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Design of Interactive Artificial Intelligence for Early Cognitive Diagnosis

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Abstract— **Due to the aging population in South Korea, the proportion of elderly people aged 65 and over is expected to increase from 14.9% in 2019 to 46.5% by 2067. The number of elderly people per 100 working-age population (15-64 years old) is also anticipated to rise to 102.4 by 2067. Population aging is recognized as a social issue, leading to problems such as increased chronic diseases, higher levels of elderly isolation, and insufficient medical infrastructure. To solve the problem of cognitive decline, such as dementia due to the aging of the population, research is actively being conducted in various fields, such as simulating cognitive ability and learning, inference, prediction, and problem-solving using artificial intelligence deep learning technology in the form of a fusion of artificial intelligence and realistic content technology. This study is on an interactive cognitive early diagnosis training system using artificial intelligence. The speech recognition technology for early cognitive diagnosis uses Selvas AI (Artificial Intelligence)'s speech recognition STT (Speech to Text)-TTS (Text to Speech). AI speech recognition interaction can increase psychological safety through conversation with users. It evaluates cognition (dementia) using MMSE (Mini-Mental State Examination)-K (DS), and it is a system that evaluates seven cognitive areas through the CERAD (Consortium to Establish a Registry for Alzheimer Disease)-K analysis system. The design of interactive artificial intelligence for early cognitive diagnosis aims to improve the cognitive function and daily living abilities of the elderly population.**

Keywords—**Cognitive rehabilitation; dementia; health care; recommender system; recommendations AI.**

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I. INTRODUCTION

South Korea, which has the fastest aging rate in the world, is expected to see its population aged 65 and over increase from 14.9% in 2019 to 46.5% in 2067. As the working-age population decreases due to the low birth rate trend, the burden of support will increase significantly, and the number of elderly people supported per 100 working-age people aged 15 to 64 is expected to grow more than fivefold from 18.8 in 2017 to 102.4 in 2067.

To solve the problem of increasing chronic diseases due to the aging of the population, an increasing number of elderly people living alone, labor shortage, and lack of specialized personnel in welfare infrastructure and health and healthcare, technologies such as Augmented Reality (AR)[2], Virtual Reality (VR)[3], Mixed Reality (MR), and eXtended Reality (XR) are being studied in the form of merging with Artificial Intelligence[1], [23] to optimize the user experience through content. The decline in cognitive function due to aging is recognized as a social problem [4], [5], [6].

Artificial intelligence technology refers to science and technology that implements human intellectual ability into machines and is developing as a general-purpose technology that spreads to all industries and societies, determining future competitiveness and becoming a key driving force for innovative growth. Research is conducted in various fields, from learning deep learning technology to finding the optimal answer, making inferences and predictions, and action steps that discover and solve given problems independently [7], [8].

With increased research and interest in the brain, cognitive function is closely related to daily life ability. If cognitive function is improved and problems are minimized, daily life performance ability will be enhanced [9], [10], [11].

In addition, dementia management using a cognitive early diagnosis interactive training system that combines artificial intelligence and realistic content technology is expected to be a cognitive rehabilitation service that can provide various services to user interaction and secure national competitiveness. Based on the research on cognitive judgment technology using Augmented Reality [12] as a background study for cognitive early diagnosis interaction in this study, the design and development of a cognitive judgment platform[13] and the design of a cognitive rehabilitation training system using artificial intelligence[23] are presented as background studies, and an interactive artificial intelligence system for cognitive early diagnosis is designed. For cognitive early diagnosis, it is an AI-customized cognitive early diagnosis system that increases psychological safety through periodic and daily conversations with users who need cognitive rehabilitation through AI interaction; that is, voice recognition technology provides content related to language ability diagnosis, determines dementia (cognitive impairment) with MMSE-K(DS), and evaluates seven user areas (Orientation, Memory, Attention, Visual Perception, Language, Calculation, and Execute) through the CERAD-K analysis system.

II. Materials and Method

A. Importance of Early Cognitive Diagnosis and Cognitive Skills

The population is aging worldwide, and the elderly over 50 years of age are anxious about dementia due to cognitive impairment, which is lowering their quality of life. Dementia is thought to have no specific treatment method, and the more severe it progresses, the more the economic burden increases, and early detection and treatment are the best ways to reduce the socioeconomic burden. Therefore, cognitive rehabilitation programs and training equipment that can maintain and improve cognitive functions for these elderly and older people can be applied to various disorders and conditions such as brain damage, aging, stroke, cognitive impairment, autism, and ADHD(Attention Deficit Hyperactivity Disorder), and continuous research and development are necessary to improve individuals' cognitive abilities and promote a better quality of life in daily life.

