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MBTI Personality Type Prediction Model Using WZT Analysis Based on the CNN Ensemble and GAN

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Abstract

The Myers-Briggs Type Indicator (MBTI) personality analysis is a well-known method used to perform personality diagnosis of adolescents after a natural language processing analysis using social media data. However, directly using image data to analyze a personality type is insufficient. This research uses directly drawing image data presented by the adolescent using the Wartegg-Zeichen Test (WZT) and predicts MBTI personality types by mixing various representations of the convolutional neural network (CNN) and generative adversarial network (GAN) models. The study aims to analyze the data from 808 junior high school students. We employ a binary approach that divides MBTI personality types into four classes and presents improved prediction performance using the CNN ensemble and GAN techniques. As a result, the initial average predicted value of the CNN is 17.2%, but the average predicted value in the method using the final GAN is 27.2%, indicating an increase of 10%. This study is the first to predict various personality types and automatically analyze drawing images, expressed in the WZT of adolescents based on the deep learning model. Recent deep learning technologies evolve daily, and this study aims to create many opportunities for deep learning applications.

Keywords

MBTI Prediction, CNN Ensemble with GAN, Deep Learning based Personality Analysis, Wartegg-Zeichen Test

1. Introduction

Higher education for adolescents can improve their critical thinking skills for personal growth and is critical for student development [1]. Students are exposed to increasingly challenging and complex situations during the teaching process, and cognitive complexity can increase during the learning process [2]. It is essential to distinguish between differences from other students and those that reflect the student's cognition or characteristics. Because outward behavior and predictable tendencies toward learning participation are critical elements of intervention in all aspects of teaching [3].

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Student knowledge is advantageous to teachers unless used in stereotypes or to select or reject students. It is a resource that helps teachers use their natural tendencies and preferences to develop their student's qualities [4]. Knowing what kind of personality a student has through the Myers-Briggs Type Indicator (MBTI) personality type helps teachers recognize interactions, decision choices, strengths and limitations, and the differences between people of different personality types [5]. As stated in Jung's psycho-type theory, the facts tend to be orderly and consistent, although individual behavior may appear complex due to diversity [6]. Various diagnostic tools are used for MBTI personality types, most of which are self-report questionnaires. The disadvantage is that the accuracy is lowered due to defensiveness and insincere responses, so it is difficult to obtain information for actual use [7].

A projective test is performed to compensate for these problems. The projection is a pictorial representation of the direct experience that the subject responds to subconsciously. Projective testing is used to identify anomalous personalities in psychiatry, but is now being developed in various ways depending on the theme [8]. When one projects a picture to a young person, specific patterns depend on the tendency of the young person, and a universal and similar pattern appears in a specific part of the picture.

Selecting the Wartegg-Zeichen test (WZT) for projective tests is useful for youth personality type analysis. Founded by German psychologist Ehrig-Wartegg, the WZT-based personality diagnosis covers various subjects, from infants to adults. Eight pictures are presented in the WZT, and there is also an element of play, which has the advantage that the person inspecting the pictures is unaware that he or she is inspecting them. Psychologists have endeavored to systematically understand personality and have found a link between general personality traits and various behavior types [9, 10].

The MBTI personality types identify differences in normal personality that can lead to poor communication and conflict [11]. The MBTI developers, Isabel Briggs Myers and Katharine Cook Briggs, demonstrated that predicting personality types can be helpful health care, as learners' learning outcomes depend on their personality types [12]. However, in the previous conventional research, instead of processing image data to investigate individual's personality type, natural language processing that employs online text, such as on social media, Facebook, and Twitter, is often used.

Automatic personality prediction has received considerable attention from natural language processing and social science communities [13]. Because the questionnaire survey and projection methods for character-type evaluation involve qualified experts evaluation, obtaining the results takes considerable time and expense. In addition, considering the analysis needed for the image dataset, from a modeling perspective, it makes sense to use a deep learning model [14], which is a subfield of machine learning that uses artificial neural networks.

