in tailoring interventions. The wheel's dynamic representation assists in tracking longitudinal changes and simplifies complex trait relationships. Overall, it is a valuable asset for comprehending and analysing intricate aspects of personality.

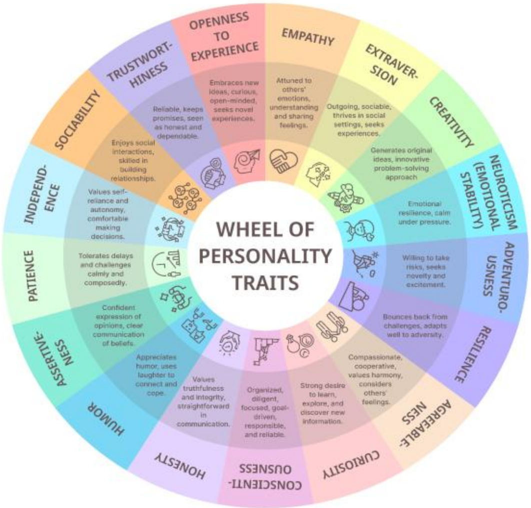

Figure 1 The Wheel Of Personality Traits

Many studies have explored the detection of personality traits through individuals' social media posts and other user-generated online content. A considerable body of research focuses on using trait theories like the Big Five (OCEAN) [3-5] and the Myers-Briggs Type Indicator (MBTI) [6-10] for psychometric testing. In recent times, machine learning techniques, particularly deep learning for natural language processing (NLP), have successfully been applied to various task-centric psychometric dimensions like sentiment and emotion, as well as user-centric dimensions such as personality traits in user-generated text. Within the field of psycholinguistics, which examines the relationship between linguistic factors and mental aspects, researchers have confirmed that an individual's personality can be revealed through their written language and writing styles. Semantic and syntactic information embedded in language serve as essential cues for discriminating different personality traits. For example, extroverts tend to be prolific writers with an unrestrained writing style and a greater use of affirmative words compared to introverts.

As natural language processing techniques (NLP) have evolved in recent years, personality recognition approaches facilitated by automatic NLP techniques, also known as psychometric NLP methodology, have proven to be valuable in the scientific literature [11]. These advances have provided new insights into understanding human personalities through the analysis of written language, paving the way for innovative applications in the field of psychology. Simultaneously, deep learning has transformed NLP through word embeddings, sequence-to-sequence models, transformers, BERT, and pre-trained models. It has achieved breakthroughs in translation, text classification, sentiment analysis, and dialogue systems, significantly enhancing accuracy and efficiency. While word embeddings such as Word2Vec and GloVe etc. capture semantic relationships, transformers excel in contextual understanding. Further, pre-trained models like BERT improve generalization and transfer learning. Certainly, deep learning's versatility has revolutionized various NLP tasks, driving progress in understanding and generating human language.

More recently, Transformer-based models such as GPT-3 [12], BERT [13-14], RoBERTa [15], ELECTRA [16], Meta OPT [17], DistilBERT [18] and XLM-RoBERTa [19] etc. have revolutionized NLP tasks by efficiently handling long-range dependencies and capturing contextual information. These models leverage attention mechanisms to capture contextual dependencies and relationships in vast amounts of text, allowing them to interpret and generate language with exceptional precision and state-of-the-art performance in various applications. These models have become the backbone of many NLP systems, providing accurate and contextually relevant outputs across a wide range of tasks. Undoubtedly, the utilization of Transformer-based models in personality detection can enable a more nuanced and comprehensive analyses of individual personalities. These models can uncover intricate patterns and subtleties in language, leading to a deeper understanding of human behaviour and thought processes.

This paper explores and compares the power of two cutting-edge approaches in personality detection: Transformer-based models and deep learning with static embeddings, both applied to English personality quotes. We meticulously curated online user-generated quotes to create a dataset called *"Personality_Quotes"* in English. Our primary focus was to explore the accurate and efficient identification of personality traits along the dimensions of introvert, extrovert, and ambivert using both deep neural networks with static embeddings and Transformer-based models. The study carefully evaluates and compares the efficacy of these techniques using appropriate evaluation metrics like precision, recall, F1-

score, and correlation with established personality assessments. The research aims to provide valuable insights into two key areas:

- Advancements in personality detection, demonstrating the potential of Transformer-based models and deep learning with static embeddings in uncovering the intricate nuances of human personalities using English personality quotes.
- The comparison of these two techniques, paving the way for further improvements in natural language processing and personalized AI-driven applications.

By conducting experiments on a diverse dataset of English personality quotes, the study sheds light on the strengths and limitations of each approach, elucidating their unique contributions to the field of personality detection.

The rest of the paper is organized as follows. Section 2 provides an overview of recent advancements in personality detection using textual data. Section 3 presents the comprehensive details of the curated English personality detection dataset *'Personality_Quotes.'* In Section 4, the paper discusses the deep learning models, static embeddings and Transformer-based model considered for this study. The in-depth comparison and the results obtained are thoroughly analysed in Section 5. Finally, Section 6 presents concluding remarks and outlines potential avenues for future improvements in this work.

RELATED WORK

Significant literature account for studies using machine learning (including the state-of-the-art transformer-based models) to detect and predict various psychological traits such as personality, behaviour as well as issues like depression and anxiety using linguistic cues from text [20-22]. But a large body of work has been reported in English language, especially from social media postings [23]. Specific to personality detection public datasets and benchmark models have been well-reported and evaluated using MBTI and Big-5 personality traits. Over the span of more than ten years, numerous dedicated researchers have diligently worked on diverse datasets, including the prominent Big Five Inventory (BFI), the International Personality Item Pool (IPIP) [24], and various datasets derived from social media sources. Among these, notable datasets encompass Kaggle_MBTI [6-7], Chalearn [25-26], and Essays [27].

In a significant contribution, Khan et al. [28] meticulously refined the publicly accessible MBTI dataset through an exhaustive data preprocessing approach utilizing TF-IDF. Their innovative XGBoost classifier achieved remarkable precision and accuracy scores of 99% for each trait.