Cognitive skills refer to various knowledge-based technologies that can use computing systems to acquire, retain, remember, and utilize information from the human brain and mind. To provide cognitive management services for the elderly and the elderly through the use of cognitive technology in the medical healthcare field, a cognitive management platform necessary for integrated management must be established. The cognitive management platform refers to a technology that combines and fuses representative technologies of the 4th industrial revolution era, such as biotechnology, databases, and artificial intelligence, to support cognitive data measurement, management, evaluation, and service modules [14].

B. Cognitive Function Assessment Tool

The MMSE, a cognitive function assessment tool, is a screening clinical tool developed to assess cognitive function and dementia. To provide more accessible and accurate judgment to people with hearing impairment, it must include the MMSE-DS[15] or the GDS(Global Depression Scale) protocol that evaluates the seven stages of cognitive decline related to dementia. The MMSE-DS evaluation items are six areas: orientation, memory, attention, visual perception, language, and calculation. The total score is 30 points, and the criteria for determining cognitive impairment are interpreted as normal with 25 points or higher, mild cognitive impairment with 21-24 points, moderate cognitive impairment with 10-20 points, and severe cognitive impairment with 9 points or less[16].

1) MMSE-K(DS) is an assessment tool that provides culturally and linguistically appropriate tools for assessing Korean-style cognitive function. It is used in diagnosing and monitoring cognitive impairment and in clinical and research fields. It is tailored to dementia patients with unique cognitive problems that are not entirely resolved by MMSE.

2) CERAD-K [17] is a global dementia diagnostic test translated into 12 languages and used by dementia centers in over 40 countries worldwide. It is a Korean-style dementia diagnostic test that has been standardized for use by the Korean-speaking population based on clinical experience and research. It is an accurate dementia diagnostic test with a very high rate of agreement with dementia diagnoses confirmed through brain tissue examination. It is a comprehensive dementia diagnostic test that can differentiate various causes of dementia, such as Alzheimer's disease, Lewy body dementia, frontotemporal dementia, and vascular dementia. The components of CERAD-K include verbal fluency, Boston naming test, word list (memory, recall, recognition), structured practice, constructive practice recall, and MMSE to analyze cognitive function

C. AI interaction Related Technology

1) DKT(Deep Knowledge Tracing) Algorithm: The DKT algorithm uses RNNs(Recurrent Neural Networks) such as LSTM(Long Short-Term Memory) or GRU(Gated Recurrent Unit) networks to activate various parameters for measuring and predicting learners' knowledge states accurately according to user learning systems. This allows the algorithm to provide personalized content. The spacing effect of the DKT algorithm is a learning method that effectively improves the learner's long-term memory by gradually increasing the time interval (space repetition) between repetitions and can predict how the user's knowledge status changes.

2) MDP (Markov Decision Process): MDP is a model that adds an Action element to MRP (Markov Reward Process) and is a method for modeling sequential decision-making problems in which an agent interacts with the environment to achieve a specific goal by utilizing probability and graphs in the AI reinforcement learning and decision-making process[18]. MDP is an algorithm that utilizes optimization problems to obtain the highest reward. It is designed based on the first-order Markov assumption that the state at time t is only affected by the state at time t-1.

3) BERT (Bidirectional Encoder Representations from Transformers): BERT is an NLP (Natural Language Processing) deep learning model developed by Google in 2018, designed to understand the context of words in search queries based on the Transformer architecture. BERT's Transformer architecture refers to a simple network structure that extracts information about sentences using only the attention technique (self-attention) without using RNN in the encoder and decoder. Since the emergence of BERT, various derivative models with added algorithms have been created, and active research on various and efficient natural language processing methods is being conducted[19], [20]. BERT is a pre-trained language model specialized in word embedding and shows excellent performance in text classification and named entity recognition. It is a bidirectional natural language processing model that can respond to various sentences. It is composed of a model with multiple layers of Transformer models.

a. Token Embedding: The process of making frequently appearing long sub-words into a single unit
b. Segment Embedding: Making words divided into tokens in a single sentence and then dividing them.

