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Intelligent Personality Traits Prediction System for Urdu Text Using a Composite Deep Learning Framework

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Abstract

A person's personality traits can provide a good description of their attributes and how they behave with others. Researchers now face difficulties in determining and identifying a person's personality from online resources (text, images, videos, and audio). The primary goal of this study is to identify a person's personality qualities from Urdu texts accessible through social media postings and comments. The four dichotomies of the Myers-Briggs Type Indicator (MBTI) personality diagnostic scale—Introvert/Extrovert: I/E trait, Sensing/Intuition: S/N trait, Feeling/Thinking: F/T trait, and Judging/Perceiving: J/P trait—were tested and examined on input text to predict personality. A composite deep learning model (TCN+BiLSTM+GRU+ATTENTION) was used to assess trait classification performance. The suggested model yielded satisfactory and encouraging results, with an F1-Score of **96%** and accuracy of **96%** for the **N-S trait**, and an F1-Score of **89%** with **88%** accuracy for the **I-E trait**. This novel work of creating an Urdu dataset and applying a composite deep learning approach provides an innovative reference point and may be utilized by organizations for enhanced hiring practices.

Introduction

The combination of thoughts, feelings, actions, interests, and emotional patterns that set an individual apart from others is referred to as personality. It can also be characterized as a distinct manner of thinking, performing, and connecting with people in various contexts. According to Santos and Paraboni (2022), personality refers to the enduring traits, unique thought processes, and behaviors that surround a person's extraordinary way of living.

Due to the Internet's widespread use and ease of access, a vast amount of data is publicly accessible. It is nearly impossible to use this volume of data for certain jobs or decision-making activities using conventional methods. In order to convert this unprocessed data into knowledge that is relevant and goal-oriented, an autonomous learning intelligence-based system technique may be used (Kosan et al., 2022). In a similar vein, social media platforms are significant sources of text data that are posted on a regular basis by various users. An artificial intelligence-based deep learning approach is needed for the evaluation and analysis of these materials in order to produce conclusive knowledge and practical solutions to challenging issues (Dandannavar et al., 2018).

Computer-based programming that demonstrates and exhibits traits similar to human intellect is referred to as an intelligent system (AI). It can increase accuracy, speed up decision-making, and carry out complicated jobs more effectively. AI technology is forward-thinking and has the potential to innovate various economic sectors, including manufacturing, healthcare, finance, and transportation, by providing added value that human decision-making is unable to provide. As AI systems learn from experience to improve and enhance their outcomes and provide creative answers to complex challenges in the future, it is anticipated that these systems will tackle difficult and more complex tasks with better solutions.

Different methodologies (machine learning and deep learning) are used to classify and determine an individual's personality based on their textual content. (Mavis et al., 2021) Used Turkish as a source language for conducting research, and two datasets, one in English and the other in Turkish, were experimented with. (Yang et al., 2023) Examined and evaluated three benchmark datasets, namely PAN-DORA, Personality and Essay from Reddit, to carry out a personality measurement task. (A. S. Khan et al., 2020) utilised and experimented with the same dataset using supervised machine learning classifiers with different parameter settings. XGBoost classifier achieved the highest accuracy and efficiently predicted an individual's personality traits using the MBTI binary measurement scale. According to Wikipedia, with more than 230 M Urdu speakers worldwide, it is the 10th largest spoken language in the world. However, research work in finding an individual's personality traits using Urdu text for assessment and trait classification is negligible. (I. A. Khan et al., 2019) worked on the Big Five personality measurement, namely the "Big Five IPIP-NEO Model" translation into Urdu. As the Big Five IPIP-NEO Model is available in English as a personality assessment tool, the Urdu version of the personality assessor makes it easy for Urdu speakers to determine their Big Five personality through this instrument. Similar work was also performed by creating an Urdu inventory of the IPIP-NEO-300 of the Big Five model. However, pure Urdu font text was not evaluated and experimented with for personality trait classification. (Ul Mustafa et al., 2020) Extracted Urdu font tweets from Twitter and made a dataset of 6000 tweets in the Urdu language. Urdu tweet contents were classified into five categories: politics, Sports, Entertainment, Business, and Weather. Although his research was based on Urdu font text, this study still needs to address personality trait detection. A CNN+LSTM-based hybrid deep learning model was presented to predict MBTI personality traits from English textual content. A benchmark dataset of the MBTI-based personality measurement scale was experimented with. The results were analyzed and equated with other deep learning and supervised learning classifiers; however, this hybrid approach obtained tremendous results for all evaluation metrics.