Developing convolutional neural network (CNN) models that train on image data using deep learning has contributed to achieving improved accuracy [15]. Automation with the CNN ensemble can mitigate the cost and improve the process. The CNN is a widely used method for extracting complex visual features from digital images, and we use the CNN model to extract functionality from images [16, 17]. In visual work, CNNs are the most commonly used and provide good results personality detection [18, 19]. Image classification performance requires many training images. Increasing the data using a generative adversarial network (GAN) can preserve the characteristics of student-created WZTs, secures image data, and prediction rates.

This study predicted 16 personality types of MBTI using the CNN model for images displayed in the WZT of adolescents. The CNN ensemble and GAN techniques increase the predictive value of the MBTI personality types. This research creates many opportunities to use deep learning to predict the MBTI personality type by discovering the unique characteristics of an individual from pictures created directly by the students.

We organized the paper as follows: Section 1 gives an overview of MBTI as it affects the community; Section 2 provides a related work overview of CNN ensemble with GAN as an approach for MBTI personality prediction; Section 3 presents the proposed method for prediction model pipeline MBTI personality type, using binary classification, personality analysis sequences, and deep learning based ersonality analysis in CNN ensemble with GAN; Section 4 presents the results of the proposed method and discusses the results; and finally, Section 5 concludes the paper.

2. Related Work

2.1 Wartegg-Zeichen Test

The WZT is a drawing inspection and has achieved tremendous success for decades. In the WZT, an individual draws a picture in cooperation with a stimulus picture provided in eight 4×4-cm square frames [20]. The characteristics of the WZT make it possible to clearly understand the subconscious attitude and unique relationship of the assessed individual toward the world. Adolescents draw open pictures and naturally expressed themselves without defensiveness, and the pictures contain specific patterns according to individual tendencies [21]. Jung [22] classified individual attitudes and mental functions with similarities and homogenous characteristics, even if they are not the same in psycho-type theory, because morphologically similar patterns appear in certain parts of a youth's drawing. However, each unique type has some degree of universality.

2.2 Myers-Briggs Type Indicator

The MBTI is one of the most well-known and widely used descriptors of personality type [23, 24]. The MBTI personality type, helps adolescents understand their traits and those of others, and allows teachers to understand and guide the traits of student behavior, facilitating the relationship between teachers and students [6]. A more positive relationship between the teacher and student, has a greater influence on student performance assessment, and the teacher's style and characteristics significantly influence the overall assessment [25, 26].

The MBTI model has four dichotomous dimensions, each consisting of two mutually exclusive categories. The personality types in MBTI are extroversion (E) versus introversion (I), sensing (S) versus intuition (N), thinking (T) versus feeling (F), and judgement (J) versus perception (P) [6]. The four dichotomies of the MBTI are outlined in Table 1.

Table 1. Four dichotomies of the Myers-Briggs Type Indicator

Extroversion-Introversion dichotomy by attitude or direction of energy	
E (*Extroversion*)	*I* (*Introversion*)
Directing energy mainly toward the outer world of people and objects	Directing energy mainly toward the inner world of experiences and ideas
Sensing-iNtuition dichotomy by functions or processes of perception	
S (*Sensing*)	*N* (*iNtuition*)
Focusing mainly on what can be perceived by the five senses	Focusing mainly on perceiving patterns and interrelationships
Thinking-Feeling dichotomy by functions or processes of judging	
T (*Thinking*)	*F* (*Feeling*)
Basing conclusions on logical analysis with a focus on objectivity and detachment	Basing conclusions on personal or social values with a focus on understanding and harmony
Judgement-Perception dichotomy by attitudes or orientations toward dealing with the outside world	
J (*Judgement*)	*P* (*Perception*)
Preferring the decisiveness and closure that result from dealing with the outer world using one of the Judging processes (Thinking or Feeling)	Preferring the flexibility and spontaneity that results from dealing with the outer world using one of the Perceiving processes (Sensing or Intuition)

2.3 CNN Ensemble, GAN, and Deep Learning

The CNN is widely used to extract visual features from images and provides excellent results [27]. The ensemble method can also be used with various models to reduce overfitting problems. The results of the CNN ensemble are more reasonable and perform better with different models than with a single CNN [28–30]. The GAN is one of the generative models in which two neural networks, a generator and a discriminator, learn while competing [31]. This study use GAN to enhance the new data by synthesizing the open image used in the tensor flow with the original image data. Deep learning is a subfield of machine learning, well known for image processing and computer vision. Developing CNN models trained using image data and deep learning effectively achieves good recognition accuracy [32].

