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DETECTION OF DM AND NPDR FROM TONGUE USING MACHINE LEARNING TECHNIQUE

Prof.Muhammadu Sathik Raja.[1], Ageela.N.,[2].
Assistant Professor [1], PG Scholar [2]
Department of Medical Electronics Engineering,
Sengunthar College of Engineering. Tiruchengode,Tamil Nadu, INDIA
scewsadik@gmail.com[1], ageeabiya@gmail.com[2]

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Abstract: Smart Chinese medicine has emerged to contribute to the evolution of healthcare and medical services by applying machine learning together with advanced computing techniques like cloud computing to computer-aided diagnosis and treatment in the health engineering and informatics. Specially, smart Chinese medicine is considered to be potential to treat the difficult and complicated diseases such as diabetes and cancers. Unfortunately, smart Chinese medicine has made very limited progress in the past few years. In this paper, we present a unified smart Chinese medicine framework based on the edge-cloud computing system. The objective of the framework is to achieve computer-aided syndrome differentiation and prescription recommendation, and thus to provide pervasive, and patient-centralized healthcare and medical services. Personalized and patient-centralized services in healthcare and medicine. To accomplish this objective, we integrate deep learning and deep reinforcement learning into the traditional Chinese medicine. Furthermore, we propose a multi-modal deep computation model for syndrome recognition that is a crucial part of syndrome differentiation. Finally, we conduct experiments to validate the proposed model by comparing with the staked auto-encoder and multi-modal deep learning model for syndrome recognition of hypertension and cold.

INTRODUCTION

Recently, cyber-physical-social systems have made a great progress by the deep fusion of many cyber and physical systems with some emerging technologies such as Internet of Things and cloud computing. Cyber-physical-social systems integrate various enabling techniques like smart space design, artificial intelligence, big data analytics, and cloud computing that are needed for building healthcare and medical systems. An important objective of healthcare systems is to provide personalized, pervasive, and patient- centralized healthcare and medical services. To accomplish this objective, some smart medical systems based on cyber-physical-social systems have been developed for computer-aided diagnosis and treatment. As a component of medicine, the traditional Chinese medicine shows its promising therapeutic effect for some chronic and complex diseases such as hypertension, diabetes, and cancers. More recently, smart Chinese medicine has been proposed, and conceptually it integrates various potential artificial intelligence techniques such as deep learning, clustering, and reinforcement learning into the various potential artificial intelligence techniques such as deep learning, clustering, and reinforcement learning into the traditional Chinese medicine for computer-aided diagnosis and prescription recommendation.

SYNDROME RECOGNITION

Specially, Zhang et al presented a potential deep learning model for syndrome recognition in the treatment of hypertension. At present, smart Chinese medicine is considered to be promising to treat the difficult and complicated diseases such as hypertension, diabetes and cancers, and therefore it is potential to provide pervasive and personalized health- care and medical services.