However, the need to acknowledge its ethics is very important. Concerns about context, consent, and the potential abuse of personality data must be urgently addressed. The researchers using this model must follow stringent codes of ethics and be honest about the methods of collection, analysis, and application of data (Mehta et al., 2020).

The above discussion indicates that a lot of work has been conducted for personality trait determination and classification; however, there are two main limitations in the previous studies:

- English language text was mainly focused on classification and trait recognition; Pure Urdu font text has never been used for personality trait determination and assessment.
- The Composite Deep learning approach has never been applied to Urdu text for personality trait detection.

This proposed study addresses the loopholes mentioned above. The already available benchmark data set (kaggle_mbti) tweets were translated into Urdu font, and then they were classified and evaluated in MBTI types according to the input text. Similarly, to address the second issue, a hybrid deep learning model was implemented for personality traits assessment.

This research is expected to make significant contributions to the field of personality prediction by constructing a new hybrid deep learning model for MBTI prediction from Urdu textual data that offers a detailed analysis of the suitability of various deep learning architectures to process Urdu text about personality estimation, as well as creating a reference point for further studies in this field (William et al., 2022).

Objective of the study

(I) Detection of personality traits from pure Urdu font text by applying composite deep learning models based on the MBTI measurement scale.

(II) The contents of the benchmark dataset kaggle_mbti have been translated into Urdu text to classify Urdu texts for trait recognition.

(III) Comparing the proposed work result obtained by analyzing Urdu text for personality traits assessment with prior work using deep learning techniques to find the efficiency.

Literature review

Literature review regarding personality traits measurement and other related work is described here in the following paragraphs. The reviewed studies of proposed work are classified into four sub-categories based on methodologies and machine learning models utilized in these studies, namely: i) Supervised learning model, ii) Deep learning model and iii) Hybrid machine learning model, and iv) Unsupervised machine learning model.

The reviewed studies collectively demonstrate the effectiveness of supervised machine learning models in predicting personality traits from textual data, employing psychological frameworks such as MBTI, DISC, and the Big Five (OCEAN). Most research utilized datasets from Kaggle or social media platforms like Twitter and Reddit, applying prepossessing steps such as tokenization, lemmatization, and TF-IDF for feature extraction. Common classifiers included Naïve Bayes, SVM, Random Forest, Logistic Regression, XGBoost, and deep learning models like CNN, RNN, and LSTM, with ensemble methods and hyperparameter tuning often enhancing performance. While models like XGBoost, AdaBoost, and LightGBM achieved the highest accuracies (up to 100% in some cases), several studies highlighted data imbalance and limited linguistic diversity as key limitations. Emerging works in Urdu and multilingual contexts—such as those by Mustafa et al. and Khan et al.—expanded personality prediction beyond English, emphasizing the importance of linguistic, cultural, and cross-language adaptability. Overall, the literature suggests that combining robust preprocessing, hybrid learning architectures, and diverse datasets can significantly improve the accuracy and generalizability of personality trait prediction systems.

The reviewed literature highlights the significant progress made in automatic personality traits prediction using deep learning approaches across various datasets, models, and psychological frameworks such as MBTI and the Big Five (OCEAN) model. Researchers have employed diverse architectures, including LSTM, BiLSTM, CNN, BERT, and multimodal frameworks, to enhance text-based personality assessment accuracy from social media and other textual data sources. Studies such as Mohan et al. (2023) and Čerkez & Vareškić (2021) demonstrated the superior performance of LSTM-based models with accuracies exceeding 90%, while BERT and XLNet-Caps models achieved remarkable improvements in feature understanding and prediction precision. Multimodal and hybrid deep learning models integrating textual, audio, and visual cues have shown notable performance gains and ethical awareness, as noted by Mehta et al. (2019) and Feizi-Derakhshi et al. (2022). Other frameworks, such as PersoNet (Sandra et al., 2024) and Deep Person (Yang et al., 2023), further emphasized the effectiveness of composite architectures in multilingual and real-world contexts. Overall, the studies reveal that deep learning significantly outperforms traditional machine learning in personality prediction tasks, particularly when enhanced through data preprocessing, class balancing, and multimodal data fusion. Future research directions focus on using larger, more diverse, and multilingual datasets, hybrid models, and ethically designed algorithms to ensure robust and interpretable personality prediction systems. The summary of the selected study is mentioned in Table 2.1 below.

