of intelligent computer systems. Interoperability should be understood as the interaction of intelligent computer systems based on mutual understanding between these systems themselves. Achieving the quality of interoperability allows the construction of a multi-agent network of interoperable intelligent computer systems for medical purposes.

The multi-agent architecture of ostis-systems involves the development of communicative aspects of machine "thinking", which can be traced in multi-agent systems [7]–[9].

OSTIS Technology makes it possible to effectively solve the problems of integrating various medical systems into a single interoperable network. To do this, it is necessary and sufficient to create an intelligent user interface (IPI) for each individual medical system, many of which form a single interoperable network. The IPI network will combine (integrate) traditional medical information systems (MIS), conventional diagnostic systems (DS), intelligent diagnostic systems (IDS), consulting systems (CS), telemedicine systems (TMS), external medical knowledge bases (MBZ) and other computer systems for medical purposes.

As part of the OSTIS development strategy, the concept of a personal intellectual assistant (secretary, referent) has been developed.

In line with this concept, the intelligent health FSDmonitoring system will act as a personal intellectual consultant on individual health-improving and preventive regimes of a healthy lifestyle, on the expediency of additional diagnostic studies, on the desired timing of treatment to a doctor of a particular specialty. The ostissystems development strategy includes the position of developing a set of tools for individual comprehensive permanent medical control and health monitoring within the framework of a personal intelligent assistant.

V. CONCLUSION

Doctors have understood the need for regular monitoring of the health of an individual and the population for a very long time. It is also well understood that the possibilities of such control are limited by the set of diagnostic technologies used, in which there are no positions with a sufficiently high efficiency/cost ratio, that is, with high efficiency and low cost. In relation to the tasks of health control, effectiveness is determined, first of all, from the point of view of the possibilities of early diagnosis of diseases.

Today, the system of medical examination can be conditionally attributed to the monitoring of an individual's health, but the frequency of a year or two is too high for effective monitoring. The cost of functioning of the medical examination system is also high and, unfortunately, the diagnostic effectiveness of the existing medical examination system is low, which was shown in the pilot project of using FSD diagnostics in medical examination with subsequent verification of diagnoses [10].

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Интеллектуальные системы мониторинга здоровья

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В работе рассмотрены проблемы современного состояния комплексного мониторинга здоровья человека, а также соответствующих диагностических технологий. Предложен подход к интеллектуализации процесса регулярного контроля здоровья на основе систем ФСД-диагностики

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Technology of Neurological Disease Recognition Using Gated Recurrent Unit Neural Network and Internet of Things

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***Abstract*—In this paper, authors proposed a neurological disease recognition technique using gated recurrent unit neural network and supporting Internet of Things (IoT), which was checked by taking Alzheimer's disease (AD) and Parkinson's disease (PD) as examples. In this method first pre-emphasized and denoised the voice data, then segmented the voice signals with a sliding fixed window using the Hamming window function. Then we were extracted the eGeMAPSv02 voice features from the window signal, fed the features into the gated recurrent unit neural network model for its training, testing and achieve the disease diagnosis. The results of the study showed that despite the limited generalization ability of the gated recurrent unit model, it can still efficiently achieve voice recognition detection of a portion of neurological diseases. The model is implemented on the basis of the IoT platform for building a subsystem of IT diagnostics of patients as part of the smart city project. The code is stored in https://github.com/ HkThinker/Technology-of-neural-disease-recognition.** ***Keywords*—gated recurrent unite neural network, Internet of things, voice recognition, neurological disease**

I. INTRODUCTION

Neurological disease usually result in structural or functional changes in the nervous system, causing patients to suffer from perception, thinking, emotion and behavior, and present a significant challenge to the global healthcare system. They are a group of diseases that affect the nervous system and include a variety of disorders such as neurodegenerative diseases, autoimmune diseases, cerebrovascular diseases, and brain injuries. For example, PD is a neurodegenerative disease that affects motion management and is characterized by symptoms such as hand tremors, limb stiffness, slow movements, and postural instability. AD is similar and results in memory loss, cognitive decline, and abnormal language and behavior. They tend to occur in older age groups, currently have no complete medical cure, but early diagnosis and prompt treatment can alleviate symptoms and slow progression. Traditional diagnosis of neurological diseases is usually based on doctors' clinical experience, medical history, physical examination and specific tests, which has limitations and requires a lot of labor and resources. In recent years, with the rapid development of artificial intelligence and IoT technologies, neurological disease identification technologies using neural networks and supporting IoT are expected to become a new breakthrough point. The main purpose of this paper is to investigate the Gated Recurrent Unit (GRU) neural networks and IoT technologies to recognition for neurological diseases. To be specific, our research aims to achieve the following objectives:

1. To develop a GRU neural network model, which was trained through a publicly available database to implement the diagnosis and prediction of PD and AD.
2. By using IoT technology, we collected patients' voice data and combined these data with the GRU neural network model to improve the precision and accuracy of diagnosis and prediction of neurological diseases.
3. To deploy the GRU neural network model to the Thingspeak IoT platform.

II. RELATED WORK

A. Application of IoT in Neurological Disease Diagnosis

Neurological disease diagnosis systems that are based on neural network technology and IoT technology have been widely used.