Medicine theory and practice. Moreover, a large volume of traditional Chinese medicine experience that has been accumulated for thousands of years has not been well summarized with the modern artificial intelligence models. In this paper, we present a unified smart Chinese medicine framework based on edge-cloud computing system to integrate advanced machine learning models including deep learning and deep reinforcement learning into the traditional Chinese model effectively for the increasing evolution of smart Chinese medicine. By the fundamental theory of the traditional Chinese most important two steps of this idea. In differentiation and prescription selection are the medicine. For example, the cold medicine like Advil and Tylenol will be selected when people catch a cold. However, drugs and prescriptions are usually chosen according to the patient's syndrome rather than the patient's disease in the traditional Chinese medicine. For example, the traditional Chinese medicine classifies the cold into several types of syndrome, the typical two of which are cold pathogen of Taiyang and affection of Taiyang by wind. Furthermore, the patient affected by cold pathogen of Taiyang will be given the mahuang decoction while the patient with affection of Taiyang by wind will be given the guizhi decoction. Another representative example is hypertension which is classified into five types of syndrome like liver qi stagnation and abundant phlegm-dampness in the traditional Chinese medicine. Xiaochaihu decoction is the most appropriate prescription selected for treating the hypertension of the syndrome of liver qi stagnation whereas wendan decoction is selected to treat the hypertension of the syndrome of abundant phlegm-dampness. Therefore, the presented unified smart Chinese medicine framework aims at computer-aided syndrome differentiation and prescription recommendation. To achieve the aim of the framework, we integrate the advanced machine learning models, edge-cloud computing system that combines cloud computing and edge computing is designed to improve the efficiency of machine learning models in the presented framework. Particular, syndrome differentiation points out one key difference between the traditional Chinese medicine and the modern medicine. In detail, drugs and prescriptions are selected according to the patient's disease in the modern especially deep learning and deep reinforcement learning, into the traditional Chinese medicine. Moreover, most machines learning models are inefficient for the tasks of recognition and decision-making because they often have many parameters to However, real-time computer-aided At present, inquiry and tongue inspection are the most widely used ways for obtaining the patient's symptoms data which is heterogeneous. Specially, the symptoms data obtained from inquiry is typically structural while tongue inspection obtains a image of the patient's tongue. In this paper, we present a multi-modal deep computation model to recognize the syndrome based on the heterogeneous symptoms data obtained by inquiry and tongue inspection. In the presented model, a stacked auto- encoder and a convolutional neural network are built to learn the features of the symptoms data from inquiry and the image of the patient's tongue, respectively. Afterwards, the vector outer product is used to concatenate the learned features to form a feature matrix which is taken as input of a deep computation model for syndrome differentiation. Finally, we conduct experiments to validate the potential of the presented learning model on two Chinese medical datasets for recognizing the syndrome of hypertension and cold in terms of the classification accuracy.

CONTRIBUTIONS

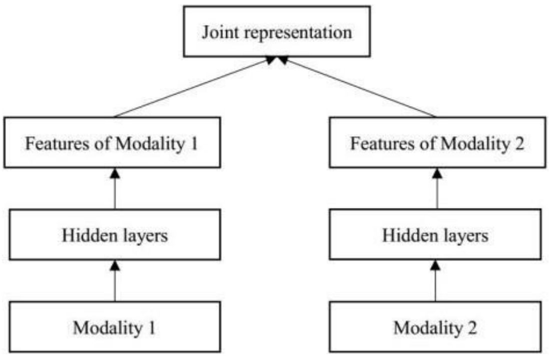
Their contributions of this paper can be summarized as follows:

- We present a unified smart Chinese medicine frame- work for providing healthcare and medical services based on the edge-cloud computing system to integrate advanced machine learning models including deep learning models and deep reinforcement learning models into the traditional Chinese **medicine** effectively.
- We present a multi-modal deep computation model by combining two deep learning models including a stack auto- encoder and convolutional neural network with a deep computation model to recognize the syndrome based on the symptoms obtained from inquiry and tongue inspection.
- We evaluate the potential of the presented model regarding the classification accuracy by comparing with the stacked auto- encoder and the multi-modal deep learning model for the computer-aided diagnosis on the syndrome differentiation of hypertension and cold.
- The rest of this paper is organized as follows. The unified smart Chinese medicine framework based on the edge-cloud computing system is presented and described in Section II. Section III illustrates the presented multi-modal deep computation model and the corresponding training algorithms and Section IV reports the experimental results in terms of the training error.

Finally, the paper is concluded in Section V. Inspection is also an important way of collecting the patient's symptoms, including inspecting the patient's face, tongue, and the whole body. Specially, tongue inspection is especially important for syndrome differentiation since the appearance of the tongue can accurately reveal the patient's diseases. For example, teeth-printed tongue implies that the patient suffers from dampness while the tongue with yellow fur indicates that the patient may have syndrome of endogenous heat due to yin deficiency. Typically, the tongue inspection mainly includes tongue quality inspection and fur inspection. Table 2 summarizes some representative pathologic tongue manifestations.