Position Embedding: Encoding the order of each token

III. Results and Discussion

A. Design of Interactive AI for Early Cognitive Diagnosis

To design interactive AI for early cognitive diagnosis, reliable recent achievements in cognitive science and measurement science and computerized data should be DBed, and the cognitive characteristics of the elderly who need cognitive technology should be considered based on reliable data. In the measurement module, it is essential to provide practical content to users and early cognitive diagnosis through the construction of a big data DB combined with content for evaluation and voice recognition technology and analysis, and transparent criteria are needed to determine risks and vulnerabilities based on measurement data.

Fig. 1 is a diagram of this study's overall system configuration. Based on cognitive ability training content data, user cognitive ability data, and user training records, deep learning training content interacts with the user to assess cognitive ability.

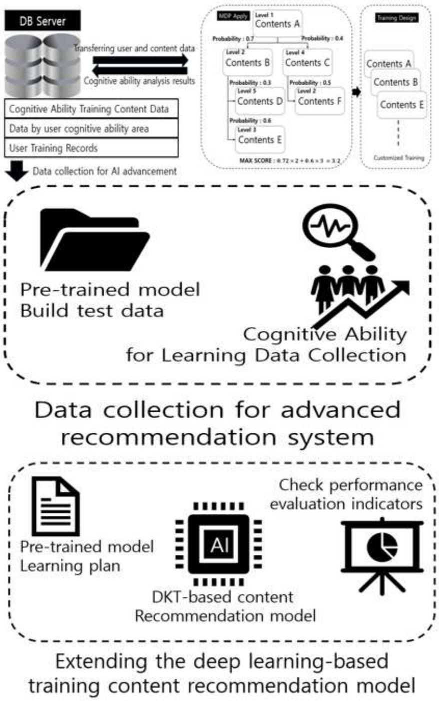

Fig. 1 Interactive Artificial Intelligence for Early Cognitive Diagnosis

B. AI Voice Recognition Interaction Software

AI voice recognition technology refers to understanding and interacting with human natural language. Recent trends include voice language models based on the Transformer architecture and utilizing large-scale data sets suitable for voice recognition tasks such as GPT. Research is being conducted on LLM(Large Language Model), which can understand and generate natural language and enable highly accurate situational understanding [21].

Selvas AI provides STT and TTS services with HCI (Human Computer Interaction) technology and Korean AI solutions capable of voice recognition, synthesis, OCR (Optical Character Recognition), and natural language processing.

1) STT: Technology that converts human-spoken speech into natural language by a computer. It predicts the syllable sequence of each speech phrase through acoustic modeling, language modeling, and decoding processes and then collates and converts it into a bundle of suitable words that have been pre-learned

2) TTS: Technology that converts input sentence text into voice, a form of human speech. The core elements of TTS are text analysis, language analysis, and digital signal processing, and deep learning is utilized to analyze and generate voices with intonation and rhythm similar to natural human voices.

The system was developed using Selvas AI's Selvy MediVoice and Selvy Note to develop the AI voice recognition interaction software for the study. Selvy MediVoice is specifically designed for the medical industry and is an AI medical voice recognition solution that writes medical records generated during the medical process as voice, providing high accuracy, efficiency, integration with existing systems, and security for processing sensitive parts such as medical records. Selvy Note is a voice-to-text application that facilitates AI voice recording through voice recognition technology.

By introducing the STT ↔ TTS of the Selvas AI voice recognition engine, we developed voice recognition software that can accurately recognize the voices of dementia, the aged, and patients with cognitive impairment. We configured it so that chatbot AI services can be utilized without a separate visual interface. Through this, we were able to analyze the vocabulary and vocalization characteristics of dementia in the aged and cognitively impaired patients and improve the accuracy of voice recognition technology.

We trained the STT model loaded on the AI voice recognition engine using AI-HUB's free conversation voices of elderly men and women and the voice datasets of dementia patients and the elderly. This fine-tuning improved the accuracy of voice recognition technology.

C. AI interaction Training Content

The AI Interaction Cognitive Rehabilitation Training Content System is designed to recommend content according to the difficulty level through a protocol combining AI reinforcement learning, DKT, and MDP [22]. The AI Interaction Training Content was designed by adding the user's name, age, gender, and seven cognitive areas (stamina, memory, attention, visual perception, language ability, calculation ability, and executive function) to the cognitive rehabilitation evaluation and training protocol into Level 1 (less than 50% of the evaluation score), Level 2 (50%-75% of the evaluation score), and Level 3 (75-90% of the evaluation score). It was produced so that multiple disabilities can be evaluated through a cognitive rehabilitation evaluation algorithm that reflects cognitive evaluation.