Table 2.1: Summary of studies utilizing Machine Learning with Deep learning Model to classify personality traits.

SNo	Author	Purpose of the study	Model/ Algorithm	Performance	Limitations and Future Suggestions
1	Basto et al. (2013)	Natural Language Processing (NLP) methodology for personality traits prediction	Naive Bayes, Random Forest, Support Vector, LSTM, and BERT	Traditional ML classifiers, when applied to quality data, outperform complex models.	The dataset used is highly imbalanced. For acquiring quality data, feature engineering techniques should be focused on in the future.
2	Ontoum and Chan (2022)	Prediction of personality traits from textual data using the MBTI model.	Naïve Bayes, SVM, RNN	Naïve Bayes = 86.95% SVM = 87.32% RNN = 93.22%	In future content, from multiple social media sites may be experimented with for further enhancement in personality prediction.
3	Nisha et al. (2022)	Classification of personality traits from text using the MBTI model.	NB, SVM and XGBoost	NB = 85% SVM = 86% XGBoost = 90% (Maximum accuracy was gained by the N/S trait)	Some traits are highly imbalanced. Data from various social platforms could improve the prediction performance in the future.

4	Mitra et al. (2022)	to correlate the social media content and personality traits utilizing different machine learning classifiers.	Random Forest, KNN, SVM, Naïve-Bayes (NB), LSTM, and CNN	CNN outperforms other algorithms. CNN accuracy for four traits' I/E = 79.18% S/N = 85.55% T/F = 73.22% J/P = 70.07%	Combining different learning models for optimization through hyperparameter fine-tuning will further enhance the results in the future.
5	(Mohan et al., 2023)	To construct a system to enhance personality classification capability using the MBTI model	Word2Vec model, LSTM, MBTI Model	The LSTM got a high accuracy of 97% and showed outstanding performance as compared to other existing models.	Experimenting Large and diverse dataset will further improve the performance of the personality traits prediction system.
6	(Mehta et al., 2020)	Multimodal technique for automated personality prediction using the Big Five personality scheme.	Machine learning models like SVM, CNN, ML, and LSTM were utilized in this review paper to examine the textual, audio, and visual data.	The study shows a promising interest in combining various machine learning (ML) algorithms for more calculable personality identification.	In the future, ethical issues regarding data collection for personality prediction may be addressed.

7	(Feizi-Derakhshi et al., 2022)	Multimodal approach based on the commonly used psychological Big Five Model for personality assessment.	LIWC, MRC, and word embedding, PLM-free APPs, PLM-based APPs, Multimodal APPs:	This review study notes that hybrid and ensemble models often outperform traditional methods	Developing a dataset with multiple personality traits will yield better results in the future.

Research Methodology

The working procedure of this study will follow the steps given as (i) Developing Labelled dataset comprising of Urdu language text, (ii) Re-sampling of developed Dataset, (iii) Cross Validation using Stratified K-Folds, (iv) Text Preprocessing Techniques, (v) Mayers-Briggs Type Indicator (MBTI) model, (vi) Text-based Personality classification, (vii) Using composite deep learning approach for personality traits assessment, (viii) Performance measurement, and (ix) Applied example.