Palpation and pulse taking is another important way of collecting the patient's symptoms. Pulse taking is the core of this way since many diseases will be reflected in pulse manifestation. For example, the patient may catch a cold when he/she presents floating pulse. When he/she suffers from dampness, the patient has slippery pulse. At present, pulse manifestation is usually taken as a corroboration of syndrome differentiation. Listening and smelling is the fourth way of collecting the patient's symptoms and it is also helpful to recognize the syndrome. For example, a patient in delirium may suffer from the syndrome of heat disturbing heart-mind while a patient with halitosis may suffer from the syndrome of many questions that are less related to the patient's diseases usually lead the patient to tell some secondary symptoms which will sometimes increase the difficulty of syndrome differentiation. In general, the number of questions should not exceed 7 during an inquiry case. However, it is usually hard to identify the closely related questions for most difficult and complication diseases. How to design an automatic question and answering system that could identify questions closely associated with the patient's diseases is a challenging issue. Li et al. [16] presented a dialog generation system using the deep reinforcement learning model in 2016. An automatic question and answering system can be viewed as a special dialog generation system. So, the deep reinforcement learning models such as the deep Q- network and the deep Q-learning are potentially used to design such an automatic question and answering system for computer- aided syndrome differentiation in smart Chinese medicine framework.

When a patient uses the camera that may be an independent one or inside any edge device to take his/her tongue picture, the picture will include the background such as his/her mouth or face. Such the background will increase data traffic on the network, and more importantly it will disturb the syndrome differentiation as the noise. Thus, a tongue localization algorithm should be embedded the edge layer for exacting the tongue image or removing the background. Recently, deep reinforcement learning has achieved state- of-the-art performance for tackling the problem of object localization. Furthermore, it has been used for landmark detection in medical imaging data.



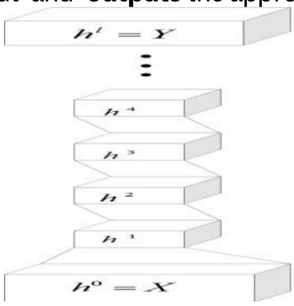
For instance, Ghesu et al. [19] applied the deep reinforcement learning model to anatomical landmark detection on 2D magnetic resonance images. Therefore, the deep reinforcement learning model is the most promising model for the task of tongue localization in the smart Chinese medicine framework [20].The cloud layer is responsible for syndrome differentiation and prescription recommendation. Syndrome differentiation is achieved by two tasks, i.e., syndrome recognition and the main accompanied symptoms recognition, based on the symptoms data and tongue image uploaded from the edge layer. Specially, syndrome recognition can be viewed as a classification problem that takes the symptoms and the tongue image as input and outputs the patient's syndrome as the class label. For example, a patient with the symptoms of aversion to cold, rigidity of nape and headache, and anhidros is suffers from the syndrome of cold pathogen of Taiyang. When a patient with hypertension feels vertigo and headache, he/she suffers from the syndrome of liver qi stagnation. In the past ten years, deep learning has shown its promising results for the task of classification in image recognition and natural language processing and thus it is the most potential for syndrome recognition. However, the symptoms data and the tongue image are heterogeneous. It is difficult for the traditional deep learning models to classify the heterogeneous data since they are initially designed for singe type of data feature learning [21], [22]. Recently, multi-modal deep learning models have been proposed for multi-modal data feature learning. A representative example is multi-modal deep Boltzmann machine which was presented by Srivastava and Salakhutdi- nov [23] to learn features on bimodal data that is composed of text and images. Ngiam et al. [24] proposed a bimodal deep auto-encoder for feature learning on bimodal data with image and audio. Specially, Fig. 2 shows an example of the multi-modal deep learning model.

MULTI-MODAL DEEP LEARNING MODEL

More recently, Zhang et al. presented a deep computation model which generalizes the deep learning models with tensor-based big data representation for heterogeneous data feature learning.