Similarly, in 2020, Zhao et al. [29] formulated a dataset extracted from social networks, categorizing it into 32 distinct personalities. They introduced an attention-based LSTM model, yielding a commendable F1-score of 72.2%. In 2021, Christian et al. [30], delving into the prediction of personality traits from Facebook and Twitter datasets, adopted a multi-model deep learning architecture. This approach integrated various pre-trained language models, including BERT, RoBERTa, and XLNet, to effectively extract features from social media data. Employing model averaging for final predictions, their work showcased promising results. In the same year Kaushal et al. [31], explored a spectrum of machine learning algorithms—such as KNN, logistic regression, naive Bayes, and random forest—on the MBTI dataset to predict personality traits. Salsabila et al. [32], in their research, achieved an impressive 79.35% accuracy by combining support vector machine (SVM) and BERT. Further enhancements through the Linguistic Inquiry Word Count (LIWC) tool elevated accuracy to 80.07%. Lucky et al. [33], took a distinct approach by leveraging multiple BERT models for contextual word embedding extraction from textual data. Addressing the challenge of imbalanced datasets, they applied the Multilabel Synthetic Minority Oversampling Technique (MLSMOTE), yielding substantial improvements of 19.91% in accuracy and F1-score.

In 2022, Vijay and Sebastian [34] innovatively employed the k-means clustering technique to group individuals based on their shared personality behaviours. Further, Jain et al. [7] introduced the PersonalityBERT[5] model, which demonstrated its prowess over the Kaggle_MBTI dataset, achieving an F1-score of 0.6598. Notably, in 2023, Siraspalli and Malla [35] creatively mapped datasets like MBTI and Essays onto the Big Five personality traits framework. They harnessed pre-trained language models, including BERT, ELMo, and ULMFiT, and meticulously fine-tuned the fusion of mapped data with the myPersonality dataset. Their efforts culminated in an outstanding accuracy of 87.89% for the openness trait and 78.32% for extraversion, with an overall average accuracy of 75.69% for their proposed model.

The motivation behind this research project is rooted in advancing the comprehension of personality detection using advanced language models. With the emergence of sophisticated techniques like Transformer-based models and deep learning with static embeddings, there's a strong drive to uncover the intricate nuances of human personalities encoded in language. By comparing these approaches, the study aims to foster methodological progress in natural language processing and enhance personalized AI-driven applications.

_PERSONALITY_QUOTES_ DATASET

The development of the *Personality_Quotes* dataset involved the application of web scraping techniques to aggregate user-generated quotes associated with three distinct personality archetypes: introvert, extrovert, and ambivert. Each personality category comprises approximately 350 textual quotes. These quotes were systematically generated de novo through the utilization of web scraping methodologies, involving the extraction of textual content from diverse online platforms. A comprehensive tabular representation of the dataset's statistical particulars is provided in Table 2.

TABLE 2 _PERSONALITY_QUOTES_ DATASET STATISTICS

Description	Statistics
Total number of instances	1028
Total number of “Extrovert” instances	365
Total number of “Introvert” instances	385
Total number of “Ambivert” instances	278

The dataset constitutes1029 instances organized into a structured format with two columns. The first row of the dataset is used for the header, which describes the attributes present in the dataset. The main column contains textual quotes, while the second column contains categorical labels that classify each instance as either an extrovert, ambivert, or introvert expression. A visual representation, shown in figure 2, displays these quotes alongside their corresponding categorical labels. Regarding the categorical labels, label 0 is used to represent instances displaying introverted traits, label 1 corresponds to instances showcasing extroverted attributes, and label 2 is assigned to instances exemplifying ambivert characteristics.

	text	label
576	extroverts want us to have fun because they as...	1
542	they say that extroverts are unhappier than in...	1
844	my life is a constant battle between needing ...	2
102	introvert fact we love our alone time	0
257	stay true to your own nature if you like to do...	0
...	...	...
534	as an introvert you can be your own best frien...	1
52	inside was where she lived physically and ment...	0
998	when it comes to trusting other people someti...	2
996	some people think i am quiet while others thi...	2
932	my personality confuses people i enjoy being a...	2

FIGURE 2 _PERSONALITY_QUOTES_ DATASET SNAPSHOT

The *Personality_Quotes* dataset introduced in this context holds great potential as a foundational asset for creating a benchmark in the field of personality detection within user-generated content. Notably, the abundance of quotes found in posts shared across diverse social media platforms like Facebook and Instagram makes this dataset particularly well-suited for driving advancements in research within this field. The use of introversion, extroversion, and ambiversion as personality dimensions in this study is justified for several reasons. Firstly, these traits are well-established and widely recognized personality dimensions in psychological research. The introversion-extroversion spectrum captures fundamental variations in how individuals respond to social stimuli, with introverts generally being more reserved and reflective, and extroverts being more outgoing and sociable. The addition of ambiversion acknowledges the nuanced nature of personality, encompassing individuals who exhibit characteristics of both introversion and extroversion.

Furthermore, introversion, extroversion, and ambiversion traits are accessible and easily understood by both researchers and the general public. This simplifies the annotation and interpretation of personality labels in the dataset, promoting consistency and facilitating communication about the research findings. additionally, these dimensions have real-world implications, influencing various aspects of an individual's life, from social interactions to career choices. By focusing on introversion, extroversion, and ambiversion, the study addresses a relatable and relevant aspect of human behaviour, contributing to the potential practical applications of the research. Overall, the choice to use introversion, extroversion, and ambiversion as personality dimensions is grounded in their established psychological significance, ease of interpretation, and their relevance in understanding and characterizing individual differences in personality expression.