The AI Interaction Recommended Training Content evaluates the executive ability of brain injury patients and dementia patients. AI recommends personalized content based on the results, and the correlation and difficulty between cognitive areas are It is intelligent considering. The user-tailored training content recommendation system acquired much user training data and then learned the model using the DKT-based RNN algorithm. By reflecting the learning results of the model and utilizing the decision-making scenario of the MDP algorithm based on the training results of each user, the pre-trained model, a recommendation AI system that provides customized training content, can be developed to adjust the learning difficulty according to the user's cognitive level. In addition, it has the advantage of solving adverse problems by utilizing immediate feedback and interaction between group members and enabling repetitive training.

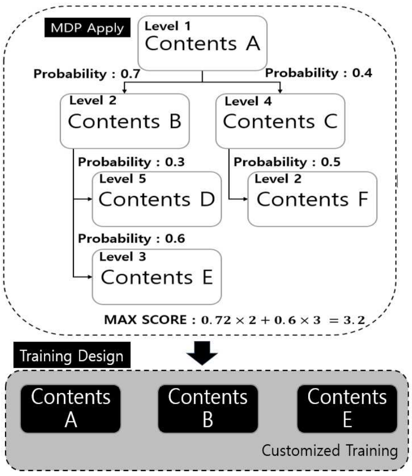

Fig. 2 AI System for recommending customized training content using MDP

D. Development of cognitive early diagnosis interactive AI system

BERT is designed to understand words and contexts in sentences through a two-way interaction approach by utilizing the functions of the natural language processing model NLP, and its main features are situational understanding, question-and-answer function, provision of customized recommended content, and conversational interaction.

Since Korean is a morpheme-based language, it is difficult to use a general-purpose BERT model. Therefore, the RoBERTa (robustly optimized BERT approach) model, which shows improved performance in various NLP tasks, was used as a base model algorithm. Dementia judgment conversation data was input into the pre-trained BERT model to be fine-tuned. To improve the accuracy of natural language processing, the clustering technique (SVM) and RNN were used to design a sentence token classification algorithm to improve efficiency.

The Dynamic Masking model uses a Single Static Mask to mask tokens in data processing before learning. Since the mask is applied to the exact location without change for each learning, new masking is performed for each epoch. Compared to the existing BERT model, it was confirmed that the performance of the RoBERTa model was improved. The dementia diagnosis AI model consists of input values, questions, and answers. Since dementia patients' answers tend to be discontinuous from the questions, it is necessary to select a base model considering this characteristic. In the case of the BERT model that reflects NSP (Next Sentence Predication), there is a high possibility of learning errors in the context recognition function due to the characteristics of the dementia judgment AI model, so the RoBERTa model without NSP was determined to be suitable.

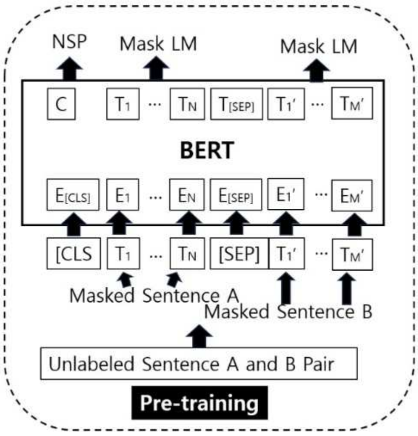

Fig. 3 BERT Pre-training

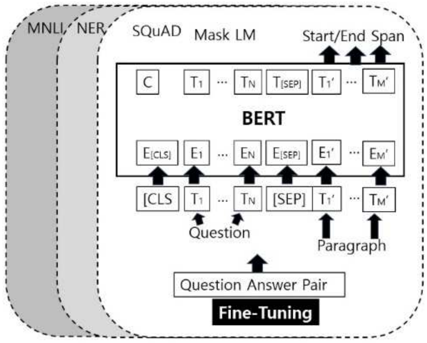

Fig. 4 BERT Fine-Tuning

TABLE I
MODEL EXPERIMENT DEVELOPMENT ENVIRONMENT UTILIZING PYTHON AND HUGGING FACE

Utilizing Python 3.9.16, PyTorch 2.0.0 library
Using the Huggingface library
Learning in NVIDIA GeForce RTX 3070 Ti, cuda 11.8 environment
AI learning record management using WanDB