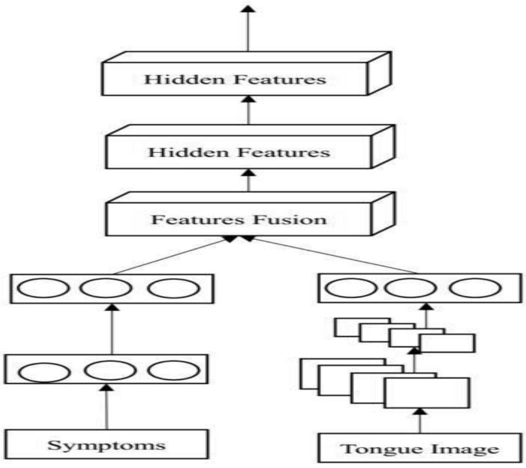
EXAMPLE OF THE DEEP COMPUTATION MODEL

Multi-modal deep learning models and deep computation models have achieved state-of-the-art results for the tasks of feature learning and classification for heterogeneous data, and therefore they are promising for syndrome recognition in smart Chinese medicine. Specially, multi- modal deep learning models learn the features of each modality and then construct a joint representation for each multi- modal object by concatenating the learned features. However, multi-modal deep learning models do not achieve the desirable results sometimes since they cannot capture the correlations over the different modalities effectively by concatenating the learned feature in a simply linear way. To address this problem, we present a multi-modal deep computation model for syndrome recognition by combining the ideas of multi-modal deep learning models and deep computation models in this paper. Specially, we use the outer product to concatenate the learned features to construct a feature tensor for each object, which will be described in next section. Re-organization can be viewed as a multi-step decision- making problem. In detail, one Chinese medicine is decided to be added and/or removed in each step. Deep reinforcement learning is especially good at solving the problem of continuous decision- making and it has achieved remarkable results in recent years [26]. For example, it has achieved considerable level in some The ultimate goal of the cloud layer is prescription recommendation. This goal can also be achieved by two tasks, i.e., prescription selection and prescription re-organization. To select the most appropriate prescription, a deep learning model that takes the patient's syndrome and the main accompanied symptoms as input and **outputs** the appropriate prescription is required to train.



Specially, the prescription selection depends on both the patient's syndrome and the main accompanied symptoms. For example, mahuang decoction should be selected to give the patient with the syndrome of cold pathogen of Taiyang. However, if the patient is accompanied by the symptoms of dysphoria and floating and rapid pulse, guizhi decoction should be selected. Prescription re-organization aims to provide the personalized and patient-centralized treatment plan by adding one or more Chinese medicine into the selected prescription and/or removing one or more Chinese medicine from the prescription based on the patient's primary symptoms ac- companied with the syndrome. For example, a hypertensive patient suffers from the syndrome of liver qi stagnation; he/she should take xiaochaihu decoction. However, when the patient has the symptoms of dry mouth, red urine and red tongue, the stir-baked Cape jasmine fruit should added into xiaochaihu decoction. Specially, prescription computer games as human professional. Specially, a deep reinforcement learning model- based agent, AlphaGo, beat Fan Hui, the European Go champion, five times out of five in tournament conditions. Therefore, deep reinforcement leaning is the most promising model for prescription re-organization. However, how to define the appropriate reward function that is the key in deep reinforcement learning for prescription re-organization poses a big challenge. It requires the in- depth cooperation between medical scientists and artificial intelligence scientists for this problem.

MULTI-MODAL DEEP COMPUTATION MODEL FOR SYNDROME RECOGNITION



In this section, we present a multi-modal deep computation model for syndrome recognition based on the symptoms and the tongue image that are uploaded from the edge layer. The architecture of the presented multi-model deep computation model is shown in Fig. 4. Specially, the hyperbolic tangent function $f(x) = (e^{X}\ e^{-X})/(e^{X} + e^{-X})$ is used as the encoding function. The hyperbolic tangent function has two important properties. First, its range is in (-1,1), as shown in Fig. 5. Second, the derivative of the hyper bolictangent function regarding its argument is $f(x) = 1\ f\ 2(x)$. Afterwards, the decoding function g is used to map the hidden representation to the output layer y:

$$y=g(W^{(2)}h+b^{(2)}), \qquad (2)$$

where the hyperbolic tangent function is employed as the decoding function g as well in the presented model.To train the parameters, an error function $J\theta$ regarding m training instances is defined as:

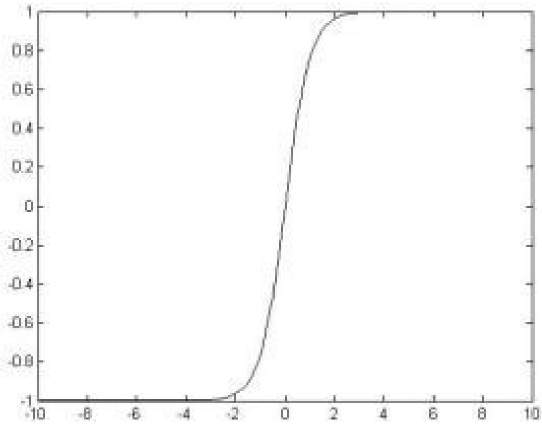


Fig. 5. Graph of hyperbolic tangent function.