2.4 Previous Studies

Previous studies have assessed using texts to predict MBTI personalities in natural language processing analysis and have achieved better predictions using the dichotomy in MBTI personality classification. Personality analysis is a crucial tool for assessing the emotional domain, where a text mining method is applied to assess the emotional domain, and the dichotomy method is used to predict the MBTI. The accuracy results of using social media for 8,600 people were highest in the E–I dichotomy and lowest in the J–P dichotomy [33]. Some social media platforms have begun to understand how to take advantage of the user experience and interface improvements. The user's personality is associated with many interaction types and helps predict interface preferences. As technology expands, it becomes possible to determine an individual's personality automatically. Twitter acted as a data source, with the highest E–I dichotomy in binary MBTI character prediction at 80% accuracy and the other four dichotomies at 60% [34]. Using machine learning algorithms with public information shared on Twitter, MBTI personality traits demonstrated accuracy results between 11% and 18% [9].

The MBTI classification used a machine learning and deep learning approach. The MBTI multiclass classification reached 23% accuracy, and the highest accuracy for the binary approach was 38% for the long short-term memory network [11]. Personality and demographics are important in social sciences, have potential interpretations, and were analyzed with a neural network approach employing demographic data (age, gender, location, and language) from over 10,000 people. The type-level classification accuracy achieved for MBTI training was 45% [35]. Personality represents an individual's unique traits that influence patterns, such as habits, behaviors, and attitudes, and texts used on social networking sites can automatically recognize an individual's personality traits. Dataset distortion was minimized by oversampling, and the dataset was balanced. In addition, MBTI was classified, and term frequency-inverse document frequency was used [36].

In previous studies, texts were most often used to predict MBTI. Unlike most previous research, we used an individual-drawn image rather than text to predict the MBTI personality type.

3. Methods for Predicting the MBTI Personality Type

3.1 CNN Ensemble

To predict the personality type of MBTI, 16 ratings were divided into multi-class classifications. We clearly show in Table 2 the ratio of a dataset is the number of samples used for training, validation, and death; 63% (4,077) of data for training, 27% (1,747) of data for verification, and 10% (640) of data for testing were used separately.

Fig. 1 illustrates that learning and evaluation were repeated to use the CNN ensemble and to train the original image, random sampling, data augmentation, and class weight prediction models. By comparing the predictive model performance evaluation with the performance evaluation on the CNN ensemble, we selected a satisfactorily performing model as a predictive model that classifies MBTI personality types.

Table 2. Detailed training, verification, test percentage, and number of datasets

	Training data	Verification data	Test data	Total
Proportion (%)	63	27	10	100
Drawing image piece	4,077	1,747	640	6,464