3.1 Dataset

The widely used MBTI-based personality dataset was initially developed and created by Mitchell Jolly in 2017 on Kaggle. It collected the contents from the Personality-cafe forum, where each record contains the user's last fifty recent tweets and their MBTI personality type. The MBTI dataset serves as a rich resource for testing personality prediction methods, often leading to insights into the efficacy of machine learning techniques in capturing personality characteristics through text (Ryan et al., 2023). This dataset is available on Kaggle for educational and research purposes, specifically in text processing and personality analysis (*Mitchell J | Master | Kaggle*, n.d.).

The available dataset utilized by Bharadwaj et al. (2018; Cerkez & Vareskic, 2021; Khan et al., 2020) in their research work to assess individuals' MBTI personality traits from their textual contents.

TABLE 3.1 Table showing the occurrence of all eight traits of the MBTI dataset.

Introversion-Extroversion (I-E)		iNtuition-Sensing (N-S)		Feeling-Thinking (F-T)		Judging-Perceiving (J-P)	
Introversion	Extroversion	iNtuition	Sensing	Feeling	Thinking	Judging	Perceiving
6664	1996	1194	7466	3975	4685	5231	3429

3.2 SMOTE (Synthetic Minority Over-sampling Technique)

To sort out the skewness of the data SMOTE technique was applied to resample the data. SMOTE is a complex method of oversampling the minority class in that it creates artificial examples rather than copying existing ones. This method identifies samples from the minority class, finds the nearest neighbor for those samples, and the method generates artificial samples on the line from a given sample to its neighbor. It generates more samples, synthesizing a variety of new content that contributes to lower overfitting problems inherent in replication. It can improve model accuracy as well as its robustness by offering data for the underrepresented classes.

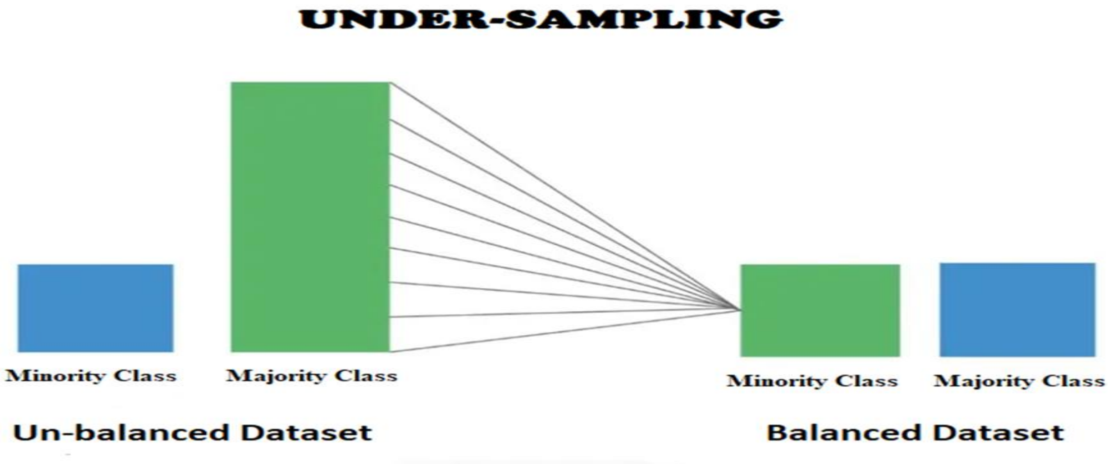


Figure 3.2: Smote technique

3.3 Cross Validation using Stratified K-Folds

An approach that is specifically utilized in machine learning systems to measure a model's predictive accuracy on unseen data. It performs the splitting of data into k folds, one fold (subset of the dataset) is reserved for validation, while the model is trained on all the remaining subsets of data. Similarly, in the next iteration, another fold is reserved for testing and validation purposes, while the remaining k-1 folds are used for training the model. This process continues until all reserved subsets of data are tested against the remaining folds to ensure robust performance (Basto, 2021).