The following data processing procedures were implemented on a compilation of quotes:

- *Initial Extraction:* After gathering the quotes, they were subjected to a process of categorization.
- *Stratification:* These quotes were then sorted into three distinct classes, forming categories based on their characteristics.
- *Data Cleansing and Pre-processing:*
- Refinement of Text: A series of sophisticated techniques were applied to enhance the quality of the textual content.
- Removal of Symbols: Punctuation marks, hyperlinks, and specialized symbols were methodically eliminated from the text.
- Tokenization: The text was fragmented into separate linguistic units through tokenization.
- Elimination of Stop Words: Commonly used but insignificant words were taken out to enhance the dataset's linguistic integrity.
- Standardization through Stemming and Lemmatization: Word forms were standardized by utilizing stemming and lemmatization procedures, resulting in linguistic congruence.

METHODOLOGY

Before the ascendancy of Transformer-based models, the landscape of Natural Language Processing (NLP) was shaped by a diverse array of traditional deep learning architectures. These diverse architectures, including Recurrent Neural Networks (RNNs) [36] and their refined variant, Long Short-Term Memory (LSTM) [37], pioneered sequence processing by capturing dependencies over time. Gated Recurrent Units (GRUs) [38] offered a streamlined alternative for similar tasks. Convolutional Neural Networks (CNNs) [39] transitioned from image analysis to NLP, extracting local features from text. These models, while effective, faced challenges in capturing longer-range context. The subsequent rise of Transformer-based models revolutionized NLP, yet the legacy of these traditional architectures persists as foundational pillars in the field's development. In this section our focus centers on classical deep learning models, specifically Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional Long Short-Term Memory (BiLSTM) [40]. Additionally, we delve into static embeddings—Common Crawl, GloVe, FastText, PubMed, and GoogleNews. These embeddings complement the aforementioned deep learning models in predicting personalities for personality quotes. Further, we discuss five most recent transformer-based models, namely ELECTRA, BERT, DeBERTa [41], Meta OPT and XLNet [42].

The use of deep learning and transformer models on a small dataset like "*Personality_Quotes*" is justified for several reasons:

- *Complex Relationships:* Deep learning and transformer models are designed to capture intricate relationships and patterns in data, even when the dataset is relatively small. They excel at learning representations from data with multiple layers of abstraction, which is beneficial when dealing with complex concepts like personality traits.
- *Feature Extraction:* Deep learning and transformer models can automatically extract relevant features from raw text data. This is particularly advantageous when dealing with unstructured text, as seen in personality quotes, where manually crafting features might be challenging or insufficient.
- *Transfer Learning:* Transformer-based models like BERT, ELECTRA, and DeBERTa are pre-trained on large text corpora, which enables them to generalize well to smaller datasets. The pre-trained knowledge can be fine-tuned on the specific task of personality detection, making them effective even with limited data.
- *Performance Improvement:* Deep learning models have shown remarkable performance improvements in various natural language processing tasks, even on small datasets. This suggests that their ability to capture intricate linguistic nuances can lead to meaningful insights even with limited training examples.
- *Potential for Generalization:* While small datasets may raise concerns about overfitting, the transfer learning and regularization mechanisms present in deep learning and transformer models can mitigate this issue. This allows the models to learn from the data while also incorporating general language understanding.
- *Rich Representations:* Transformers are known for generating rich contextualized embeddings that can capture the meaning of words in the context of the entire sentence. This is highly beneficial when dealing with personality detection, where context plays a crucial role in understanding traits.

- *Framework for Future Data:* Training deep learning and transformer models on small datasets can lay the groundwork for future improvements as more data becomes available. The models can be retrained or fine-tuned with larger datasets to further enhance their accuracy.
- *Comparative Analysis:* The use of these advanced models on a small dataset can provide a comparative analysis of their effectiveness. This can shed light on their potential benefits, limitations, and generalization capabilities in scenarios with limited data.

In summary, while the dataset might be small, the complex nature of personality traits and the ability of deep learning and transformer models to learn intricate patterns and representations make them well-suited for this task, potentially leading to valuable insights and practical applications. The following sub-sections provide a concise overview of the utilized models.

CLASSICAL DEEP LEARNING MODELS IN NLP

Deep learning has revolutionized Natural Language Processing (NLP) by enabling the development of sophisticated models that can understand, generate, and process human language with remarkable accuracy. Deep learning techniques, particularly neural networks, have proven effective in various NLP tasks due to their capacity to capture intricate patterns and relationships within text data.

A.1 CONVOLUTIONAL NEURAL NETWORKS (CNN)

Convolutional Neural Networks (CNNs) have found a niche in Natural Language Processing NLP) by adapting their image processing prowess to sequential data like text. In this realm, CNNs excel at tasks like text classification and sentiment analysis. Text data is first transformed into word embeddings, such as Word2Vec or GloVe, capturing word relationships. The CNN's convolutional layer then slides over these embeddings, using filters to identify patterns within n-grams of words. The resulting feature maps encapsulate diverse linguistic nuances. Subsequent max pooling reduces dimensionality while preserving key insights. Flattening and fully connected layers further distill information, culminating in a task-specific output layer. Though excellent for local features, CNNs might not grasp long-range dependencies as well as recurrent models. However, with the ascendancy of Transformer-based models, like BERT and GPT, in NLP, their dominion has expanded even further, harnessing contextual understanding for a gamut of NLP endeavours.

A.2. GATED RECURRENT UNIT (GRU)

Gated Recurrent Unit (GRU), a specialized form of recurrent neural networks, has gained prominence in Natural Language Processing (NLP) for its adeptness in managing sequential data and capturing extended contextual dependencies in text. Addressing the vanishing gradient challenge, GRUs retain valuable information over sequences, making them adept for tasks like text generation, sentiment analysis, and machine translation. With update and reset gates, GRUs regulate past information and selective retention, enabling them to comprehend intricate language structures and relationships. While newer Transformer-based models with self-attention mechanisms dominate certain NLP realms, GRUs maintain significance in scenarios where efficiency and interpretability are paramount, offering a pragmatic balance between performance and complexity.