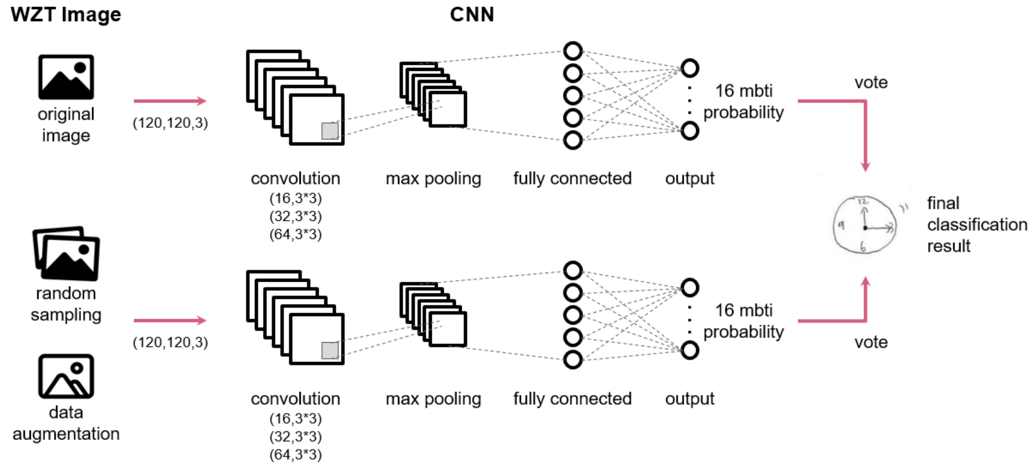

Fig. 1. Prediction model pipeline Myers-Briggs Type Indicator (MBTI) personality type.

Random sampling is a method with the same selection chance for all elements of a population. The random sampling extraction method has an acceptable classification error, and it is relatively easy to analyze the data. As the given data are limited, bias and overfitting problems can occur. This research expanded the dataset that can be learned using data augmentation. Weight adjustment is a method of finding the desired correct answer by assigning an initial weight value in learning to optimize it by changing the value. This research used various changes in weight values. This paper uses the CNN ensemble as a model for learning using the original image, random sampling, data augmentation, and class weight. The average accuracy and personality types were classified.

3.2 Binary Classification

We generated four binary classification prediction models that classify the dataset into E–I, S–N, T–F, and J–P, and measured the accuracy by combining the four prediction values. Reveals that the accuracy increased using binary classification, and the MBTI was predicted for four personality positions and then combined to measure the accuracy. When training four binary classification prediction models, we used the pipeline in Fig. 2 to select the model influencing learning.

3.3 Myers-Briggs Type Indicator Personality Analysis Sequences

A binary classification prediction model is generated so that predictions can be made using the personality analysis sequence at each location of the MBTI. To achieve the highest result according to Jung's sensing and intuition, the order of analysis starts from S–N and learns in the order of T–F, J–P, and E–I.

Fig. 3. illustrates that if the S–N binary classification predicts S based on the predicted value, sensing and thinking (ST) or sensing and feeling (SF) is predicted through the sensing T–F (S–TF) binary classification model, and the binary classification prediction model to be used next is determined

according to the result. In each case, we created a binary classification prediction with 15 prediction models. When training 15 binary classification prediction models, we saved the model using random sampling and applied image proliferation and weight adjustment to select the model that affects training.

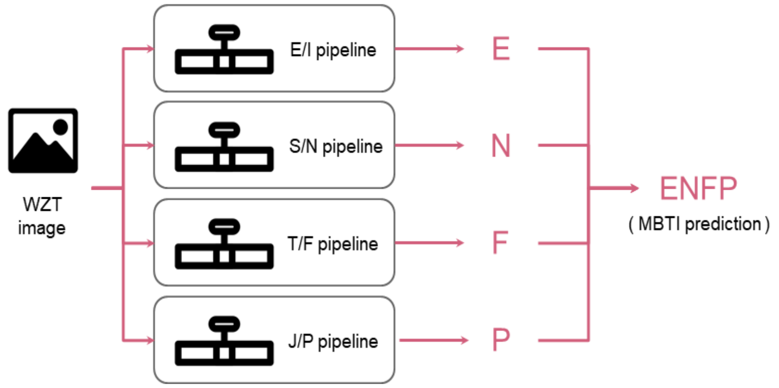

Fig. 2. Myers-Briggs Type Indicator (MBTI) personality prediction using binary classification.