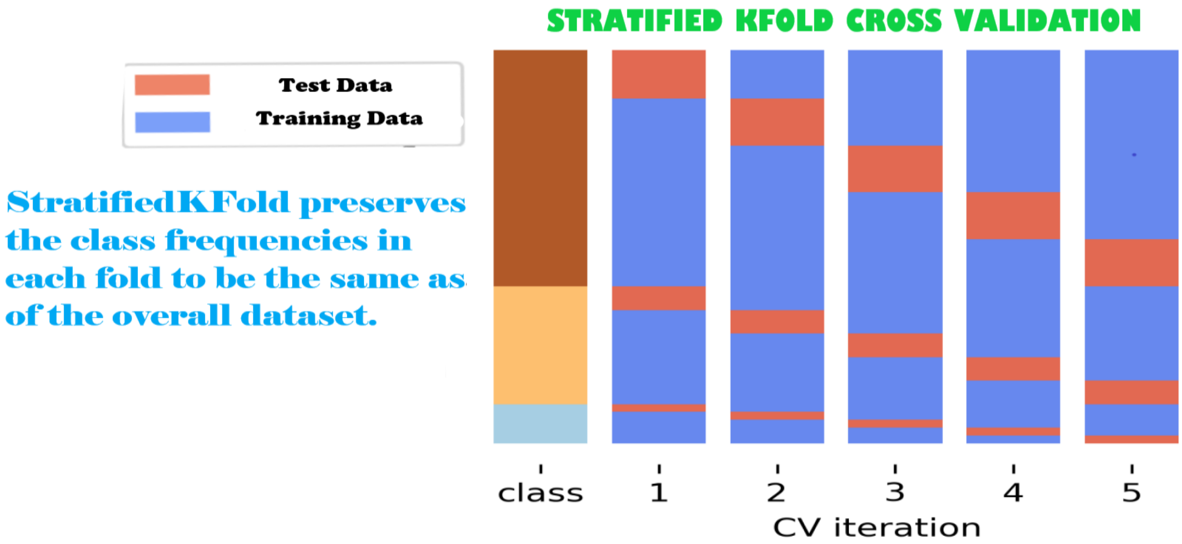
This methodology is very useful in minimizing overfitting and helps in the generalization of the model. Steps involved in cross-validation:

1. Split the dataset into multiple folds, usually five or ten folds.
2. Train the model on all (k-1) folds while one subset of the dataset is reserved for validation.
3. Repeat the process so every fold is used as the validation set for another iteration.
4. Compare the numbers of accuracy, precision, etc., across each iteration and then arrive at an average of them to conclude the efficiency of the model.

A variation of cross-validation is Stratified KFold, whereby each fold holds a similar number density of a particular class as in the general data set. It becomes even more advantageous in dealing with the imbalanced datasets where one or several classes have significantly fewer samples than other classes, as it avoids some of the fold combining recurrently having minimum samples of a specific class. This brings better generalization performance by keeping balanced class data distribution with the help of folds instead of having a major effect of bias and more reliable of the evaluation of the model. This stratification is very useful when subdividing classes in the training and testing sets and maintaining the balance of classes in each fold when dealing with concerning imbalanced datasets (P. Wang et al., 2020).

3.4 Text Preprocessing Techniques

These preprocessing techniques are basically used to remove the anomalies present in the dataset



to achieve acceptable and efficient results. To reduce the noise from the available dataset, the text is cleaned by removing URLs and stopwords from the input textual data. Similarly, the input text is lowercased, lemmatized, and all non-alphabet characters are removed during preprocessing. Filtering may also be utilized for cleaning of data and for generating the most pertinent textual contents for classification. Removal of non-textual data like hashtags, URLs, more than one space, and special characters is also performed. Spell checkers are also used to correct the spelling errors that occur due to linguistic irregularities. That is why the preprocessing of text data is very significant, especially when converting text data into machine learning and NLP format by eliminating the noise data and the normalization of the text inputs.

3.5 Feature Engineering:

It concerns the preparation of raw data in textual form for feeding into machine learning models while preserving its semantically significant properties. Tokenization, padding, and reshaping are instances of feature engineering because they are important processes of transforming text data that can be used as input data for the model. Feature selection is so crucial to a model because if done appropriately, it can boost model performance due to improved learning by algorithms (Sujatha et al., 2023).