A.3. LONG SHORT-TERM MEMORY (LSTM)

Long Short-Term Memory (LSTM) is a specialized recurrent neural network architecture that has become a crucial tool in Natural Language Processing (NLP) for its ability to process sequences and capture intricate relationships in text. LSTMs were designed to address the vanishing gradient problem in traditional RNNs, and they incorporate memory cells with gates that regulate information flow - input, output, and forget gates. These gates allow LSTMs to maintain important context across long sequences, making them highly effective for language modeling, machine translation, and speech recognition tasks in NLP. By considering the entire history of word sequences, LSTMs excel in understanding contextual nuances and uncovering complex patterns. While newer Transformer-based models with parallel processing and attention mechanisms have gained prominence in NLP, LSTMs continue to be relevant in situations where the understanding of sequential information remains essential.

A.4. BIDIRECTIONAL LONG SHORT-TERM MEMORY (BILSTM)

Bidirectional Long Short-Term Memory (BiLSTM) has emerged as a potent tool in Natural Language Processing (NLP) by enhancing the understanding of sequential data and capturing contextual nuances in text. Building upon the LSTM architecture, BiLSTM processes input data in both forward and backward directions, allowing it to capture dependencies from both past and future words. This bidirectional approach is particularly advantageous for tasks such as named entity recognition and sentiment analysis, where context from surrounding words is vital. By combining information from both directions, BiLSTM excels in grasping complex linguistic relationships. However, BiLSTM's computational complexity can be higher compared to traditional LSTMs due to the bidirectional nature. Despite this, its capability to exploit complete contextual information makes BiLSTM a valuable asset in NLP, complementing other advanced architectures like Transformer-based models.

With the advent of deep learning, embedding layers became vital in NLP due to their ability to transform words into continuous vectors, capturing semantic relationships. Unlike traditional methods, these embeddings harnessed distributional semantics, learning from context, and allowing transfer learning. Embedding layers bridged the gap between raw text and neural networks, enabling nuanced language understanding and driving significant progress in NLP performance. The following figure 3 diagrammatically summarizes the pairings between classical deep learning models and static embeddings used in this study.

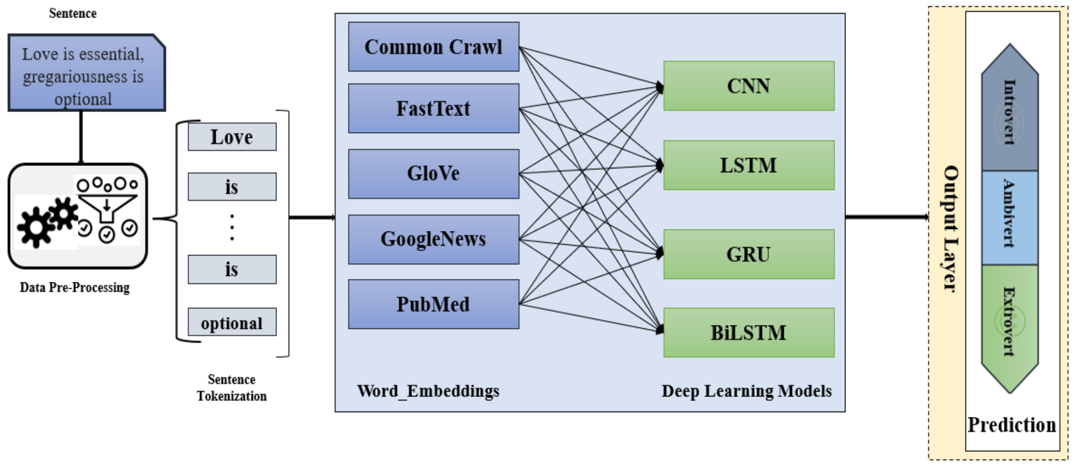

Figure 3 Pairing Between Classical Deep Learning Models With Static Word Embeddings

The next sub-section discusses these static word embeddings.

STATIC WORD EMBEDDINGS

Static word embeddings are pre-trained numerical representations of words in a fixed-dimensional vector space. Created through unsupervised learning on large text datasets, they capture semantic relationships based on co-occurrence patterns. These embeddings facilitate tasks like sentiment analysis, translation, and classification by quantifying word meanings in a continuous vector space. Despite lacking context adaptability, they offer transferability, enhancing downstream NLP tasks.

B.1. COMMON CRAWL

Common Crawl embeddings [43] are word vectors pre-trained on the vast and diverse textual content of the Common Crawl project. This project involves regularly scraping and archiving web pages from across the internet. The embeddings are generated by analysing the co-occurrence patterns of words within this extensive dataset. These patterns allow the embeddings to capture semantic relationships and contextual information. Common Crawl embeddings provide a way to transfer the knowledge embedded in the wide range of web content to various natural language processing tasks, making them particularly useful for tasks that involve understanding and processing text from different sources on the internet.

B.2. FASTTEXT

FastText[1] is a word embedding model developed by Facebook's AI Research. It introduces sub-word information by breaking words into character n-grams. Word vectors are created by averaging the vectors of these sub-word units. The training objective is similar to skip-gram, predicting nearby words based on sub-word units. FastText handles out-of-vocabulary words by summing sub-word vectors. It's effective for morphologically rich languages, compound words, and rare words. While it enriches word representations, its use of sub-word units can increase model size and might not capture all word-level nuances.

B.3. GLOVE

GloVe [44], or Global Vectors for Word Representation, is a word embedding model that combines global and local word co-occurrence statistics to generate word vectors. It constructs a co-occurrence matrix that reflects how often

[1] https://github.com/facebookresearch/ fastText

words appear together in a given context window. The model then factorizes this matrix to produce word vectors, optimizing a global objective function that captures the relationships between words. Unlike methods like Word2Vec, GloVe doesn't rely solely on local context, making it able to capture both syntactic and semantic relationships. These embeddings have been pre-trained on large corpora and can be directly used in various NLP tasks due to their semantic-rich nature.

B.4. GOOGLENEWS

The GoogleNews word embeddings are high-dimensional vectors created by training a Word2Vec model on a large corpus of news articles collected from the Google News service [45]. These embeddings capture semantic relationships between words and are commonly used for a variety of natural language processing tasks. Due to the size and quality of the training data, GoogleNews embeddings offer rich semantic information and are especially useful for tasks that require general language understanding. They can be used to compute word similarities, analogies, and as features for different NLP applications.