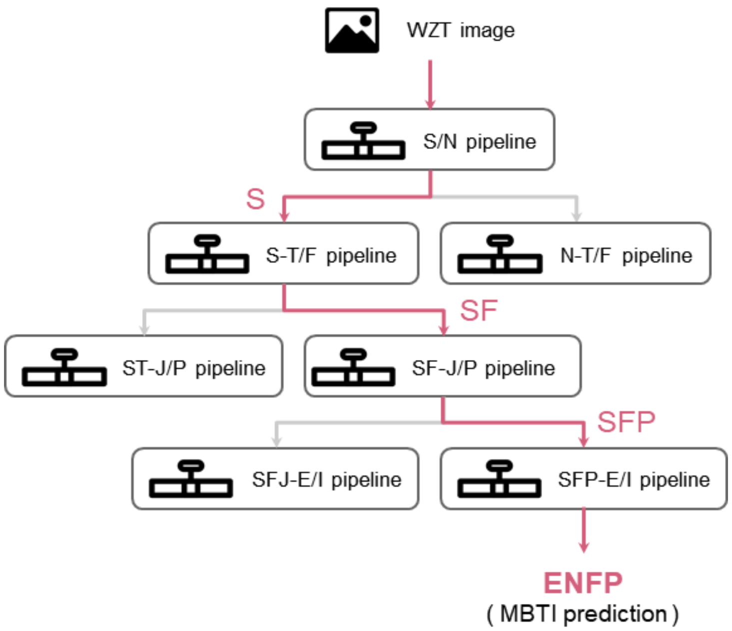

Fig. 3. MBTI example of MBTI prediction model using personality analysis sequences.

3.4 Generative Adversarial Network

The image classification performance has mixed results depending on the trained image. Maintaining image features carefully and reinforcing various images is a method to prepare for performance degradation [37]. The GAN reinforces the image while preserving the characteristics of the student's WZT drawings. This study used an open image with style transfer and GAN. An example of using GAN for MBTI personality type prediction is depicted Fig. 4.

A common characteristic of the WZT drawing created by students is the many blank spaces in the picture, which makes it is difficult to determine characteristics from the picture. In this research, we apply style transfer, one of the GAN methodologies, to compensate for this. The image from the WZT created by the students was not deformed, and the pattern was revealed by combining noise using the GAN in the margin [38].

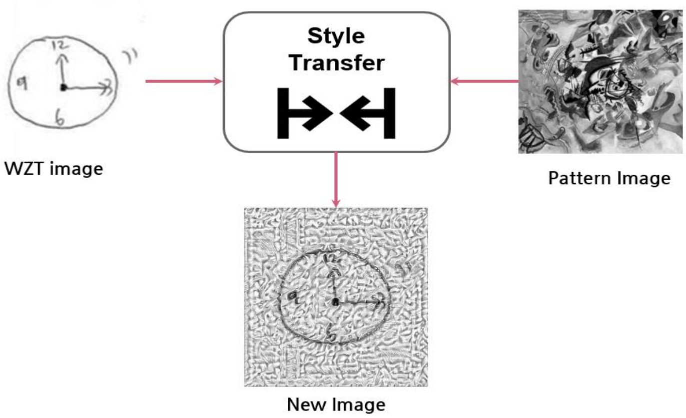

Fig. 4. Personality prediction type for general adversarial network for Myers-Briggs type.

4. Deep Learning for Predicting MBTI and a WZT Image

4.1 MBTI 16 Personality Types

The research target comprised 813 junior high students, and the WZT was conducted from April 2012 to March 2013. Data from images appearing in the 813 WZTs without the following existing types were removed, and the final dataset of 808 was analyzed. The data distribution and frequency in the dataset are presented in Fig. 5.

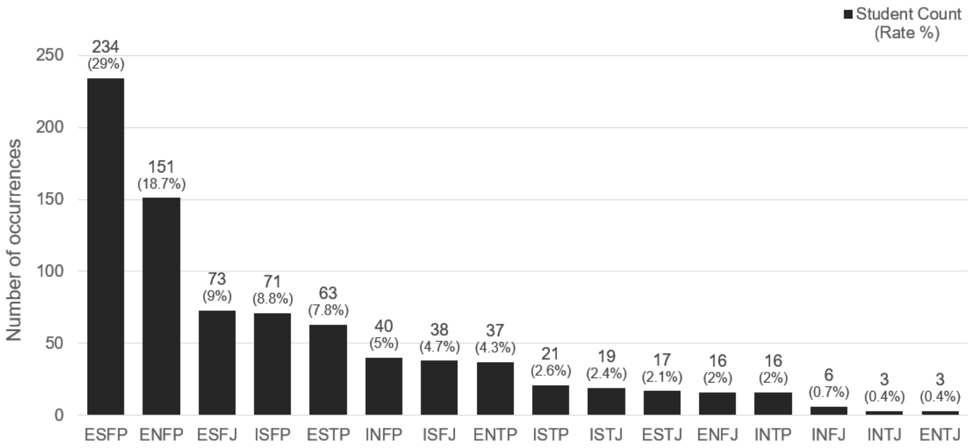

Fig. 5. Distribution and frequency of MBTI personality types for 808 people.