3.6 Proposed Hybrid Model

Different deep learning models are integrated together to take advantage of each model and create a robust framework, especially for text classification tasks. Here in this proposed work, four models, namely TCN, BiLSTM, GRU, and the Attention mechanism, are combined to build a new model, making it an ideal and powerful architecture to handle text classification and a personality traits prediction system.

a) TCN

This paper also introduces a TCN (Temporal Convolutional Network) for capturing long-range temporal dependencies. TCNs are good at handling sequential data for a long time. As a result, TCNs are capable of detecting correlations between elements in a sequence that are far apart due to the application of dilated convolutions. In tasks like text classification, it may be extremely important to capture long-range dependencies (e.g., relations between the words or phrases located in different sentences). The TCN increases its receptive field through dilation to make sure it will be able to capture both the short-range and long-range dependencies from the sequence without losing important information.

Mathematical representation of (TCN)

The TCN layer uses causal and dilated convolutions:

- Filters: $F \in \mathbb{R}^{k \times d \times c}$, where k is the kernel size, d is the input dimension, and c is the number of filters.
- Dilation rate: d_{rate}.

For each timestep t, the output is:

$$Y_t^{\text{TCN}} = \sigma\left(\sum_{i=0}^{k-1} F_i \cdot E_{t-i \cdot d_{\text{rate}}} + b\right),$$

where σ is the activation function (e.g., ReLU). The output has shape $\mathbb{R}^{N \times T \times c}$.

b) BiLSTM

BiLSTM processes the sequences twice, once in the forward and once in the reverse direction. It means that it relates both past and future context while generating the features of the element in the sequence. Many tasks in natural language processing depend on the relationship of the word or phrase to the words that precede it as well as to the words that follow. The BiLSTM consists of two LSTM layers, but different because it can make its own forward and backward passes (Asghar et al., 2021; Sandra et al., 2024).

i) One executes the sequences in the forward direction.

ii) While the other operates it from right to left (backward). This bidirectional context together offers a deeper temporal analysis of the process by sequence (Yousafzai et al., 2021).

Mathematical representation of BiLSTM (Bidirectional Long Short-Term Memory)

The BiLSTM processes the TCN output in both forward and backward directions:

$$h_t^{\text{forward}} = \text{LSTM}\left(Y_t^{\text{TCN}}, h_{t-1}^{\text{forward}}, c_{t-1}^{\text{forward}}\right),$$

$$h_t^{\text{backward}} = \text{LSTM}\left(Y_t^{\text{TCN}}, h_{t+1}^{\text{backward}}, c_{t+1}^{\text{backward}}\right).$$

The BiLSTM output combines the two directions:

$$H_t^{\text{BiLSTM}} = \left[h_t^{\text{forward}}, h_t^{\text{backward}}\right],$$

where $H_t^{\text{BiLSTM}} \in \mathbb{R}^{N \times T \times 2h}$, and h is the hidden size.

c) Attention for Relevance-Focused Feature Weighting

The model applied in this paper, known as the Attention mechanism, offers distinct weights to the various parts of the sequence. It enables the model to emphasize the most suitable parts of the input data. All the elements in a sequence are not equally significant towards a particular task. For instance, in the content "I enjoyed the meal but disliked the service," the words "enjoyed" and "disliked" are more inclined to sentiment analysis than "the" or "but". The Attention mechanism assigns weights in the form of how similar or different one portion of the sequence is to another portion (for example, the query with the value in self-attention). It then applies these weights to bring out the more relevant features and underemphasize the irrelevant features (Yousafzai et al., 2021; Asghar et al., 2021).

Mathematical Representation of Attention for Relevance-Focused Feature Weighting

The attention mechanism computes the relevance of each timestep:

$$\text{Score}(t, t') = H_t^{\text{BiLSTM}} \cdot W \cdot H_{t'}^{\text{BiLSTM}},$$

where W is a learnable weight matrix.

The attention weights are normalized:

$$\alpha_{t,t'} = \frac{\exp(\text{Score}(t, t'))}{\sum_{t''} \exp(\text{Score}(t, t''))}.$$

The context vector C_t is computed as:

$$C_t = \sum_{t'} \alpha_{t,t'} \cdot H_{t'}^{\text{BiLSTM}}.$$

3.7 Performance measurement

The efficiency of the model was evaluated using different metrics. These metrics present a real picture of the performance of the model experimented with for personality traits prediction using Urdu text as an input snippet of text. There are a number of evaluation metrics like accuracy, AUC-ROC, RMSE, confusion matrix, F1 score, precision, and recall. The given pseudocode describes step step-wise processing mechanism to determine the performance and efficiency of the entire model.