B.5. PUBMED

PubMed embeddings [46] characterize specialized word vector representations meticulously crafted to cater specifically to the intricacies of biomedical and life sciences literature. Derived from the vast expanse of the PubMed repository, these embeddings exhibit a refined capacity to encapsulate domain-specific terminologies, thereby facilitating nuanced investigations within the intricate landscape of the biomedical domain. The nuanced semantic intricacies inherent in scientific discourse find meticulous representation within PubMed embeddings, rendering them pivotal in augmenting a spectrum of tasks, including medical text mining, disease classification, and precise biomedical information retrieval.

TRANSFORMER-BASED MODELS

The transition from classical deep learning models to transformer-based models marks a fundamental shift in Natural Language Processing (NLP). Traditional models like RNNs and CNNs struggled with contextual nuances, but transformers introduced self-attention mechanisms that revolutionized context understanding. Models such as BERT, GPT, and T5 emerged, with BERT capturing bidirectional context, GPT excelling in text generation, and T5 framing tasks uniformly. XLNet and RoBERTa further refined training strategies, and ELECTRA introduced efficient pre-training. Despite resource-intensive training, transformers' pre-trained embeddings have elevated NLP through transfer learning, significantly improving benchmark performance and propelling the field into an era of enhanced language comprehension. This section of the paper discusses the transformer-based models such as BERT, DeBERTa, ELECTRA, Meta’s OPT and XLNet which help in personality prediction from the dataset personality_quotes as shown in figure 4.

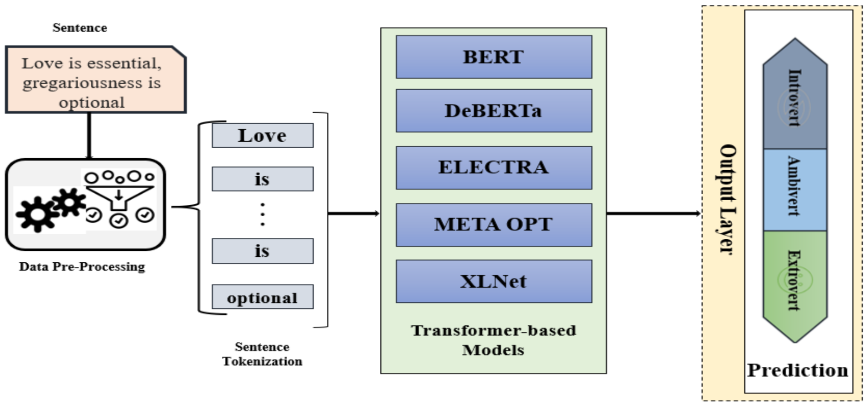

Figure 4 Personality Prediction Using Transformer-Based Models

C.1. BIDIRECTIONAL ENCODER REPRESENTATIONS FROM TRANSFORMERS (BERT)

BERT (Bidirectional Encoder Representations from Transformers) is a groundbreaking transformer-based model for natural language processing (NLP). It employs a two-step pre-training process: Masked Language Model (MLM) and Next Sentence Prediction (NSP). During MLM, BERT randomly masks words in input sentences and predicts them using surrounding context, enabling bidirectional understanding. In NSP, BERT predicts whether two sentences follow each other in a document, enhancing context awareness. BERT's architecture includes multiple layers of self-attention mechanisms, allowing it to capture contextual dependencies across words in both directions. It produces contextualized word embeddings that are fine-tuned for downstream tasks like classification, question-answering, and more. BERT's impact lies in its ability to understand complex context, enabling state-of-the-art performance across a wide range of NLP tasks by leveraging large-scale, diverse pre-training data.

C.2. DECODING-ENHANCED BERT WITH DISENTANGLED ATTENTION (DEBERTA)

Decoding-enhanced BERT with Disentangled Attention (DeBERTa) is an advanced transformer-based model tailored for natural language processing (NLP). It introduces disentangled attention mechanisms that disentangle different types of dependencies, enhancing contextual understanding. DeBERTa further integrates decoding techniques during both pre-training and fine-tuning stages, improving generation capabilities. The model's architecture combines bidirectional and unidirectional training, mitigating the shortcomings of traditional BERT models. DeBERTa achieves state-of-the-art performance across NLP tasks by leveraging disentangled attention, multi-granular tasks, and enhanced bidirectional and unidirectional information flows. Its holistic approach to context modeling and decoding makes it a potent tool for diverse NLP applications.

C.3. EFFICIENTLY LEARNING AN ENCODER THAT CLASSIFIES TOKEN REPLACEMENTS ACCURATELY (ELECTRA)

Efficiently Learning an Encoder that Classifies Token Replacements Accurately (ELECTRA) is a cutting-edge model designed for natural language processing (NLP). It introduces a unique pre-training task that involves replacing tokens within a sentence and training the model to differentiate between original and replaced tokens. This approach enhances pre-training efficiency by focusing on the replaced tokens. ELECTRA employs a generator-discriminator framework, where a generator creates replacements, and a discriminator judges their authenticity. This adversarial training refines the model's ability to discern meaningful tokens. By efficiently utilizing training data, ELECTRA improves upon traditional masked language model (MLM) pre-training. It has shown promising results on various NLP benchmarks, benefiting tasks like text classification, named entity recognition, and more, while also being computationally efficient.

C.4. META’S OPEN PRE-TRAINED TRANSFORMER LANGUAGE MODELS (META OPT)

Meta’s Open Pre-Trained Transformer Language Models (Meta OPT) is a framework that extends pre-trained transformer-based models for natural language processing (NLP). It emphasizes the importance of adaptability and customization of these models to various tasks and domains. Meta OPT introduces a meta-learning approach, where the model is trained on a diverse range of tasks during pre-training. This prepares the model to rapidly adapt and fine-tune on new tasks with minimal data. By leveraging a shared parameter space across tasks, Meta OPT aims to achieve improved performance and efficient utilization of training resources. This framework advances the concept of transfer learning in NLP by providing a versatile tool for building domain-specific models that can quickly adapt to new challenges.