The data for the 16 personality types are uneven and biased. For example, there are 234 ESFPs, and only three each of INTJs and ENTJs. There was a data imbalance in the dataset, with a bias toward a particular personality type. Overall, ESFP was 29.0%, followed by ENFP at 18.7% for most personality types. In addition, INFJ, INTJ, and ENTJ were the personality types with the lowest distribution at less than 1%. This study has experimented with various methods to analyze the character-type disproportionate distribution of the dataset and the unformatted WZT images.

4.2 CNN Ensemble

This paper uses the CNN ensemble as a model for random sampling, data augmentation, and class weight learning. Eight personality types were classified with an average accuracy of 17.2%. At the highest value, ESFP had an accuracy of 42.9%. As the lowest value, ENTP reached an accuracy of 3.1%. Moreover, INFP, ISTP, INTP, ISTJ, ESTJ, ENTJ, INTJ, and INFJ were unpredictable. The results are listed in Table 3.

Table 3. Convolutional neural network ensemble prediction

Myers-Briggs Type Indicator	Number of correct answers	Number of data	Accuracy(%)
ESFP	79	184	**42.9**
ESFJ	11	64	17.2
ENFP	9	88	10.2
ESTP	7	40	17.5
ISFP	1	16	6.3
ENTP	1	56	1.8
ENFJ	1	8	12.5
ISFJ	1	32	**3.1**
⋮	⋮	⋮	⋮
SUM	110	640	17.2

E=extroversion, I=introversion, S=sensing, I=intuition, T=thinking, F=feeling, J=judgement, P=perception., The bold fonts indicate the highest and lowest.

4.3 Binary Classification Prediction Results

For the binary classification ensemble, random sampling, data augmentation, and class weight models were used. Of these, random sampling exhibited the best results. The average accuracy values for the E–I, S–N, T–F, and J–P binary classifications were at 61.4%, 64.2%, 62.8%, and 68.6%, respectively. The results are provided in Table 4.

This research classified nine character-types with 18.4% accuracy when using a random sampling CNN ensemble as a training model. At the highest value, ESFP reached an accuracy of 49.5%. The lowest value was for ISFJ, with an accuracy 3.1%. In addition, INFP, ISTP, INTP, ISTJ, ENTJ, INTJ, and ENFJ were unpredictable. The results are presented in Table 5.

Table 4. Prediction using binary classification with CNN ensemble

Myers-Briggs Type Indicator	Number of correct answers	Number of data	Accuracy (%)	Model selected and CNN ensemble
Extroversion	323	472	68.4	Random sampling
Introversion	70	168	41.7	
SUM	393	640	61.4	
Sensing	377	400	94.2	Random sampling, Data augmentation, Class weight
iNtuition	34	240	14.2	
SUM	411	640	64.2	
Thinking	354	432	81.9	Random sampling
Feeling	48	208	23.1	
SUM	402	640	62.8	
Judgement	25	168	14.9	Random sampling
Perception	414	472	87.7	
SUM	423	640	68.6	

Table 5. MBTI model using binary classification and CNN ensemble

Myers-Briggs Type Indicator	Number of correct answers	Number of data	Accuracy(%)
ESFP	91	184	**49.5**
ENFP	7	88	8.0
ISFP	6	16	37.5
ESFJ	5	64	7.8
ESTP	4	40	10.0
ENTP	2	56	3.6
ESTJ	1	16	6.3
INFJ	1	8	12.5
ISFJ	1	32	**3.1**
⋮	⋮	⋮	⋮
SUM	118	640	**18.4**

E=extroversion, I=introversion, S=sensing, I=intuition, T=thinking, F=feeling, J=judgement, P=perception., The bold fonts indicate the highest and lowest.