E. Experiment and Results

More than 1,000 data were used and repeated more than 20 times to measure the accuracy and error rate of the cognitive early diagnosis interactive artificial intelligence system. The method of measuring correct and incorrect answers in training content was used based on the solution history in 7 areas of the user's early diagnosis of dementia (cognition) reality training content. When the artificial intelligence prediction model uses only a part of the user's problem-solving content as input, it is used to check whether other training content has the correct answer. As a result of the test certification, dementia classification for 1,000 question-and-answer data achieved an accuracy of over 80%.

```
# model_ckpt = "distilbert-base-uncased"
model_ckpt = "klue/roberta-base"
tokenizer = AutoTokenizer.from_pretrained(model_ckpt)

# 훈련 인자 정의
batch_size = 16
logging_steps = len(dataset_encoded["train"]) // batch_size
model_name = f"{model_ckpt}-finetuned-chatbot"
training_args = TrainingArguments(
    output_dir=model_name,
    num_train_epochs=10,
    learning_rate=2e-5,
    per_device_train_batch_size=batch_size,
    per_device_eval_batch_size=batch_size,
    weight_decay=0.01,
    evaluation_strategy="epoch",
    disable_tqdm=False,
    logging_steps=logging_steps,
    push_to_hub=False,  # 로컬 훈련에서는 push_to_hub를 비활성화
    save_strategy="epoch",
    load_best_model_at_end=True,
    log_level="error"
)

# 트레이너 초기화
trainer = Trainer(
    model=model,
    args=training_args,
    compute_metrics=compute_metrics,  # compute_metrics 함수를 정의 필요
    train_dataset=dataset_encoded["train"],
    eval_dataset=dataset_encoded["validation"],
    tokenizer=tokenizer
)

# 모델 훈련
trainer.train()
```

Fig. 5 Dementia judgment AI model learning code

```
class BertTestModel:
    def __init__(self) -> None:
        new_model_name = "../models/klue-test"

        new_tokenizer = AutoTokenizer.from_pretrained(new_model_name)
        new_model = AutoModelForSequenceClassification.from_pretrained(new_model_name,  id2label={0: '정상', 1: '치매의심(재질문 필요)', 2: '치

        # pipeline 함수에는 모델 이름이나 태그를 지정해야 합니다.
        self.dementia_pipe = pipeline(task="text-classification", model=new_model, tokenizer=new_tokenizer)


    def process_dataset(self, dataset: pd.DataFrame):
        """
        Args:
        - dataset: 성능지표 측정을 위한 test 데이터셋
        """
        processed_dataset = dataset.copy()

        processed_dataset['text'] = processed_dataset['질문'].astype(str) + processed_dataset['대답'].astype(str)
        # processed_dataset['text'] = processed_dataset['대답']
        processed_dataset.rename(columns={'분류': 'label'}, inplace=True)

        processed_dataset.drop(columns=['번호', '질문', '대답'], inplace=True)

        processed_dataset['label'].value_counts()
        processed_dataset = processed_dataset[['text', 'label']]

        return processed_dataset
```

Fig. 6 Code for testing dementia diagnosis AI model

TABLE II
ACCURACY EXPERIMENTAL TEST

Round	Accuracy
1	0.890
2	0.900
3	0.900
4	0.900
5	0.800
6	0.870
7	0.910
8	0.900
9	0.900
10	0.860
Average	0.844

IV. CONCLUSION

Cognitive function decline due to the aging population is emerging as a social problem. With the increase in research and interest in the brain, cognitive function is closely related to daily life, and if cognitive function can be diagnosed early, dementia can be prevented. Cognitive technology systems that combine artificial intelligence and realistic content technology are being actively studied in various fields to solve the problem of cognitive function decline due to the population's aging.

This study is a dementia early diagnosis system that builds a database for storing and analyzing voice data through artificial intelligence-based interaction and analyzes and processes voice data. It provides content that can increase psychological stability through periodic interaction with patients who need cognitive rehabilitation. In particular, it is a cognitive early diagnosis system that evaluates seven areas through the MMSE-K(DS) or CERAS-K analysis system.

Significant progress is being made in early dementia diagnosis and management based on BERT in artificial intelligence and healthcare. Based on the characteristics of Korean, we were able to confirm that it improved over BERT by utilizing a large data set, more extended training, and specific training optimization based on RoBERTa. The cognitive early diagnosis interaction experiment improved the accuracy and efficiency of NLP tasks by more than 80% through 1,000 question-answer data sets.

As a future research task, we should analyze the general characteristics of the experimental participants and check the mean and standard deviation descriptive statistics, secure data from many subjects to secure the significance of clinical effects, and study artificial intelligence models that can utilize the GPT API.

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