C.5. XLNET

XLNet is an advanced transformer-based model for natural language processing (NLP) that combines bidirectional and autoregressive training. It introduces a novel permutation-based training approach, enabling the model to capture both contextual information from surrounding words and the predictive nature of autoregressive models. This results in improved handling of bidirectional context and fine-grained relationships between words in text. XLNet's architecture enhances its understanding of context and relationships, leading to state-of-the-art performance on various NLP tasks such as text classification, sentiment analysis, and language generation.

RESULTS AND DISCUSSION

This section is organized into four sub-sections that analyse the performance of different models for personality detection. The first subsection focuses on classical deep learning models, displaying accuracies based on various word embeddings and model types. It highlights the best-performing combination and emphasizes the impact of embeddings and model architectures. The second subsection presents the performance metrics of transformer-based models, including accuracy, F1 score, recall, precision, and MCC. It discusses the strengths and weaknesses of models like ELECTRA, DeBERTa, BERT, Meta OPT, and XLNet. The third subsection offers a comparative analysis between classical deep learning models and transformer-based models, underscoring the importance of optimal model selection and embedding choices in influencing performance outcomes. The final subsection provides valuable perspectives and tangible real-world applications within the realm of personality detection.

PERFORMANCE OF DEEP LEARNING MODELS

Table 3 displays accuracies for different combinations of word embeddings and deep learning models. The accuracies are an indication of how well the models perform on a given task. Here's a breakdown of the tabular data:

- *Embedding Type:* The table lists different types of word embeddings used in the experiment: Common Crawl, FastText, GloVe, GoogleNews and PubMed.

- *Deep Learning Models:* For each type of embedding, the experiment used different deep learning models: CNN (Convolutional Neural Network), LSTM (Long Short-Term Memory), GRU (Gated Recurrent Unit), and BiLSTM (Bidirectional LSTM).
- *Accuracy:* The accuracy represents the performance of each model configuration on the task at hand. It's a percentage that indicates how accurate the model's predictions are compared to the actual labels in the test dataset.

Table 3 Accuracies For Classical Deep Learning Models With Various Static Embeddings

Embedding + Deep Learning Model	Accuracy
Common Crawl CNN	0.728
Common Crawl LSTM	0.723
Common Crawl GRU	0.791
Common Crawl BiLSTM	0.752
FastText CNN	0.655
FastText LSTM	0.708
FastText GRU	0.786
FastText BiLSTM	0.708
GloVe CNN	0.762
GloVe LSTM	0.786
GloVe GRU	0.757
GloVe BiLSTM	0.776
GoogleNews CNN	0.752
GoogleNews LSTM	0.713
GoogleNews GRU	0.776
GoogleNews BiLSTM	0.762
PubMed CNN	0.737
PubMed LSTM	0.708
PubMed GRU	0.713
PubMed BiLSTM	0.723

Following observations can be made from the results shown in the table:

- ***The Best Performing Combination:*** The experiment indicates that the "Common Crawl" embeddings combined with the GRU model achieved the highest accuracy of 0.791. This suggests that for this particular dataset and task, using Common Crawl embeddings with the GRU model resulted in the most accurate predictions.
- ***Embedding Comparison:*** Among the different types of embeddings, the "GloVe" embeddings show better results across a variety of models (CNN, LSTM, GRU, BiLSTM). This indicates that Glove embeddings are well-suited for this specific task compared to the other
  embeddings like fastText, GoogleNews and PubMed.
- ***Model Performance:*** Among the deep learning models, the results vary. GRU models generally perform well, but LSTM and BiLSTM models also show competitive performance. CNN models generally have slightly lower test accuracies compared to the RNN-based models (LSTM, GRU, BiLSTM).
- ***Embedding Comparison with Models:*** Combining the observations on embeddings and models, the best-performing combination is Common Crawl embeddings with the GRU model, achieving an accuracy of 0.791.
  In conclusion, the results demonstrate that the choice of word embeddings and deep learning models significantly impacts the performance on the given task. Common Crawl embeddings with the GRU model stand out as the top-performing combination, while GloVe embeddings consistently perform well across multiple models.

1. PERFORMANCE OF TRANSFORMER-BASED MODELS

The table 4 presents the performance metrics of transformer-based models for personality detection. The metrics include accuracy, F1 score, recall, precision, and the Matthews Correlation Coefficient (MCC).

- *Accuracy:* The proportion of correctly predicted instances out of the total instances. It gives an overall measure of the model's correctness.
- *F1 Score:* A metric that balances both precision and recall. It's the harmonic mean of precision (ability to not label a negative sample as positive) and recall (ability to find all positive samples).
- *Recall:* The proportion of true positive instances out of all actual positive instances. It measures how well the model is able to identify positive cases.
- *Precision:* The proportion of true positive instances out of all predicted positive instances. It indicates how many of the predicted positive cases are actually correct.

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- *MCC (Matthews Correlation Coefficient):* A measure of the quality of binary (two-class) classifications. It takes into account true and false positives and negatives. A higher MCC value indicates a better model performance, where 1 represents a perfect prediction, 0 represents a random prediction, and -1 represents complete disagreement between predictions and true labels.