Results and Assessments

In this portion of the study, the results of the planned and proposed work have been presented by fulfilling the requirements of the work with satisfactory answers to all the pointed-out research questions.

4.1 Answer to Research Question 1

To explain and comment on the RQ_1 (*How to detect personality traits from Urdu text by applying composite deep learning models?*) First, the combination of different deep learning classifiers, such as TCN+BiLSTM+GRU or CNN+Bi-LSTM, and other suitable fusions of two or three models was experimented with for traits assessment based on the MBTI personality measurement scale using Urdu language pure font text as an input. Most prior work performed in trait classification was based on a single deep-learning approach. In this work, a hybrid deep learning model, TCN+BiLSTM+GRU with an attention mechanism, was applied for trait detection.

Results of TCN+BiLSTM+GRU+AATTN Model for Urdu text (Proposed Mode).

Table 4.1: Results of TCN+BiLSTM+GRU+AATTENTION Model for Urdu text

Parameters and Hyperparameters	Metrics	I-E	N-S	J-P	T-F
TCN (nb_filters=64,kernel_size=3, dilations=[1, 2, 4, 8], dropout_rate=0.3)	Accuracy	88	96	77	76
epochs=10, batch_size=32, verbose=0, validation_split=0.2	Precision	84	93	80	78
optimizer=Adam(learning_rate=0.0005), loss='binary_crossentropy'	Recall	96	99	71	73
bilstm_layer = Bidirectional(LSTM(64, return_sequences=True,))	F1_Score	89	96	75	75
attention_layer = Attention(name='attention_layer')([bilstm_layer, bilstm_layer])	ROC-AUC	95	99	83	82
gru_layer = GRU(64, dropout=0.2, recurrent_dropout=0.2)	PR-AUC	94	98.5	79	78
kf = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)					

Answer to Research Question 2

In response to RQ_2 (*How to develop a benchmark dataset comprising Urdu text along MBTI personality type for traits recognition from input text?),* a new benchmark dataset was developed by translating the kaggle_mbti dataset's tweets from English into Urdu text. This developed dataset was evaluated to judge the predictive behavior of the model.

A user-defined Python function is used to convert text from the English language to the Urdu language textual contents. By utilizing an external translation API, Microsoft Azure Translator, the function sends the provided text to the service and gets back the translated result. The function uses parameters for source and target languages, the API key, region, and the endpoint URL to authorize and format a request. It creates an HTTP post request with the text data, parses the JSON response, and extracts the translated text. This function is generic and can be easily plugged into different applications. It helps maintain generic multilingual support in various applications where content improbability for translation is required.

	posts	I-E	N-S	T-F	J-P	translated_text	type
0	moment sportscenter top ten play prank life...	0	0	1	0	اسپورٹس سینٹر کے ٹاپ ٹین کھیل وں کی زندگی ک...	INFJ
1	finding lack post alarming sex boring positio...	1	0	0	1	اس وقت گرل فرینڈ نے کاؤ گرل مشنری کو تخلیقی ط...	ENTP
2	good one course say know blessing curse absol...	0	0	0	1	اچھی بات یہ ہے کہ جان لیں کہ نعمت کی لعنت بال...	INTP
3	dear enjoyed conversation day esoteric gabbi...	0	0	0	0	بات چیت کے دن سے لطف اندوز ہونے والی بات چیت ...	INTJ
4	fired another silly misconception approaching...	1	0	0	0	ایک اور احمقانہ غلط فہمی کو منطقی طور پر حل ک...	ENTJ
5	science perfect scientist claim scientific in...	0	0	0	0	سائنس کے بہترین سائنس دان نے سائنسی معلومات پ...	INTJ
6	draw nail haha done professional nail yes gel...	0	0	1	0	ناخنوں کی کھدائی پیشہ ورانہ طور پر کیل بنوائی...	INFJ
7	tend build collection thing desktop use frequ...	0	0	0	0	ڈیسک ٹاپ کے استعمال سے اکثر ہر چیز کو ترتیب د...	INTJ
8	sure good question distinction two dependant p...	0	0	1	0	یقینی طور پر دو پر انحصار کرنے والے تصورات میں...	INFJ
9	position actually let go person due various r...	0	0	0	1	مختلف وجوہات کی بنا ء پر انسان کو مشکلات کا س...	INTP