B. Lu [1] built a practical brain MRI-based AD diagnostic classifier using deep learning/transfer learning on datasets of unprecedented size and diversity. The purpose of Mukherji [2] was to identify non-invasive, inexpensive markers and develop neural network models that learn the relationship between those markers and the future cognitive state. David Payares-Garcia [3] proposed a classification technique that incorporates uncertainty and spatial information for distinguishing between healthy subjects and patients from four distinct neurodegenerative diseases: AD, mild cognitive impairment, PD, and Multiple Sclerosis. Abbas Sheikhtaheri [4] aimed to identify and classify the IoT technologies used for AD dementia as well as the healthcare aspects addressed by these technologies and the outcomes of the IoT interventions.

Researchers had identified the feasibility of integrating deep learning, cloud, and IoT, Syed Saba Raoof [5] explained a summary of various techniques utilized in smart healthcare, i.e., deep learning, cloud-basedIoT applications in smart healthcare, fog computing in smart healthcare, and challenges and issues faced by smart healthcare and it presents a wider scope as it is not intended for a particular application such aspatient monitoring, disease detection, and diagnosing and the technologies used for developing this smarta systems are outlined. Reyazur Rashid Irshad [6] proposed a novel healthcare monitoring system that tracks disease processes and forecasts diseases based on the available data obtained from patients in distant communities. Rafael A Bernardes [7] presented a perspective on integrating wearable technology and IoT to support telemonitoring and self-management of people living with PD in their daily living environment.

B. *Classification of Voice Features*

Since more than 90 % of PD patients have varying degrees of dysphonia in the early stages of the disease, the diagnosis of PD based on voice features has the merits of being non-invasive and convenient. Darley [8] first used voice to diagnose aphasia in 1969. Saker et al. [9] preprocessed the voice data and extracted features, then applied SVM and KNN classification algorithms to the feature matrix for classification, eventually obtaining an average accuracy and a maximum accuracy of 55 % and 85 %, respectively, which initially confirmed the feasibility of voice features to classify PD. To further improve the accuracy of model prediction and simplify the algorithmic model, scholars have applied different feature selection algorithms.

III. METHODOLOGY AND DATASETS

A. *Pre-emphasis and Denoising of Voice Signals*

It is difficult to obtain the high-frequency part of the unprocessed voice signal because the power of the voice signal will be significantly attenuated after the sound gate excitation as well as the influence of mouth and nose radiation, combined with the smaller energy corresponding to the high frequency while the larger energy corresponding to the low frequency in the spectrogram of the voice signal. In order to facilitate the spectrum analysis, this paper adopted a first-order FIR high-pass digital filter for the pre-emphasis processing of the voice signal. The purpose of pre-emphasis is to improve the high-frequency part, so that the spectrum of the voice signal becomes flat, thus the spectrum can be obtained with the same signal-to-noise ratio in the whole frequency band.

Voice denoising is an effective part of signal preprocessing, mainly to improve the quality of voice and obtain more pure voice signals. The Fig. 1 shows the process of voice signal denoising.

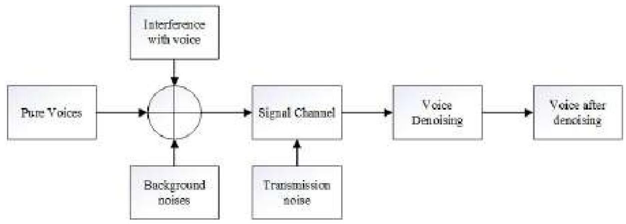

Figure 1. Flow chart of voice denoising.

According to the different parts of the noise introduction, voice noise can be divided into background noise and transmission noise. In this paper, spectral subtraction algorithm was used to denoise the voice. The spectral subtraction algorithm is designed based on the principle that pure voice is statistically independent of the noise signals.

B. *Framing and Windowing of Voice Signals*

The Fourier transform commonly used in voice signal processing calls for a smooth signal, but the main feature of the voice signal is the short-time smoothness, i.e., the stability of the voice signal in 10–30 ms period. Therefore, if we want to characterize the voice signal, it is necessary to analyze the short-time characteristics of the voice signal, the original signal is framed, and the frame frequency signal with short-time smoothness is derived. In the process of frame splitting, the signal tends to produce spectral deficiencies, so a windowing process must be performed between frames to keep the signal at the truncation without distortion. The windowing function used in this paper is the Hamming window function, with window size of 1024, frequency of voice signal is 44.1khz, and the overlap rate of window is 50 %, hence the voice time of one window is about 23 ms.

C. *Feature Extraction of Voice Signals*

We used an extended version of GeMAPS (Basic Affective Parameter Set), eGeMAPSv02 [10], a speech feature set. It uses acoustic features and spectral-based features to describe the speech signal, with a total of 88 features. It contains 25 low-level descriptor features, namely pitch, jitter, gating frequency, gating bandwidth, gloss, loudness, harmonic-to-noise ratio (HNR), Alpha ratio, Hammarberg index, spectral slope 0–500 Hz, spectral slope 500–1500 Hz, 3 gating relative energies, 3 relative energies, 3 harmonic differences, 4 Mel–Frequency Cepstral Coefficients, 1 spectral flux. 53 other parameters are derived from these basic parameters.

D. *6–layer Gated Recurrent Unit Model*

In the paper, a multi-layer GRU model is constructed for voice data recognition. two mechanisms, an update gate and a reset gate, are included in the GRU module. The internal equation of a single GRU model is :