Table 4 Performance of Transformer-Based Models On *Personality_Quotes* Dataset

Model	**Accuracy**	**F1_Score**	**Recall**	**Precision**	**MCC**
ELECTRA	0.8106	0.8106	0.8106	0.8106	0.7195
DeBERTa	0.8106	0.8106	0.8106	0.8106	0.7156
BERT	0.8058	0.8058	0.8058	0.8058	0.7162
Meta OPT	0.7427	0.7427	0.7427	0.7427	0.6101
XLNet	0.3300	0.3300	0.3300	0.3300	-0.0578

The summarized analysis of the observations is as follows:

- **ELECTRA, DeBERTa, and BERT:** These models exhibit very similar and high levels of performance across all evaluated metrics, including accuracy, F1 score, recall, precision, and MCC. Their performance is consistent, indicating that they are well-suited for the task of personality detection.
- **Meta OPT:** This model has slightly lower performance compared to ELECTRA, DeBERTa, and BERT. It has an accuracy of 0.7427 and an MCC of 0.6101. While its performance is still notable, it lags behind the others in terms of accuracy, F1 score, recall, precision, and MCC.
- **XLNet:** XLNet has the lowest performance among all models. Its accuracy, F1 score, recall, and precision are notably lower compared to the other models. The negative MCC value (-0.0578) suggests that its predictions are not consistent and might even be worse than random chance.

In summary, the observations highlight the performance differences between these transformer-based models on the personality detection task being evaluated. ELECTRA, DeBERTa, and BERT exhibit very similar and high levels of performance, Meta OPT has slightly lower performance, and XLNet performs the least effectively among the models, showing particularly poor performance according to the provided metrics. Figure 5 gives an overview of the F-1 scores achieved by the transformer-based models.

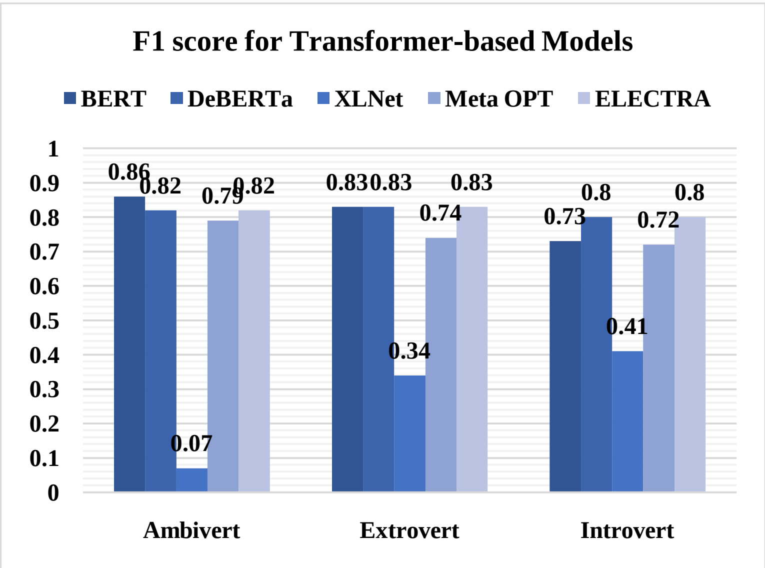

Figure 5 Comaprison Of F1 Scores Of Transformer-Based Models

The confusion matrix for the top-performing model, ELECTRA is given in figure 6. The given confusion matrix represents a classification model's performance for three personality types: "Introvert," "Extrovert," and “Ambivert” on the test data. The training-test set split was taken as 80-20. Notably, it accurately predicted 52 instances for each of these classes. While there were various correct predictions, false positives occurred, including 7 Introverts misclassified

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as Introvert and 40 Extroverts mislabelled as Introvert. False negatives were also present, such as 25 instances of Introverts incorrectly identified as other classes. The matrix underscores the model's strengths and weaknesses in classifying the different personality types.

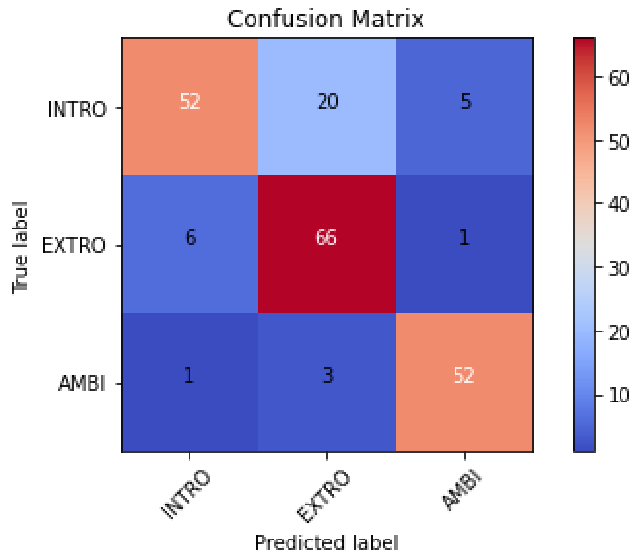

Figure 6 Confusion Matrix For The Top-Performing Model, Electra

COMPARISON OF THE PERFORMANCE OF CLASSICAL DEEP LEARNING MODELS WITH TRANSFORMER-BASED MODELS

Among the models, ELECTRA, DeBERTa, and BERT exhibit top performance with accuracies of 0.8106, showcasing the power of pretrained transformers. GRU and LSTM variants with various embeddings achieve competitive results, notably " Common Crawl GRU" (0.791), "GloVe LSTM" (0.786), and "GoogleNews GRU" (0.776). Notably, "XLNet" lags with an accuracy of 0.33. The diversity in results highlights the impact of embedding choice and architecture on outcomes, reinforcing the need for context-driven model selection. Figure 7 depicts the comparison of test accuracy of all models studied in this work.