Learn features of the patient's symptoms. Specially, the stacked auto-encoder can be trained by two auto-encoders from bottom to up. In each auto-encoder, the hidden representation h is obtained by the encoding function f . In the experiments, each model was trained for five times and the parameters were initialized differently every time so that the robustness of the presented model can be evaluated.

ARCHITECTURE OF THE MULTI-MODAL DEEP COMPUTATION MODEL

The multi-modal deep computation model is made of three components, i.e., a stacked auto-encoder, a convolutional neural network and a deep computation model. The stacked auto-encoder that is made of an input layer and two hidden layers is used to typically; the gradient descent method with the back- propagation algorithm that is used to compute the partial derivatives is employed to train the parameters for minimizing the error function $J\theta$, described in Algorithm 1. Specially, the forward propagation for calculating the output of each unit in the network is on lines 3-8 while the back propagation for calculating the partial derivatives is on lines 10-21. Finally, the gradient descent method is on lines 22-23 for updating the parameters.

EXPERIMENT

In the experiment, we validate the presented model (MD- CM) by comparing with the stacked auto-encoder (SAE) and the multi- modal deep learning model (MDLM) for syndrome recognition of hypertension and code in terms of classification accuracy on two Chinese medical datasets. Specially, the experiments were conducted using MATLAB on the Think Server with 6-cores, 2.4GHz Intel E5-2620V3 CPU and 64GB DDR memory. The first Chinese medical dataset consists of 400 training instances and 100 test instances of patients with hypertension. Specially, hypertension is divided into five types of syndrome, i.e., liver qi stagnation, liver fire flaring up, upper hyperactivity of liver yang, deficiency of both yin and yang, and abundant phlegm-dampness.

The classification results with each initialization are displayed. Such the experimental results indicate that the presented model can learn the joint representation more effectively than the multi-modal deep learning model. The stacked auto-encoder performed the worst since this model did not take the features of the tongue image into account. Such the results indicate that the tongue inspection is very important to the syndrome differentiation. However, the stacked auto- encoder could still obtain relatively good classification results (e.g., greater than 80%) according to the inquiry data, implying that inquiry is the most important to the syndrome differentiation for computer-aided diagnosis. The experimental results demonstrated the potential of the presented model for syndrome recognition of hypertension in smart Chinese medicine. The second dataset consists of 400 training instances and 100 training instances of patients suffering from cold. Cold is divided into two main types of syndrome, i.e., cold pathogen of Taiyang and affection of Taiyang by wind.

Summarizes the primary symptoms of each type of syndrome of cold. Presented model performs better than the other models in terms of the worst accuracy, the best accuracy, and the mean accuracy. Specially, for each initialization, the presented model could obtain the classification accuracy greater than 90%, implying that the presented model is more robust than the other two models. Moreover, the presented model produced 2.2% and 3% higher mean accuracy than the multi-modal deep learning model and the stacked auto- encoder, respectively. Such the results demonstrate the potential of the presented model for syndrome recognition of cold.

However, only distinguishing the cold pathogen of Taiyang and affection of Taiyang by wind is not enough for prescription recommendation in clinical practice. Generally, mahuang decoction should be chosen to treat the cold pathogen of Taiyang while guizhi decoction should be chosen to treat the affection of Taiyang by wind. However, when a patient with the cold pathogen of Taiyang is suffering from the deficiency of healthy qi, the mahuang decoction should not be used. In this case, the guizhi decoction should be chosen. Therefore, the presented model will be validated for detailed syndrome differentiation in the future work. Finally, we compare the training time and the inference time of the three models on the two Chinese medicine clinical datasets. To present the results more clearly, the training and inference time is normalized regarding the highest training and inference time. Table 6 and Table 7 present the average training time and the average inference time of the three models, respectively.

CONCLUSION

Recently, some healthcare and medical systems have e-merged to provide personalized, pervasive, and patient-centralized healthcare. Specially, smart Chinese medicine has more recently been proposed to contribute the evolution of healthcare 4.0. In this paper, we presented a unified smart Chinese medicine framework based on an edge- cloud computing system to integrate the advanced machine learning models including deep learning models and deep reinforcement learning models into the traditional Chinese medicine. The objective of the framework is to provide computer-aided syndrome differentiation and prescription recommendation in Chinese medicine clinic practice.

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