HUMAN HEARING DISORDER RECOGNITION MODEL USING EEG-AEP BASED SIGNAL

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SUPERVISOR'S DECLARATION

I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Master of Science.

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STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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ABSTRAK

Kekurangan pendengaran adalah gangguan deria yang tersebar luas di seluruh dunia dan menghalang pembelajaran dan komunikasi manusia. Teknik yang sesuai untuk menangani isu ini adalah diagnosis pendengaran awal yang tepat menggunakan elektroensefalogram (EEG). Modaliti yang paling signifikan untuk mendiagnosis kekurangan pendengaran dalam kalangan isyarat kawalan EEG adalah potensi yang dibangkitkan pendengaran (AEP) yang dihasilkan di bahagian kortikal otak melalui rangsangan pendengaran. Kajian ini bertujuan untuk membina sistem pintar untuk diagnosis kekurangan pendengaran. Pertama, lima belas kaedah pengekstrakan ciri digunakan untuk mengekstrak maklumat daripada ciri-ciri AEP mentah. Kemudian, ciri yang diekstrak dikelaskan menggunakan pembelajaran mesin dan algoritma pembelajaran mendalam. Prestasi pendekatan yang dicadangkan telah disahkan menggunakan set data percubaan yang dikumpul (UMP-Emotiv-AEP) dan set data AEP yang tersedia secara umum. Dalam kajian ini, model pembelajaran mendalam (penambahbaikan-VGG16) direka untuk mengesan kekurangan pendengaran. Untuk meningkatkan reka bentuk VGG16, beberapa lapisan model asas VGG16 telah digantikan dengan lapisan baru dalam blok yang bersambung sepenuhnya. Di samping itu, semasa latihan model yang dicadangkan, beberapa lapisan convolutional model asas VGG16 telah dibekukan di mana model menggunakan berat pra-terlatih. Seterusnya, teknik penalaan halus telah digunakan untuk lapisan yang tinggal agar sesuai dengan set data dengan model VGG16 yang dipertingkatkan yang dicadangkan. Kajian ini juga menyiasat dua algoritma pembelajaran mesin konvensional: mesin vektor sokongan (SVM) dan jiran terdekat k (KNN), dan dua teknik pembelajaran mendalam: rangkaian neural konvolusi (CNN) dan model VGG16 yang dipertingkatkan. Antaranya, cadangan transformasi wavelet berterusan (CWT) dengan seni bina VGG16 yang dipertingkatkan menunjukkan prestasi cemerlang untuk diagnosis kekurangan pendengaran. Di sini, CWT digunakan untuk menukar isyarat AEP mentah kepada imej frekuensi masa. Dua jenis isyarat AEP dikumpulkan menggunakan peranti wawasan Emotiv lima saluran (UMP- Emotiv-AEP) yang direkodkan daripada sepuluh subjek. Tiga analisis eksperimental telah dijalankan dengan UMP-Emotiv-AEP, reka bentuk yang dicadangkan menunjukkan peningkatan yang ketara dengan ketepatan ujian 99.90%. Reka bentuk yang dicadangkan mencapai peningkatan ketepatan 2.09% dan 0.32% berbanding dengan pendekatan KNN dan CNN. Kedua, set data yang tersedia secara umum digunakan, iaitu dikumpulkan dari enam belas subjek. Tiga analisis eksperimental telah dijalankan dengan set data yang tersedia secara umum, manakala reka bentuk yang dicadangkan mengatasi kajian canggih dengan peningkatan ketepatan klasifikasi kepada 96.87%. Reka bentuk yang dicadangkan mencapai peningkatan 1.58% dan 1.66% berbanding prestasi pendekatan SVMs. Hasil eksperimen menunjukkan bahawa pembelajaran mesin tradisional dan algoritma CNN mencapai ketepatan yang lebih rendah daripada model yang dicadangkan. Selain itu, kajian ini telah menghasilkan antara muka pengguna grafik (GUI) yang mesra pengguna. Prestasi pendekatan yang dicadangkan menunjukkan bahawa ia dapat menangani tindak balas AEP secara signifikan untuk diagnosis kekurangan pendengaran.

ABSTRACT

Hearing deficiency is the most prevalent sensory impairment worldwide, impeding human learning and communication. The appropriate technique for dealing with this concern is an early and accurate hearing diagnosis using an electroencephalogram (EEG). The most significant modality for diagnosing hearing deficiency among EEG control signals is the auditory evoked potential (AEP), which is generated in the cortical region of the brain through auditory stimulus. This study aims to build an intelligent system for hearing deficiency diagnosis. Firstly, fifteen feature extraction methods were used to extract information from the raw AEP features. Then, the extracted feature was classified using machine learning and deep learning algorithms. The performance of the proposed approach was validated using the experimental collected dataset (UMP-Emotiv-AEP) and well-known publicly available AEP datasets. In this study, a deep learning model (improved-VGG16) was designed for detecting hearing deficiency. To improve the VGG16 architecture, some layers of the based VGG16 model were replaced with new layers in the fully connected block. Additionally, during the training of the proposed model, some convolutional layers of the base VGG16 model were frozen where the model used the pre-trained weights. Next, the fine-tuning technique was used for the remaining layers to fit the dataset with the proposed improved-VGG16 model. This study investigated two conventional machine learning algorithms: support vector machine (SVM) and k-nearest neighbors (KNN), and two deep learning techniques: convolutional neural network (CNN) and improved-VGG16 model. Among these, the proposed continuous wavelet transforms (CWT) with improved-VGG16 architecture showed outstanding performance for hearing deficiency diagnosis. Here, the CWT was used to convert raw AEP signals into time-frequency images. Two types of AEP signals were collected using a five-channel Emotiv insight device (UMP- Emotiv-AEP), recorded from ten subjects. Three experimental analyses were conducted with the UMP-Emotiv-AEP, the proposed architecture showing a significant improvement with 99.90% testing accuracy. The proposed architecture achieved a 2.09% and 0.32% improvement in accuracy compared to the KNN, and CNN approaches. Secondly, a popular publicly available dataset was used, collected from sixteen subjects. Three experimental analyses were conducted with the publicly available dataset, whereas the proposed architecture outperformed the state-of-art studies by improving the classification accuracy to 96.87%. The proposed architecture achieved a 1.58% and 1.66% improvement over the performance of the SVMs approach. The experimental outcomes demonstrated that traditional machine learning and CNN algorithms achieved comparatively lower accuracy than the proposed model. Additionally, this study developed a user-friendly graphical user interface (GUI). The proposed approach’s performance indicates that it can significantly deal with AEP response for hearing deficiency diagnosis.

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