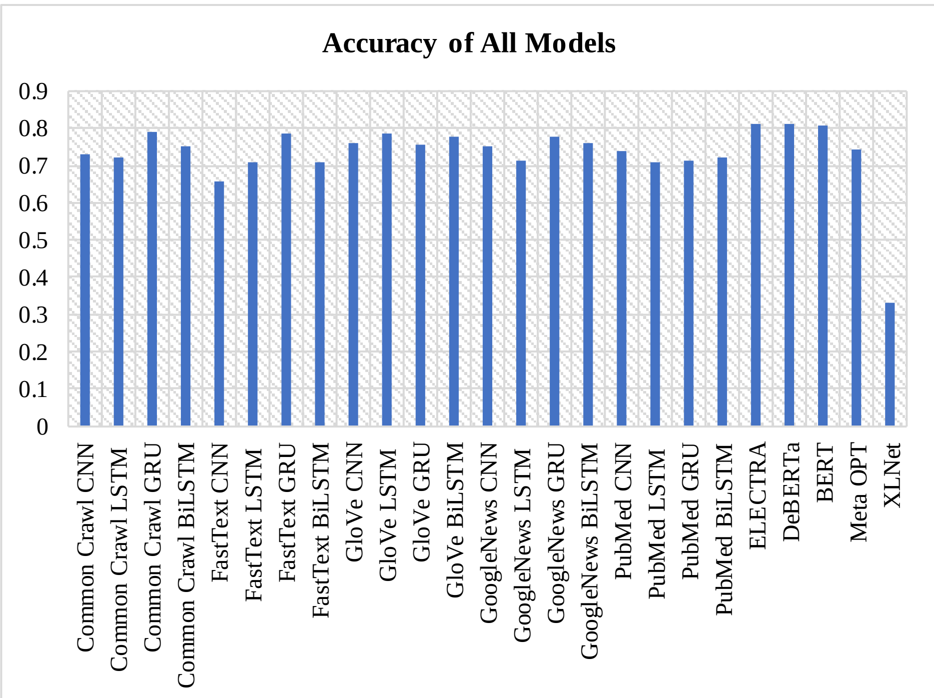

Figure 7 Comparison Of Accuracy Of All Models

Contributions and Practical Implications In Personality Detection

This research contributes valuable insights and practical applications in the field of personality detection:

- *The Personality Trait Wheel:* The wheel would aid in studying how traits interact, assessing trait development, and comparing traits across individuals and cultures. Furthermore, it would enhance communication among researchers, support educational efforts, guide research design, and facilitate clinical applications. By illustrating trait dynamics, the wheel simplifies complex concepts and provides a comprehensive approach to exploring the multifaceted world of personality traits.
- *Improved Personality Detection Accuracy:* By leveraging Transformer-based models and classical deep learning models with static embeddings, the study enhances the accuracy of personality detection from textual expressions. This improved accuracy can be pivotal in various applications where understanding personality traits is crucial, such as personalized content recommendations, mental health assessment, and human-computer interaction.
- *Guidance for Model Selection:* The detailed comparison of classical deep learning models and Transformer-based models provides guidance for researchers and practitioners in selecting the most suitable models for personality detection. The identified models with superior performance, such as GRU, ELECTRA, DeBERTa, and BERT, offer concrete options for implementation, saving time and effort in the model selection process.
- *Embedding and Architecture Insights:* The research underscores the significance of embedding choices and model architectures in influencing accuracy. This knowledge can assist researchers in making informed decisions about embedding techniques and architectural designs when developing models for personality detection, leading to more effective results.
- *Real-world Application:* The findings hold practical implications for real-world applications involving personality detection. Whether it's tailoring marketing strategies, enhancing customer interactions, or aiding in psychological assessments, the models identified in this research can help organizations better understand and respond to individual personality traits.
- *Methodological Framework:* The study's comparative analysis offers a methodological framework for evaluating model performance in personality detection tasks. Researchers can use similar approaches to assess and benchmark their models, fostering a more standardized and effective research environment.
- *Informing Future Research:* The insights provided by this study can guide future research directions in personality detection. Researchers can build upon the findings to address remaining challenges, such as tackling model inconsistencies and exploring other dimensions of personality beyond the introversion-extroversion spectrum.
- *Bridge Between AI and Psychology:* This research bridges the gap between artificial intelligence and psychology by enabling AI systems to understand and interpret human personalities more accurately. This alignment has the potential to revolutionize personalized interactions, offering tailored experiences that resonate with individual traits.

  Overall, this study's contributions enable practitioners to make informed choices in model selection and embedding techniques, while also facilitating advancements in the practical applications of personality detection across various domains.

CONCLUSION

This research put forward a ‘Wheel of Personality Traits’ that can be a valuable tool for researchers in the field of psychology and personality studies. Further, the study advances personality detection through Transformer-based models and classical deep learning models with static embeddings, demonstrating their superior accuracy in understanding textual expressions of individual personalities. In conclusion, the results from the analysis of both classical deep learning models and transformer-based models for personality detection on a curated *“Personality_Quotes”* dataset reveal crucial insights into model performance.

The exploration of classical models underscores the impact of embedding choices and model architectures on accuracy. Notably, the combination of "Common Crawl" embeddings with the GRU model achieves the highest accuracy of 0.791, demonstrating their compatibility for this specific task. Among the deep learning models, GRU models display consistent performance, while LSTM and BiLSTM models also exhibit competitiveness. However, CNN models generally yield slightly lower accuracies. Concurrently, the investigation into transformer-based models illuminates the prowess of models like ELECTRA, DeBERTa, and BERT, showcasing consistently high performance across metrics. These models exhibit substantial accuracy, F1 scores, recall, precision, and MCC values, making them prime candidates for personality detection tasks.

In contrast, the XLNet model lags behind, displaying lower scores across the board and a negative MCC, indicating inconsistent predictions. The comparative analysis underscores the paramount importance of model selection and embedding choices in influencing task performance. This study serves as a valuable guide for navigating the complex landscape of model and embedding selection in personality detection, offering practical insights for achieving optimal outcomes in real-world applications.

One limitation of this work is the reliance on English language quotes, which may not fully capture the diversity of personality expression across different languages and cultural contexts. Additionally, the curated dataset's representation of personality traits along the introversion-extroversion spectrum, while valuable, might oversimplify the complexity of human personalities and exclude other dimensions.

Future work could involve expanding the analysis to include a wider variety of languages and cultural contexts to ensure the generalizability of the findings. Additionally, exploring more nuanced and comprehensive personality dimensions beyond introversion-extroversion could provide a deeper understanding of human personality expression. Integration with multimodal data sources, such as images and audio, could offer a more holistic view of personality traits. Furthermore, investigating interpretability techniques for the models' predictions could enhance the practical utility of the research in real-world applications.

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