4.4 Binary Classification using the MBTI Analysis Sequence

Various methods were tested and compared to enhance the accuracy of MBTI prediction. We achieved slightly higher accuracy in line with Jung's sensing and intuition. The MBTI analysis sequence starts with S/N and generates binary classification prediction models to make predictions in the order of T–F, J–P, and E–I. We created a binary classification predictive model for all cases, creating 15 predictive models. When training 15 binary classification prediction models, we saved the models with random sampling and applied image multiplication and weight adjustment to select models that influence learning. The results are provided in Table 6.

Biased data tend to cause overfitting problems and lead to poor performance. Oversampling was applied to skewed data to make them evenly distributed. We used binary classification to predict the personality type, and the CNN ensemble to predict the 16 MBTI personality types to enhance the results. In addition, ENTP, INFP, INTP, ISTJ, ENTJ, INTJ, ENFJ, and INFJ were unpredictable. Table 7 presents the final MBTI personalities predicted by the 15 models that employed the MBTI analysis sequence.

This research classified eight character-types with 22.5% accuracy. At the highest value, ESFP reached an accuracy of 55.4%. The lowest value was for ISFP, with an accuracy of 6.3%. Moreover, INFP, INTP, ISTJ, ENTJ, INTJ, ENFJ, and INFJ were unpredictable. The fact that the dichotomy is an integral part of predicting MBTI led to the same conclusion as in previous studies [39].

4.5 MBTI Prediction using a GAN

Using the GAN enhanced the results in predicting the 16 MBTI personality types. In this study, we classified the accuracy of nine personality types at 27.2%. At the highest value, ESFP reached an accuracy of 70.1%. The lowest values were ISTP and ISFJ, with an accuracy of 3.1%. Further, INFP, INTP, ISFP, ISTJ, INTJ, ENFJ, and INFJ were unpredictable. The results given in Table 8.

5. Conclusion

No matter how accurate the MBTI is, no one can explain all the human complexity. However, all types that MBTI indicators represent are worth understanding. Predicting personality using MBTI is a daunting task. The MBTI presents ways to teach students who have difficulty adapting to school, and helps effectively plan and implement learning and teaching methods. The MBTI personality type test was

Table 6. Binary classification prediction using the MBTI analysis sequence with CNN ensemble

Myers-Briggs Type Indicator	Number of correct answers	Number of data	Accuracy (%)	Model selected and CNN ensemble
S	377	400	94.2	Random sampling, Data augmentation, Class weight
N	34	240	14.2	
SUM	411	640	64.2	
ST	28	104	26.9	Random sampling
SF	249	296	84.1	
SUM	277	400	69.2	
NT	28	104	26.9	Random sampling
NF	113	136	83.1	
SUM	141	240	58.8	
ST-J	13	32	40.6	Random sampling, Data augmentation, Class weight
ST-P	51	72	70.8	
SUM	64	104	61.5	
SF-J	33	96	34.4	Random sampling
SF-P	159	200	79.5	
SUM	192	296	64.9	
NT-J	3	24	12.5	Random sampling
NT-P	71	80	88.8	
SUM	74	104	71.2	
NF-J	2	16	12.5	Random sampling,
NF-P	112	120	93.3	
SUM	114	136	83.8	
ESTJ	14	16	87.5	Random sampling
ISTJ	3	16	18.8	
SUM	17	32	53.1	
ISTP	24	32	75.0	Random sampling
ESTP	22	40	55.0	
SUM	46	72	63.9	
ESFJ	43	64	67.2	Random sampling
ISFJ	15	32	46.9	
SUM	58	96	60.4	
ESFP	157	184	85.3	Random sampling
ISFP	3	16	18.8	
SUM	160	200	80.0	
ENTJ	14	16	87.5	Random sampling
INTJ	1	8	12.5	
SUM	15	24	62.5	
ENTP	53	56	94.6	Random sampling
INTP	2	24	8.3	
SUM	55	80	68.8	
ENFJ	6	8	75.0	Random sampling
INFJ	5	8	62.5	
SUM	11	16	68.8	
ENFP	87	88	98.9	Random sampling
INFP	2	32	6.2	
SUM	89	120	74.2	

E=extroversion, I=introversion, S=sensing, I=intuition, T=thinking, F=feeling, J=judgement, P=perception.