Figure 4.1 translation techniques

Answer to Research Question 3

To accomplish RQ_3 (*Comparing the proposed work results obtained by analyzing Urdu font text for personality traits assessment with prior work using deep learning techniques to find which one is efficient?*), the results of the developed system were checked by comparing these scores with other composite deep learning, deep learning, and supervised learning classifiers' performance using different measurement metrics.

The proposed model's performance is compared with benchmark studies, and the results are illustrated in Table 4.2. This comparison will help us understand the proposed model's efficiency and performance. Although much research is conducted on personality trait assessment, comparisons are made with prior works leveraging the usefulness of hybrid deep learning models.

Table 4.2 Performance comparison with Benchmark studies.

Author/s	Model/Classifier	Metrics	I-E	N-S	T-F	J-P
Ahmad et al. (2021)	CNN+LSTM (Hybrid Deep learning Model)	Accuracy	88	91	85	80
		Precision	88	91	85	80
		Recall	88	91	85	80
		F1_Score	88	91	85	80

Kerz et al., (2022)	BERT+BiLSTM (Hybrid model)	Accuracy	85.5	92.3	85.7	82.6
Proposed Model	TCN+BiLSTM+GRU+ ATTENTION	Accuracy	88	96	77	76
		Precision	84	93	80	78
		Recall	96	99	71	73
		F1_Score	89	96	75	75
		ROC-AUC	95	99	83	82
		PR-AUC	94	98.5	79	78

According to Table 4.2, the proposed model's performance is acceptable. The proposed model's I/E and N/S traits surpassed both studies across all evaluation metrics; however, the T/F and J/P traits showed a slight reduction in performance. Consequent to the above comparison, it is concluded that the proposed model correctly evaluates and assesses the MBTI personality traits in Urdu textual content.

Conclusion

The main idea behind this work was to develop a composite deep learning model for Urdu textual data classification into MBTI personality traits. The dataset of (*Mitchell J | Master | Kaggle*, 2017) was translated into Urdu, leveraging the benefits of robust Microsoft Azure AI services. The classification was made using four dimensions of the MBTI psychology model, namely Introvert/Extrovert (I/E), iNtuition and Sensing(N/S), Feeling and Thinking(F/T), and Judging and Perceiving(J/P). The task was accomplished using the steps: (i) Developing the Urdu language dataset by translating mbti_kaggle, (ii) Text pre-processing, (iii) Applying Resample techniques, (iv) Cross Validation, (v) Accomplishment of personality trait classification task, (vii) Trait were assessed and examined using composite deep learning approach, (viii) Performance was evaluated using different measurement metrics, and (ix) Text from real life was fed to the model and the trait classification and assessment was found satisfactory.

Limitations of the study

1. Translating English textual content to Urdu text might alter or minimize its contextual and semantic meanings.
2. The combination of TCN, BiLSTM, GRU, and Attention mechanisms used in developing the proposed architecture is computationally intensive. Training such models involves a huge amount of time and resources, including high-end GPUs and a large amount of memory, which is not achievable for all researchers.
3. The dataset was acquired and developed using a translating mechanism. The main limitation is the non-availability of Urdu's own dataset.

4. The model's complex structure might lead to overfitting on training data, especially when the available data corpus is not large enough.

Future Guidelines

1. Translation tasks might be accomplished using multiple translation models, and linguistic experts should review the translated text.
2. In the future, other low-resource languages of Pakistani culture, like Pashto, may also be experimented with for personality assessment.
3. Multiple platforms' textual data and multiple available benchmark datasets should be experimented with to assess personality traits.

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