Table 7. MBTI prediction result using the MBTI analysis sequence and the CNN ensemble

Myers-Briggs Type Indicator	Number of correct answers	Number of data	Accuracy(%)
ESFP	102	184	**55.4**
ESFJ	18	64	28.1
ENFP	6	88	6.8
ISFJ	6	32	18.8
ISTP	4	32	12.5
ESTP	4	40	10.0
ESTJ	3	16	18.8
ISFP	1	16	**6.3**
⋮	⋮	⋮	⋮
SUM	144	640	**22.5**

E=extroversion, I=introversion, S=sensing, I=intuition, T=thinking, F=feeling, J=judgement, P=perception., The bold fonts indicate the highest and lowest.

Table 8. MBTI prediction result using the MBTI analysis sequence with a GAN

Myers-Briggs Type Indicator	Number of correct answers	Number of data	Accuracy(%)
ESFP	129	184	**70.1**
ESFJ	18	64	28.1
ENFP	13	88	14.8
ESTP	4	40	10.0
ESTJ	3	16	18.8
ENTJ	3	16	18.8
ENTP	2	56	3.6
ISTP	1	32	**3.1**
ISFJ	1	32	**3.1**
⋮	⋮	⋮	⋮
SUM	174	640	**27.2**

E=extroversion, I=introversion, S=sensing, I=intuition, T=thinking, F=feeling, J=judgement, P=perception., The bold fonts indicate the highest and lowest.

developed to make Jung's psycho-type theory more useful in everyday life. The diversity of human behavior is due to the different characteristics of an individual's perception and judgment [6]. The difficulty of predicting all 16 personality types is that there are many overlaps between classes, but if only one mistake is made, the personality is entirely different. For example, INTJ and INTP have overlapping details, and even when small mistakes are made, they become entirely different classes. Nonetheless, deep learning seems to be very helpful for prediction.

In this study, 16 personality types were predicted for the first time after an automatic analysis using a deep learning employing the pictures represented by the WZT drawing examination of adolescents. The class distribution of the MBTI dataset is imbalanced, but this study used GAN-based data growth to mitigate the problem. Then, efforts were made to balance the image data, and 16 character-types were predicted after binary analysis to improve the prediction accuracy. As a result, the initial average predicted value of the CNN increased to 17.2%; the average predicted value of the CNN ensemble increased to 18.4%, and the average predicted value using the final generative adversarial network increased to 27.2%. These have led to a 10% increase in the average predicted value, revealing that 9 MBTI personality types could be predicted with higher accuracy values.

The accuracy of ESFP was the highest, increasing by 14.7%, from 55.4% to 70.1%. In addition, ENTJ was predicted at 18.8% accuracy, and ENTP was predicted at 3.6% accuracy. Various personality types could be predicted. It may be significant that more data are needed for accurate predictions so that different personality types can be predicted. If the personality character type is detected by automation, it could promote the development of various applications and be used in a broader range of fields. However, poor data issues can lead to inefficiencies in determining an individual's personality type.

Recent deep learning techniques are evolving daily and have demonstrated result sufficient to make reliable personality predictions. This study is the first to introduces a study that predicts the type of MBTI personality by finding unique characteristics of an individual from pictures created directly by students. If sufficient data are available using text and complex patterns of images to which a projective test can be applied, models that automatically apply them in many fields can be studied. It is expected that this could create many opportunities for employing deep learning.

Author's Contributions

Conceptualization, KK. Investigation and methodology, KK, MK. Project administration, KK. YY, JSP. Supervision, JK. Writing of the original draft, KK, YY, MK. Writing of the review and editing, KK, YY, JSP. Software, YY. Validation, KK, YY.

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Competing Interests

The authors declare that they have no competing interests.

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